Moral Hazard in Natural Disaster Insurance Markets: Empirical evidence from Germany and the United States

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Abstract

Moral hazard in natural disaster insurance markets has the effect that policyholders prepare less for disasters, which increases the risk they face. However, moral hazard may not arise due to high risk aversion of insured individuals and/or the inherent insurance market context. We offer a comprehensive empirical study of the relation between disaster risk reduction and insurance coverage to assess the presence of moral hazard in two different natural hazard insurance markets. Four econometric models are applied to data from field surveys targeting two different natural hazard insurance markets in Germany and the United States. The results show that moral hazard is in general absent. Nevertheless, evidence for the presence of adverse risk selection is presented because we find that insured households experience higher damage from floods due to a more severe flood hazard. This has significant public policy relevance regarding the existing market structures for natural disaster insurance, such as opportunities for strengthening the link between insurance and risk reduction measures.

Keywords: Deductible; Flood insurance; Moral hazard; Natural disaster insurance; Private marketization; Risk selection.

JEL codes: Q54.

I. Introduction

Over the last several decades the economic damage from natural disasters, and floods in particular, has been increasing, and this trend is likely to continue (IPCC, 2012; Munich Re, 2013). The trend of increasing disaster losses could place pressure on private and public budgets, and society as a whole, if the risk posed by disaster events is not prepared for.

Insurance plays an important role in managing natural hazard risks and promoting recovery from disasters. It reduces financial risks by spreading risk over many policyholders, helps people to "get back on their feet" after a disaster occurs and pre-funds disaster losses by collecting premiums (Botzen, 2013). Moreover, insurance can also provide incentives for risk reduction by acting as a price signal of risk, or by providing premium discounts to policyholders who protect their property against disaster damage (Kunreuther, 1996).

On the other hand, insurance coverage may result in an increased vulnerability to natural disasters, if insured individuals take fewer measures to limit risk because they expect that insurers will compensate their damage irrespective of their risk reduction efforts (Ehrlich and Becker, 1972; Arnott and Stiglitz, 1988). The possible negative relationship between risk reducing measures and insurance can be viewed as giving rise to moral hazard because the possession of insurance coverage can directly reduce the incentive to employ risk-reducing measures (Ehrlich and Becker, 1972). Moral hazard poses problems if the resulting behavior cannot be observed by the insurer, meaning that increased risk risk-taking is not completely reflected in a higher insurance premium (Chiappori and Salanie, 2000). The presence of moral hazard would result in insured individuals suffering greater losses during natural disaster events. A moral hazard effect combined with the strong likelihood that the magnitude of extreme weather events will increase may result in an increasing reliance on government or charity schemes when the societal costs of natural disasters increase. A further problem that can arise is adverse risk selection, which obstructs the adequate functioning of natural disaster insurance markets if it is mainly individuals who face a high risk who hold insurance (Akerlof, 1970; Rothschild and Stiglitz, 1976).

Cohen and Siegelman (2010) conducted a comprehensive review of empirical studies of adverse risk selection and moral hazard effects in the following insurance markets: automobile, mortality risk, long-term care, crop, and health. Cohen and Siegelman (2010) found mixed results and concluded that whether or not adverse risk selection and moral hazard effects arise depends on individual insurance market characteristics, such as whether policyholders have private risk information or not.

Moral hazard may not be an issue if insurance purchase decisions are mostly driven by risk aversion, and if the highly risk-averse agents who purchase insurance also take other precautionary measures that limit risk (de Meza and Webb, 2001; Cohen and Siegelman, 2010). Such effects have been extensively researched for health insurance markets. Several of these studies show that adverse risk selection or moral hazard is present (Sloan and Norton, 1997; Finkelstein et al. 2005; Courbage and Roudaut, 2008; Almond and Doyle, 2011; Anderson et al., 2012), although there are studies that argue the opposite (Cardon and Hendel, 2001; Finkelstein and McGarry, 2006; Cutler et al., 2008; Einav et al., 2013). For example, Finkelstein and McGarry (2006) arrived at an opposite finding to that of a moral hazard effect since individuals with health insurance in the U.S. take more measures to reduce health risks than uninsured individuals, which may be explained by risk aversion (Dionne and Eeckhoudt, 1985). Likewise, Cutler et al. (2008) found that those individuals who engage in less risk-reducing behavior (which would result in moral hazard) are less likely to have life, acute health, long-term care, and Medicare supplemental insurance, as well as annuities. Cutler et al. (2008) proposed that this finding arises due to differing risk preferences, in part resulting from different degrees of risk aversion, between insured and non-insured individuals. Therefore, it is hardly predictable whether moral hazard is present in an insurance market. The potential ambiguity of a moral hazard effect makes it difficult to distinguish whether the results found are due to the specific statistical test or study region, or are a generalizable feature of the natural disaster insurance market.

The main objective of this study is to investigate whether the patterns of natural disaster insurance purchase and risk reduction decisions are consistent with what the presence of moral hazard would imply. We conducted an empirical analysis of field survey data to examine the relation between individual disaster risk reduction and insurance coverage in natural disaster insurance markets in the U.S. and Germany. The key finding of this study is that decisions to reduce natural disaster risk and to buy insurance are mainly and jointly driven by internal (behavioral) characteristics of individuals. Moreover, the absence of moral hazard may be a general feature of natural disaster insurance markets due to the consistency of our model results across very different insurance market contexts.

Since the presence of moral hazard is dependent on the features of the market and the particular risk (Cohen and Siegelman, 2010), it is important to examine two markets that have different risk profiles as well as economic and political contexts, which we have done. Our methodological approach is based on the wider overall literature (see e.g. Cutler et al., 2008; Chiappori and Salanie, 2000) and unlike that used in previous natural disaster studies focused primarily upon moral hazard. By providing such a focused and systematic empirical analysis of the presence of moral hazard in two different natural disasters insurance markets, we advance the relatively small amount of existing literature investigating general relations between natural disaster insurance and risk reduction (e.g., Thieken et al., 2006; Carson et al., 2013; Petrolia et al., 2015; Osberghaus, 2015).

For instance, our analysis of the German flood insurance market focused on floodplain inhabitants for whom it is more relevant to examine moral hazard effects than for a national sample such as that used by Osberghaus (2015). It is these households that primarily face flood risk, and they are most strongly exposed to the incentives to buy insurance and employ or not employ risk reduction measures. From an insurance company perspective, it is especially important to know whether floodplain inhabitants who face a high flood risk still take measures to limit flood damage once they have flood insurance coverage, which we found to be the case. Therefore, the use of actual coverage (and not the perceived coverage as used by Osberghaus (2015), which may deviate from actual coverage rates) is a suitable indicator for assessing moral hazard from the perspective of insurance companies and for deriving relevant policy implications.

Thieken et al. (2006) used simple mean comparison tests to examine whether the number of measures that German households take to prepare for flooding differs between households with and without flood insurance coverage. We improved upon this by jointly modelling the relation between risk preferences, implemented risk reduction measures and having flood insurance. Our methodology allows for determining if there are behavioral characteristics driving both the wish to be insured and employing risk reduction measures. We confirmed the presence of this behavior, which cannot be examined using simple correlations. Moreover, out of all the aforementioned studies we are the first study to use propensity score matching to estimate the degree to which household flood damage is separately influenced by risk and moral hazard. Our analysis found that households with flood insurance suffer larger losses than uninsured households due to their higher hazard level rather than due to moral hazard, which to the best of our knowledge has not been shown before.

Similarly, our U.S. analysis results in new insights by building on the work of Carson et al. (2013) and Petrolia et al. (2015). In order to examine whether decision processes when purchasing wind insurance are related to decisions to take wind damage risk reduction measures, Petrolia et al. (2015) applied mixed probit and tobit models to data from a sample of households living on the Gulf of Mexico. Our analysis for windstorm insurance examined whether the findings of Petrolia et al. (2015) hold more broadly to the U.S. by extending the analysis to different sample areas in addition to the Gulf of Mexico; namely, the mid-Atlantic and Northeastern U.S. In addition to wind insurance, we also examined relations between risk reduction and flood insurance coverage in the U.S., which is a separate insurance market. Our analysis indicates that moral hazard is absent in both the U.S. wind and flood insurance markets in diverse geographic areas. Carson et al. (2013) investigated the influence that windstorm deductibles have on a household's expenditure on, or overall decisions to use, risk-reduction measures in Florida. We extended this analysis by including areas outside of Florida as well as by investigating the relationship between the deductible and the actual number of risk reduction measures employed. Moreover, we examined whether this relationship is non-linear, which turns out to be the case. We also show that a deductible has a very minor influence on risk reduction measures taken, unless the deductible is very high, supporting our main finding that decisions to mitigate risks of disasters are mainly driven by internal (behavioral) characteristics of individuals rather than external incentives.

Lastly, our U.S. data uniquely utilizes real-time survey responses collected while respondents were under the threat of a storm. This technique remedies potential hindsight bias issues present in traditional field surveys conducted months or even years after storms have passed, and when memories of what risk perceptions were before the storm and the process by which preparation decisions were made may have faded.

Overall then, from a policy perspective our results do not support concerns that broader natural disaster insurance coverage would result in fewer risk-reducing activities by policyholders, which is important for informing ongoing policy discussions about reforming natural disaster insurance markets in both countries. An example of a recommendation based on our research is strengthening the use of risk-based insurance premiums, because we find that adverse risk selection may be present, while moral hazard is not. This supports ongoing reforms of the National Flood Insurance Program in the U.S. (such as the Biggert-Waters Flood Insurance Reform Act of 2012 and the Homeowner Flood Insurance Affordability Act of 2014) or the use of a wider range of social incentive mechanisms to stimulate flood preparedness (Section V).

The remainder of this article is structured as follows. Section II provides a theoretical framework and describes the econometric methods used. Section III provides information on the German and U.S. natural disaster insurance markets along with the specific data collection methods used. It shows that understanding the behavior that may lead to moral hazard in the market for natural disaster insurance has important public policy relevance in these countries. Section IV presents the results regarding moral hazard in Germany and the U.S. Section V consists of the conclusion.

II. Theory and methods

Theory

The work of Ehrlich and Becker (1972) provides the theoretical foundation for our investigation. They developed a model of the interaction between market insurance, self-protection (defined as actions that reduce the probability of a claimable event), and self-insurance (defined as actions that reduce the impact of an event). The model shows that market insurance and self-insurance are substitutes for one another. Ehrlich and Becker (1972) found that there is only a small incentive for self-insuring against large losses, as it is preferable to insure these large losses. This assumes that premiums are independent of risk-reduction activities, as is likely to hold. The link between risk reduction and premiums is weak in Europe (Surminski et al., 2015) and the U.S., where in general flood insurance premiums are not linked to household risk reduction other than increasing a household's elevation. Taken together this may produce a moral hazard effect whereby individuals with natural disaster insurance coverage invest less in risk reduction measures.

Dionne and Eeckhoudt (1985) extended the research of Ehrlich and Becker (1972) by investigating the role of risk aversion in household risk-reduction investments. They found that risk aversion is an important factor for self-insurance, which means that highly risk-averse agents are likely to invest more in damage prevention. This is supported by the theoretical work of de Meza and Webb (2001) showing that advantageous selection may occur in insurance markets when very risk averse individuals purchase both insurance coverage and take other measures to reduce their risk.

Moreover, the assumed rationality of individuals in standard models of adverse risk selection and moral hazard may not hold in practice. The literature suggests that individuals most often base decisions on subjective risk, which is generally an underestimation of low-probability/high-impact objective risk (Pahl et al., 2005). Individuals tend to misperceive risk, for example, due to bounded rationality (Kunreuther and Pauly, 2004). Decision processes may also deviate from expected utility theory as, for example, prospect theory predicts (Kahneman and Tversky, 1979).

Moreover, social psychological theories can explain common risk misperceptions. For instance, optimism bias can occur, implying that individuals overestimate the probabilities of pleasant outcomes (Sheppard et al., 2002; Smiths and Hoorens, 2005), while valence effects imply underestimation of bad outcomes probabilities (Rosenhan and Messick, 1966). These effects suggest that individuals do not purchase insurance or take measures to limit damage from natural disasters because such disasters are viewed as unpleasant outcomes.

Additional evidence also suggests that individuals have difficulties assessing low-probability risks or negative risk in general (e.g. Rosenhan and Messick, 1966; Sheppard et al., 2002; Kunreuther et al., 2001; Botzen et al., 2009). Moreover, individuals tend to use favorable and unfavorable information in a manner that results in positively biased views, or comparative optimism (Sharot and Garrett, 2016).

Kahlil (2010) argues that an individual's key convictions form the basis for behavior and are very resistant to updating when more information becomes available. Hence, these convictions may not change when employing risk-reduction measures or buying insurance. This argument is supported by Windschitl et al. (2013) who showed that people select information that support their beliefs and behavior. Additionally, Tyler and Rosier (2009) showed that the degree to which people feel that they are accountable is an important driver of decisions to protect against a hazard. The more autonomy individuals have over natural hazard risk, the more likely that these individuals will invest in risk-reducing measures.

The aforementioned features of the way people process low-probability hazards may translate into poor decision making with respect to natural disaster insurance purchases (Botzen and van den Bergh 2012a,b; Kunreuther et al., 2013). As a result individuals may not buy natural disaster insurance based on objective risk, but rather based on risk preferences (Lindell and Hwang, 2008) or how risk information is processed (Sheppard et al., 2015), both of which are intrinsic characteristics of the individual. This could contradict the standard theoretical economics literature, which predicts that in the absence of linkages between policyholder risk reduction and the premiums charged we should observe that risk reducing measures and insurance are substitutes for one another and that moral hazard occurs. These predictions assume that policyholders are following a traditional economically rational decision making process. However, if the purchase of insurance is driven by risk aversion or other intrinsic motivations the above substitution effect may not occur in practice when the underlying intrinsic motivations are unaffected by the purchase of insurance (Pahl et al., 2005; Sharot and Garrett, 2016).

Overall, it is ambiguous whether characteristics of natural disaster insurance markets in both countries indicate the presence of moral hazard (Section III). The theoretical literature indicates that in the absence of linkages between policyholder-level risk reduction and the premiums charged we should observe that risk reducing measures and insurance are substitutes. Similarly, the theoretical models predicting the presence of moral hazard assume that policyholders are following an economically rational decision process. However, if the purchase of insurance is driven by risk aversion the above substitution effect may not occur in practice, as the underlying risk convictions or feelings of accountability are unaffected by the purchase of insurance (Pahl et al., 2005; Sharot and Garrett, 2016). For instance, the empirical work of Carson et al. (2013) provides evidence in favor of the risk aversion hypothesis of Dionne and Eeckhoudt (1985) and but none in favor of the substitution effects proposed in Ehrlich and Becker (1972).

Insurance penetration rates vary significantly across locations, both in Germany and the U.S., signaling varying risk preferences and levels of risk aversion (Section III). Furthermore, low deductible choices could be due to risk aversion (Carson et al., 2013) also muting moral hazard incentives (Dionne and Eeckhoudt, 1985). Alternatively, deductible levels may be high enough that moral hazard behavior is muted when the deductible level is known, regardless of the policyholder's level of risk aversion.

Our statistical and methodological approach was guided by the approaches taken in previous studies investigating moral hazard in insurance markets. However, here multiple statistical methods were applied across varied market constructs to investigate different aspects of moral hazard and to act as a robustness check. As noted earlier, the presence of moral hazard is theoretically ambiguous and hard to predict; therefore, it is sensible to apply several models to different regions in order to draw a more general conclusion about moral hazard in natural disaster insurance markets, as we aim to do in our study. Several consistent model results over different datasets would indicate that the findings regarding moral hazard in natural disaster insurance is a generalizable feature of voluntary natural disaster insurance markets.

Statistical Method 1: Probit models

For the first set of statistical models we applied a similar approach to Cutler et al. (2008), who investigated the presence of moral hazard and adverse risk selection in health insurance by estimating probit models of simple relations between risk-reducing activities (as a proxy for risk preferences) and insurance. In this study, we estimated probit models that investigate the relation between risk-reducing behavior and natural disaster insurance purchases. Probit models were estimated for both the German and the U.S. datasets. The objective of this analysis was not to arrive at a 'causal' interpretation of the parameters, such as estimating the direct influence of risk reduction behavior on insurance coverage, but instead to establish a general relation between insurance and risk reduction activities.

The overall presence of moral hazard can be investigated by estimating the combined correlation between risk-reduction measures and insurance. This correlation aggregates the various relevant observable and unobservable factors that determine the joint decision process, and allows for detecting the overall moral hazard signal. In particular, an insurance disincentive (moral hazard) that systematically outweighs the risk aversion effects across the sample population should result in a negative overall combined correlation. Moreover, the theoretical model developed by Ehrlich and Becker (1972) that we tested here implies a simple negative relation between insurance and risk reduction activities since these are substitutes.

Statistical Method 2: Bivariate probit models

The second set of statistical models was drawn from Chiappori and Salanié (2000) who modeled the joint decision process of risk reduction and insurance uptake. Chiappori and Salanié (2000) applied a bivariate probit model approach to investigate the presence of moral hazard. The bivariate approach jointly estimates two probit models of risk-reduction measures and insurance uptake, which allows for estimation of the cross correlation (*rho*) between the error terms of the two probit models. A statistically significant *rho* indicates the two equations are dependent in the sense that the error terms of the equations are correlated. Therefore, the estimated *rho* is an estimate of the unobserved relationship between having insurance and carrying out risk-reducing measures and the key indicator of moral hazard[i].

The use of bivariate probit models also allows for circumventing the potential problem of endogeneity, as the dependent variables are excluded from the opposing regression, resulting in each decision being treated as “seemingly unrelated” to the other (Petrolia et al., 2015). A statistically significant negative *rho* implies moral hazard which is consistent with the theoretical prediction that insurance and self-insurance (or self-protection) are substitutes, while a statistically significant positive *rho* indicates advantageous selection based on an unobserved relationship. Our application of the Chiappori and Salanié approach jointly estimates a probit model of insurance uptake and a probit model of employing a risk reduction measure.

Statistical Method 3: Propensity Score Matching

The third approach applies propensity score matching (PSM) to the German data (for more details see Appendix A or Rosenbaum and Rubin, 1983). Our PSM approach is in line with other studies that use matching methods to investigate moral hazard in insurance markets (e.g., Barros et al., 2008). It is also similar to the studies reported in Cohen and Siegelman, (2010) that exploit natural experiments in order to detect moral hazard and adverse risk selection in damage outcomes. The PSM results provide evidence of effects on damage of possible adverse risk selection and risk-reducing behavior by insured households, which can lead to moral hazard and adverse risk selection. The presence of aspects of adverse risk selection should mean that those with insurance should suffer a greater degree of damage than those without insurance, while moral hazard could be the result of behavioral change resulting in a greater degree of vulnerability and greater damage suffered during an event.

Statistical Method 4: Sample selection models and the influence of deductibles

In the fourth and final approach we used the U.S. data to investigate the effect of known deductible levels on the likelihood of undertaking any short- or long-term preparation activities. We undertook three separate statistical estimations. First, a Heckman sample selection model (Carson et al., 2013) was used to control for endogeneity in a similar manner to that employed by Petrolia et al. (2015). Moreover, this model builds upon Carson et al. (2013) by examining the potential for a non-linear relationship between the deductible and the number of behavioral risk-reducing measures employed. Second, a probit model of the likelihood of having window protection in place was applied. Third, another probit model estimated the likelihood of having done any other risk reduction. The purpose of these last two models is to investigate whether there is a non-linear relationship between the deductible and the specific preparation actions of a household.

III. Natural disaster insurance markets in Germany and the U.S., and the datasets

Natural disaster insurance is available in both Germany and the U.S.; however, the context in which insurance is offered differs markedly between the two countries. The difference in market structures results in different implications for both the potential role and the occurrence of moral hazard due to, for instance, differences in premium pricing rules, which is why the two market structures are discussed next.

Flood insurance market in Germany

The German flood insurance market is based on free market provision and voluntary purchase (Keskitalo et al., 2014). The German government can also provide ad hoc compensation after a major flood event. Flood insurance is often provided as bundled coverage with other natural hazard risks as a supplement to regular building or contents insurance (Keskitalo et al., 2014; Seifert et al., 2013).

Flood insurance premiums are to a certain extent differentiated on the basis of flood probability. The Zürs flood zoning system uses four zones of flood probabilities ranging from 1 (less than 1/200 chance of flooding) to 4 (greater than 1/10 chance of flooding) (GDV, 2008). Moving from zones 1 to 4 entails an increase in premiums (Seifert et al., 2013). The majority of households are located in zone 1, 10–12% are in zone 2, and just 3% of households live in zones 3 and 4 (GDV, 2008). Deductibles are set as either a percentage of the damage suffered or as a percentage of the value of the insured property (Schwarze et al., 2011).

The market penetration rate of flood insurance in Germany has increased strongly in recent years. The penetration rate has grown over approximately 10 years to 19% and 33% for contents and residential buildings, respectively, (GDV, 2013) from between 3% and 10%, respectively (GDV, 2003). The national average hides large regional differences in penetration rates (Seifert et al., 2013). For instance, 95% of households are estimated to have flood insurance in Baden-Württemberg, but only 11% in Bremen (Keskitalo et al., 2014). Overall, East Germany is estimated to have higher penetration rates than West Germany, due to a history of compulsory flood insurance in the East. It has been argued that adverse risk selection is one of the reasons for the observed low market penetration of flood insurance in some areas, which has resulted in calls for introducing mandatory flood insurance coverage (Schwarze and Wagner, 2007; Seifert et al., 2013).

Thieken et al. (2006) conducted surveys of German insurance companies and households in flood-prone areas in 2002, in order to examine characteristics of flood insurance policy conditions in Germany, and whether flood insurance provides incentives for risk reduction. This survey revealed that deductibles were not dependent on the Zürs zoning system. Thieken et al. (2006) found that flood insurance deductibles in Germany ranged between €500 and €5,000. These deductibles provide a small incentive for taking risk-reducing measures; namely, an expected loss of between €2.50 and €25 in areas with a flood probability of 1/200. Deductibles and premiums were also found not to be dependent on flood risk-reduction measures implemented by policyholders (Thieken et al., 2006)[ii].

Windstorm and flood insurance in the U.S.

In the U.S, a standard multi-peril homeowners insurance policy is normally required as a condition for a mortgage. These policies cover damage from fire, wind, hail, lightning, and winter storms, among other common non-catastrophe perils (Czajkowski et al., 2012). Although catastrophe perils are covered in the standard homeowners insurance policy, in highly hazard-prone areas of the U.S. some of these perils are subjected to separate deductibles that are generally a percent of the insured value of the home. For example, both hurricane deductibles and more general windstorm deductibles are applied in hurricane and wind-prone areas of the U.S. Percentage deductibles generally vary from 1% to 15% of a home's insured value, depending on the risk faced (Insurance Information Institute, 2014).

Nineteen states in the U.S. have hurricane deductibles, including the states of Alabama, Delaware, Louisiana, Maryland, Mississippi, New Jersey, New York, North Carolina, and Virginia, where our U.S. survey respondents were situated (Insurance Information Institute, 2014). The deductibles help, potentially, to avoid moral hazard, but may substantially lower the attractiveness of the insurance for consumers (Carson et al., 2013).

Whether these deductibles can be applied in the case of recent major events, such has Hurricane Irene and Sandy, has been a contestable legal issue (Pomerantz and Suglia, 2013). It is, therefore, of interest to examine whether moral hazard is a major issue in the U.S. natural disaster insurance market, and whether deductibles are effective overall in stimulating policyholders to mitigate risks, as is being studied here.

While standard U.S. homeowners insurance covers a number of catastrophe perils, coverage for flood damage resulting from rising water is explicitly excluded in homeowners insurance policies (Michel-Kerjan et al., 2015). Since 1968 the National Flood Insurance Program (NFIP), administered by the U.S. Federal Emergency Management Agency (FEMA), has been the primary source of residential flood insurance in the U.S. (Michel-Kerjan, 2010, Michel-Kerjan and Kunreuther, 2011). The NFIP was developed in 1968 because ever since the severe Mississippi floods of 1927 the private insurance industry believed flood risk was uninsurable. This was due to adverse risk selection, the possibility of massive losses, and the inability to correctly price the product stemming from the level of sophistication in hazard assessment in the 1960s (Michel-Kerjan et al., 2015). As of January 1, 2014, there were 5.47 million NFIP policies in force nationwide, which generated $3.53 billion in premiums for a total of $1.28 trillion under coverage. Less than 5%, approximately, of total flood insurance coverage is provided by private insurers (Michel-Kerjan et al., 2015).

To set premiums and support local governments, the NFIP maps participating communities by designating flood risks through different flood zones on the flood insurance rate maps (FIRMs) (Michel-Kerjan et al., 2015). A building that was in place before the mapping of flood risk was completed in that area is often given subsidized rates, while homes built after the risk mapping are charged premiums reflecting FEMA's flood maps. Around a quarter of properties are still subsidized today (Michel-Kerjan et al., 2015). Premiums are determined using the actuarial rate formula, which is focused on the high-risk A and V 100-year flood zones[iii] (Michel-Kerjan et al., 2015).

Federal law requires property owners in these 100-year floodplains with a mortgage from a federally backed or regulated lender to purchase flood insurance. Despite the mandatory purchase requirement, due to weak enforcement take-up rates are typically low (50% or less), especially in non-coastal areas (Dixon et al, 2006; Czajkowski et al, 2012). Take-up rates can vary substantially depending upon location (Dixon et al., 2006). FEMA rates also vary depending on the elevation of the first floor of the dwelling in relation to the 100-year return flood event. However, FEMA does not collect elevation information for many of the insured houses (Michel-Kerjan et al., 2015). Michel-Kerjan et al. (2015) show that the NFIP's overall pricing strategy leads to important divergences from the true risk for a number of residents covered by the program. Rates are not risk-based at the individual level (probabilistically defined), so prices might be too high in some areas and too low in others.

The NFIP offers deductibles ranging between $500 and $5,000. Michel-Kerjan and Kousky (2010) find that 97% of NFIP policyholders choose deductible levels of $1,000 or less. Finally, to encourage risk reduction, the NFIP operates the Community Rating System (CRS), a voluntary program that rewards communities that undertake mitigating activities with premium discounts, depending on the level of actions taken. However, the risk-reduction emphasis of the CRS program is at the community level, not the individual policyholder level.

There have been recent calls for reform of the NFIP, including more private market involvement (Michel-Kerjan and Kunreuther, 2011). One example is the 2016 committee-approved House of Representatives legislation aimed at promoting private insurers to enter the flood insurance market (the Flood Insurance Market Parity and Modernization Act, 2016). Adverse risk selection would be a deterrent in this regard. Moreover, the movement toward risk-based premiums as a part of the recent flood insurance reform acts[iv] is aimed at providing incentives for risk reduction, for which it is relevant to know to what extent insurance acts as a risk reduction disincentive (moral hazard).

Survey data
Germany

The German data were obtained from surveys carried out in the Elbe and Danube river catchment areas in response to flood events occurring in 2002, 2005, and 2006. The sample population was selected by using official data to collect all of the streets that suffered from a flood. The sample population was refined into the experimental sample by drawing a random sample of households from the identified addresses. The survey was conducted as a 30-minute telephone interview directed to the person in the household with the best knowledge about flood damage. The surveys provide approximately 2,000 respondents in total (Kreibich et al., 2011), of which 42% had flood insurance. The high insurance penetration rate is the result of the majority of observations lying in the Elbe catchment area, where the insurance penetration rate is traditionally high. The surveys were intended to ascertain both damage outcomes from the flood and whether a respondent had undertaken precautionary flood risk-reduction measures.

The flood risk-reduction measures taken from the German survey to examine moral hazard were defined as the following dummy variables: water barriers (if mobile barriers to prevent water entering the building are available); adapted building use (if flood endangered floors are used in a low value way); flood-proofed home (if valuable fixed units are avoided as interior fitting in the flood-endangered floors and if water-resistant materials for interior fitting are used); flood risk information (if the household has collected any information about flood protection before or during the flood); flood awareness (if the respondent did know that s/he lives in a flood-prone area); a member of a flood-coping network (the household is a member of a citizens' initiative for the improvement of flood risk reduction and protection).

Following Ehrlich and Becker (1972), the risk reduction measures were split in the following manner: mobile water barriers were considered self-protection measures and adapted building use and flood-proofing were considered self-insurance measures. According to Ehrlich and Becker (1972) there should be a negative correlation with all of the above risk-reduction measures, because at the time of the survey there was no connection between risk reduction and premiums (Thieken et al., 2006), which is still the case across Europe (Surminski et al., 2015).

In order to model subjective risk perceptions a series of proxy variables were created from the survey data. The first is the perceived flood probability, which was derived from answers to a question about how likely a respondent thinks it is that they will be affected by a flood, with answer options ranging from *completely unlikely* to *completely likely* on a 6-point scale. Such an indicator of the perceived flood probability is commonly used for eliciting individual perceptions of flood risk, as described in a review of studies about flood risk perceptions by Kellens et al. (2013). The second proxy for risk perceptions is a dummy for the river catchment area in which a respondent is located. This variable captures differences in risk cultures between East and West Germany, which can influence flood risk reduction behavior. For example, East Germany has a history of compulsory insurance, while this is not the case for survey respondents from West Germany (Seifert et al., 2013). Moreover, this variable controls for an element of objective risk since flood protection standards are higher in the Danube than the Elbe catchment area (Jongman et al., 2014). Previous research has shown that such geographical indicators are important proxies for perceived flood risk (see Botzen et al., 2009). All variables used are described in Appendix A and more detailed information about the surveys can be found in Kreibich et al. (2011).

U.S.

The U.S. data were obtained from field surveys that measured the evolution of coastal residents' risk perceptions and preparation plans as three hurricanes ─ Irene (2011), Isaac (2012), and Sandy (2012) ─ approached the U.S. during the 2011 and 2012 hurricane seasons. The surveys were conducted by phone, and were initiated up to 72 hours before each storm's predicted landfall, and then repeated with different random samples three times a day (morning, afternoon, and evening) until 6 hours before predicted landfall. The survey shifts were timed to allow measures of subjective storm beliefs to be paired with objective storm information carried in the 5 a.m., 11 a.m. and 5 a.m. EDT National Hurricane Center advisories (see Meyer et al., 2014 for further details). Thus, in these studies, perceptions and preparation decisions were notably measured in real time as they were being made by residents threatened by the storms. This real-time approach contrasts with the traditional method of conducting these type of field surveys weeks or even years after storms have past, when memories of what risk perceptions were before the storm and the process by which preparation decisions were made may have faded, and possibly distorted, by hindsight bias.

The surveys for these three storms provided 1,698 respondents in total[v], and include information on whether respondents had a homeowners insurance policy that would pay for damages to one's home resulting from the storm, if they had a separate flood insurance policy, and whether they knew the amount of their insurance policy deductible or would have to look it up. While 86% of total respondents indicated having a homeowners insurance policy, only 32% indicated having a separate flood insurance policy. Answers to these two questions served as our indicator variables for whether a respondent had homeowner's insurance or flood insurance.

We utilized four dummy variables for the behavioral moral hazard measures: preparation (if have respondent has undertaken any of the presented short-term preparation activities); window protection (if answered 'yes' to whether their home has any sort of window protection); risk reduction (if answered 'yes' to whether ever modified their home to reduce the amount of hurricane wind damage other than having window protection); and evacuation plans (if answered 'yes' to whether they plan to evacuate to someplace safer).

Short-term preparation activities identified included whether the respondent purchased supplies for the home such as food, water, and batteries; filled car with gas; filled generator with gas (or readied generator); put up storm shutters; brought in furniture or took other outside precautions; and made reservations or plans in case evacuation is needed.

While only 8% of total respondents indicated not doing any short-term preparation activities, 67%, 78%, and 71% percent did not undertake any window protection, long-term risk reduction, or evacuation plans, respectively[vi]. These measures are self-insurance measures because in the case of hurricanes policyholders can only limit the damage and not the occurrence probability. Ehrlich and Becker (1972) predicted a negative relationship between insurance and these measures, suggesting the presence of moral hazard.

In order to account for an individual's subjective risk perception of the event in relation to undertaking any risk-reducing activities we included a measure of safety perception. Responses to the following question were given on a 0 to 100 scale: "How safe did one feel about staying in your home through the storm, considering both wind and water?" 0 indicated *certain that it will not be safe* and 100 indicated *certain that it will be safe*[vii]. The mean perception of safety values for any one storm were all above 75, indicating that survey respondents felt relatively safe concerning the impending hurricanes.

Respondent location data allowed for spatial geocoding in GIS where respondents were determined to be located in or out of the 100-year floodplain, as well as the distance in miles from the nearest coastline. 21% of survey respondents were located in a 100-year floodplain and the mean distance to the nearest coast for all respondents was 0.99 miles (0.54 miles for those in the 100-year floodplain, 1.11 for those outside), and these two measures served as objective measures of risk in our estimations (correlation of -0.17 and 0.11, respectively, vs. feeling of safety). To control for any previous damage suffered from a hurricane we used a categorical variable of damage = 1 if has ever experienced damage from a hurricane, either while living in their present home or a different home, otherwise damage = 0.

Insurers are often concerned with moral hazard, and one way to offset this is through the use of a deductible. The deductible forces the insured to have 'skin in the game' by making them at least partially responsible for any losses incurred. In the U.S. separate wind and hurricane deductibles ranging from 1% to 15% of the insured value of the home provide a potentially substantial incentive to homeowners. Unfortunately for insurers relying on a deductible to offset moral hazard behavior, our survey data suggest that homeowners are not aware of their deductible amount, or if they are aware, believe it to be relatively low. For example, from our 1,442 respondents who indicated that they have homeowners insurance, 62% did not know what their deductible was[viii]. Furthermore, only 12% believed it to be greater than $1,000. More detailed information on the real-time hurricane survey methodology, data, and specific questions can be found in Meyer et al. (2014).

IV. Empirical Models and Results

Statistical Method 1: Probit models

For both the U.S. and German samples the likelihood of a household having an insurance policy ($\mathbb{P}(insured_i = 1)$ was estimated as a probit model, $\phi(.)$, which is a function of three sets of variable vectors: behavioral measures that reduce risk, measures of subjective risk perceptions, and measures of objective risk as described below; α_n are the estimated coefficients for variable vectors.

$$\mathbb{P}(insured_i = 1) = \phi(\alpha_1 behavioral\ measures_i, \alpha_2 subjective\ risk\ perception_i, \alpha_3 objective\ risk_i) \quad (1)$$

Considering the German sample first, the behavioral measures were the employment of self-protection or self-insurance measures. German subjective risk preferences were modelled through a dummy variable for the catchment area, and whether the individual feels they will not be flooded again. Objective risk measures were if the respondent has been flooded before and is located within a 100-year floodplain[ix]. Following the approach developed by Cutler et al. (2008) for health insurance, a negative correlation between the risk-reducing behaviors and insurance would indicate that moral hazard occurs, while advantageous selection is present if there is a positive correlation.

A similar approach was taken for the U.S. data sample, whereby the behavioral measures include short-term preparation or long-term risk-reduction activities that were undertaken prior to the arrival of an impending hurricane. Undertaking these al measures are hurricane risk reducing in that they could reduce damage to one's property (putting up storm shutters, taking in furniture, permanent modifications to one's home, etc.) or oneself (purchase of food and water supplies, made reservations in case evacuation is needed, plan to evacuate, etc.). A subjective risk perception proxy is how safe one feels in staying in their home throughout the hurricane event; Objective risk is measured as a household's location in or out of a 100 year floodplain, how far they are located from the coast, and previous experience of hurricane damage.

Table 1 provides the results of the estimated German probit model. These results do not provide evidence for the overall presence of moral hazard since the undertaking of two of the three risk reducing measures are not significantly related with the likelihood of having a flood insurance policy, while those households who employed water barriers are 6.4 percent more likely to have flood insurance (the marginal effect). This indicates that the average risk preferences were such to overcome the theoretical disincentive emanating from insurance. Overall, there is no evidence of insured households being more vulnerable to floods. The significant marginal effects of the 3 information variables further complement this finding. These variables show that individuals who were more proactive in understanding and coping with the flood risk that they face are also more likely to have flood insurance. This finding would be in line with the approach findings of Cutler et al. (2008), indicating that these households are more risk averse, which translates into taking a more proactive attitude towards educating themselves about the risk[x].

[Insert Table 1 here]

We expected risk perception to be related to the purchase of insurance, but mixed results were found for the subjective risk variables. This is because the variable for the perceived future likelihood of being flooded was statistically insignificant, while the catchment area proxy for risk cultures and regional risk differences was the single most powerful influence. Two of the risk variables included in this probit model, being located in the 100-year floodplain and being flooded before, are insignificant. These variables are commonly viewed as being important determinants of flood insurance purchases. Their insignificance in this context can be explained by the importance of the risk-reducing al and informational variables that capture individual risk preferences, which outweigh the importance of subjective and objective risk factors. Overall, these probit results provide evidence that suggests that moral hazard is not present in the German flood insurance market, since the proactive actions of a policyholder in mitigating risks are mostly uncorrelated with flood insurance purchases, which is not the relation that theory would suggest.

Table 2 presents the relationship between the lack of undertaking any hurricane risk reducing behavior (self-insurance) and having homeowners (Model 1) and flood insurance coverage (Model 2) in the U.S. The data was pooled across the three hurricanes and controls for unobserved hurricane-specific fixed effects through hurricane dummy variables (Irene, Isaac, Sandy), with Sandy being the omitted category[xi]. The coefficient signs across both pooled Models 1 and 2 indicate that those survey respondents that engage in short- or long-term ex-ante property risk-reducing behavior (preparation, window protection, and risk reduction) were more likely to have homeowners or flood insurance, compared to those who did not engage in these activities. These effects were statistically significant in both models at the 1% and 5% levels. That is, those without homeowners or flood insurance were more vulnerable due to a lack of risk-reducing measures, and thus those that had insurance did not exhibit evidence of an overall moral hazard effect.

For example, for two otherwise average U.S. respondents, the probability of having homeowners or flood insurance for those that engaged in preparation activities was 23 and 12 percentage points higher, respectively, than for those that did not engage in any preparation activities. We see similar statistically significant percentages for those that engaged in window protection, who were 4% and 11% more likely to have homeowners and flood insurance, respectively. Moreover, those that engaged in long-term risk reduction were 12% more likely to have flood insurance as compared to those that did not engage in either risk-reducing activity.

[Insert Table 2 Here]

For both Models 1 and 2, those that had experienced previous hurricane damage were more likely to have homeowners and flood insurance than those respondents that had not experienced hurricane damage, which is statistically significant at the 1% level. While those that are further from the coast were more likely to have homeowners insurance, respondents located in the 100-year floodplain were more likely to have flood insurance. This effect decreases with distance from the coast, as indicated by the negative coefficient sign. Hurricane Isaac respondents were also more likely to have flood insurance than those from Sandy. This finding is likely a remnant from Hurricane Katrina striking the same geographic area as Isaac in 2005, causing massive flooding damage. Lastly, those respondents that engaged in ex-ante personal risk-reducing behavior or have plans to evacuate were less likely to have homeowner's insurance. These results suggest a trade-off in risk aversion to property losses vs. risk aversion to personal harm among our respondents. The results in Table 5 do not indicate the presence of moral hazard in regard to U.S. natural disaster coverage[xii].

The probit models applied to both the U.S. and Germany were estimated with two different datasets with different relevant explanatory variables. Neither set of probit models indicated the presence of moral hazard in either market. This suggests that the absence of moral hazard is a robust finding that is independent of the market features, and may be the result of behavioral characteristics of those who voluntarily buy natural disaster flood insurance.

Statistical Method 2: Bivariate Probit Models

The probit models discussed in the previous subsection were further confirmed by estimating bivariate probit models, based on Chiappori and Salanie (2000). Bivariate probit models were estimated for both the German and the U.S. samples. The likelihood of a household having both an insurance policy and conducting behavioral risk reducing measures as shown in Eq. 2, $\mathbb{P}(insured_{i,1} = 1, behavioral\ measures_{i,2} = 1)$, was estimated as a joint probit model, $\Phi(.)$. This is a function of two sets of variable vectors (as behavioral measures are now a dependent variable): (1) measures of subjective risk perceptions and (2) measures of objective risk as described in the previous section. $\beta_{n,j}$ are the estimated coefficients for variable vectors where j=1 if the individual probit model is estimating the probability of holding insurance, and j=2 if estimating the probability of employing a risk reduction measure. ρ is the correlation between the error terms of the individual probit models.

$$\mathbb{P}(insured_{i,1} = 1, behavioral\ measures_{i,2} = 1) = \Phi(\beta_{1,1} subjective\ risk\ perception_i, \beta_{2,1} objective\ risk\ measures_i, \beta_{1,2} subjective\ risk\ perception_i, \beta_{2,2} objective\ risk\ measures_i, \rho) \quad (2)$$

The variables included in the bivariate models for both the German and U.S. samples follow the same principles as for the probit models described above for the same reasons. The most striking difference between these two sets of models is that the two probit models are jointly estimated. Therefore, there is one model predicting insurance use and another predicting the use of a risk-reduction measure. The use of a risk reduction measure in these models is defined in both Germany and the U.S. as employing one of the household self-protection or self-insurance measures. The new variable of interest is ρ, which is the cross-correlation of probit error terms and can be directly estimated.

The German bivariate probit model was estimated twice: once with the informational variables included and once without. The results are presented in Table 3. It can be argued that the results of the two estimated models support the absence of moral hazard because they show the importance of proactive information gathering. When these information variables are excluded there is a strong positive relation (*rho*) between the models of flood insurance purchases and carrying out risk reduction measures. The proactive information-gathering activities of the insured households implies a higher degree of risk aversion, which outweighs the moral hazard disincentive for protection activities that originate from insurance. Once proactive information gathering activities have been controlled for there is no longer a statistically significant unobserved relationship driving the joint decision process.

[Insert Table 3 Here]

The bivariate probit models for the U.S. sample are similar to the bivariate probit models presented for Germany, in that they estimate the relation between having either homeowners or flood insurance and employing risk-reducing measures. Table 4 shows the estimate of *rho (ρ)* for these bivariate probit models, which is statistically significant. This implies a dependency between the two equations and also that the joint decision process is positively related due to an unobservable relationship. This indicates advantageous selection rather than moral hazard.

[Insert Table 4 here]

In parallel with the previous subsection, the bivariate probit models do not present evidence for moral hazard, due to the lack of a statistically significant negative *rho* estimate (which would indicate a negative relationship between insurance and risk-reduction measures). The results of the bivariate probit models further confirm the absence of moral hazard in voluntary natural disaster insurance markets.

Moreover, we find some evidence for advantageous selection, since the U.S. results show a positive joint dependency between insurance purchases and risk reduction, which suggests that similar behavioral characteristics influence both decisions to insure and to reduce risk. A similar relationship was found for Germany where households that are aware of their flood risk or develop social coping networks were more likely to have both flood insurance coverage and at least one risk reduction measure in place. These results indicate that households with flood insurance have a different mind-set or intrinsic behavior than those without insurance. The bivariate model results confirm that the absence of moral hazard is due to the intrinsic behavior of the households with insurance.

Statistical Method 3: Propensity Score Matching

Our application of PSM is a novel approach to estimating a causal relationship between insurance purchase and damage outcomes. The method follows two steps: The first step refines the control (the non-insured group) and treatment groups (the insured group) to a sub-sample that is strongly comparable with one another with respect to risk defined as vulnerability (susceptibility to damage), exposure (the value of what can be damaged) and hazard (the probability and intensity of an event) (Kron, 2005). The second step compares the damage outcomes of the control and the treatment groups in order to estimate the effects of the treatment, which is in this case having an insurance policy.

The key PSM equation is shown in Eq. 3. It shows that the presence of a behavioral change due to insurance would be detected though an average treatment effect on the treated (ATT) estimate that is significantly different from zero. The ATT is the difference in expected flood damage, *E(.)*, if a household suffers damage while insured ($Flood\ damage_1|Insured = 1$) compared to the damage suffered when not insured ($Flood\ damage_0|\ Insured = 0$). However, as $Flood\ damage_0$ cannot be directly observed, we must use the flood damage suffered by the non-insured population. This potentially introduces a confounding bias (SB) due to risk selection into insurance, which has been filtered out from this ATT. This provides an indication of the importance of risk traits in determining both damage outcomes and insurance purchasing.

$$E(Flood\ damage_1|Insured = 1) - E(Flood\ damage_0|\ Insured = 0) = ATT + SB \quad (3)$$

We report results of five different matching methods in order to provide an informal robustness check. See Appendix A for more details on PSM.

The propensity score matching analysis was applied to Germany and focused on the link between insurance and flood damage outcomes. The matching analysis of flood damage outcomes provides further support for the absence of an overall moral hazard effect. The presence of adverse risk selection or moral hazard would cause systematic differences in these variables between the insured and the non-insured samples. A mean comparison of experienced flood damage between groups of individuals with and without flood insurance reveals that insured individuals in Germany suffered significantly higher flood damage to contents and buildings (Table 5). It can be argued that because a mean comparison contains the ATT and a selection bias (for more details see Hudson et al., 2014) it estimates the combined effect of the risk selection and the al element of moral hazard. Adverse risk selection would be expected to increase damages. The behavioral effect of having insurance coverage is more ambiguous, as insurance could cause individuals to become more lax, or insured individuals may take more risk-reducing measures because they are generally very careful (risk averse). It is thus an empirical issue to estimate whether individuals with flood insurance experience a systematically different level of flood damage than uninsured individuals.

[Insert Table 5 here]

Panel A of Table 6 presents summary statistics of the hazard experience. It shows that an element of adverse risk selection may be present because the treatment group scored higher on various hazard indicators than the control group. In other words, respondents with flood insurance suffered from a worse flood event, as the difference in water levels shows. This suggests that households with flood insurance face a higher flood risk, as the overall shape of the water-level distribution can be argued to be the same across different flood magnitudes, although it is centered at different locations. Furthermore, water level can be considered to be the most important variable of influence on flood damage (DEFRA, 2006; Merz et al. 2010). In conclusion, adverse risk selection may be present in the German flood insurance market, since the insured households faced higher risk than non-insured households, which indicates that higher risk households have a greater incentive to purchase flood insurance coverage. Problems with adverse risk selection can, in practice, be limited by reflecting in insurance premiums the higher flood risks of individuals in floodplains who demand flood insurance.

[Insert Table 6 here]

The PSM estimates can be regarded as providing an indication of the presence of a moral hazard effect, because the method removes risk selection effects on flood damage. The results presented in Table 5 show that the expected difference in flood damage between the groups with and without flood insurance is lower once adverse risk selection has been controlled for using PSM. The latter removed effects on flood damage resulting from risk-related factors that determined whether people purchased flood insurance. The ATT estimates suggest that any al change by insured people does not increase flood risk, because the difference in damage between the insured and non-insured was statistically insignificant. For moral hazard to be present the insured group would have to undertake fewer protective measures, resulting in higher overall damage once adverse risk selection has been controlled for. The results presented in Tables 1 and 3, however, indicate this is not the case.

The summary statistics displayed in Panel B of Table 6 indicate that the insured group was more informed about the risk they face as well as being more likely to be a part of a flood support network. It is also arguable that the insured group is more risk averse than the non-insured group, as every member of the insured group employed at least one of the flood-coping measures indicated in Table 6, while only 56% of the non-insured group did so[xiii]. Therefore, it is possible that the higher level of risk aversion has reduced any negative moral hazard effect.

The previous results are based on data from both the Elbe and Danube River catchment areas; however, there may be differences between these two catchments. For historical reasons, the flood insurance cultures in the two catchment areas have developed differently. The Elbe catchment is mainly located in the former German Democratic Republic (East Germany), where flood insurance was a part of the compulsory insurance policies a household must have. Even now, after the reunification of Germany, a large number of households in that area still have an equivalent set of contracts, while insurance penetration in the former West Germany (including the German part of the Danube catchment) is much lower (Thieken et al., 2006). In order to investigate if the PSM results are being driven by regional effects, the model was estimated first using only the sample of households located in the Elbe catchment area, and then restricted to the Danube catchment. The results of these spilt sample models are presented in Table B1 in Appendix B. These results are broadly similar to the pooled model results, and do not provide evidence of a moral hazard effect after controlling for risk selection into insurance. Moreover, a split sample analysis of the relation between flood risk reduction activities and flood insurance coverage (Table B2) reveals that the positive relation between insurance and risk reduction is stronger in the area where the decision to buy flood insurance is more consciously made (the Danube catchment)[xiv].

The analysis of relations between flood insurance and flood damage outcomes provides an additional confirmation of the absence of moral hazard. The novel finding of the propensity score matching analysis is that the results confirm that German households with flood insurance suffer greater losses during a flood not because insured households prepare less well for floods, but because these households face on average higher levels of flood risk.

Statistical Method 4: Sample selection models and deductibles

Sample selection models and a focused analysis of the role of insurance deductibles was applied to the U.S. data. The purpose was to investigate the deductible's role in the likelihood of undertaking any short- and long-term preparation activities, while controlling for having flood insurance in place, previous hurricane damage experience, the perceived level of safety, and objective measures of risk[xv]. These models were only applied for those respondents who had homeowners insurance.

We undertook three separate statistical estimations pooled across hurricanes, as shown in Eq. 4. The first element of Eq. 4 is a Heckman sample selection model (Carson et al., 2013), where the selection stage is a probit model of the likelihood of undertaking any short-term preparation and the outcome component of the model estimates the effects of the explanatory variables on the actual number of preparation activities undertaken. In the first element of Eq. 4, $E(event\ prep_i|x, short\ term = 1)$ is the expected number of pre-event preparation activities that takes place, given that the household has employed at least one short term preparation measure; ψ is a vector of estimated coefficients for the independent variables; $\lambda\left(\frac{x\gamma}{\sigma_2}\right)$ is the inverse Mills ratio; $\bar{\rho}$ is the correlation between the error terms of the two stages; and σ_1 is the standard deviation of the outcome component.

The second element of Eq. 4 is a probit model of the likelihood of having window protection in place, $\mathbb{P}(Window\ protection_i = 1)$. The third element of Eq. 4 is a probit model of the likelihood of employing preparation measures other than window protection, $\mathbb{P}(other\ measure_i = 1)$. Across all three models four dummy variables for deductibles of various sizes are included ($deductibles_i$).

$$models = \begin{cases} E(event\ prep_i|x, short\ term = 1) = (insurance_i, subjective\ risk\ perception_i, objective\ risk_i, deductibles_i)\psi + \bar{\rho}\sigma_1\lambda\left(\frac{x\gamma}{\sigma_2}\right) \\ \mathbb{P}(Window\ protection_i = 1) = \phi(insurance_i, subjective\ risk\ perception_i, objective\ risk_i, deductibles_i) \\ \mathbb{P}(other\ measure_i = 1) = \phi(insurance_i, subjective\ risk\ perception_i, objective\ risk_i, deductibles_i) \end{cases} \quad (4)$$

Table 7 presents the pooled hurricane results from the Heckman sample selection (Model 1) and probit (Models 2 and 3) estimations.

[Insert Table 7 here]

Similar to the results presented in Table 5, we see little evidence of moral hazard for the insured. In contrast, the likelihood of undertaking any short- or long-term preparation activities, as well as the number of preparation activities undertaken, has a positive and statistically significant relationship with having flood insurance in place. As would be expected, coefficient signs indicate that having experienced hurricane damage in the past, feeling less safe, and living in the 100-year flood plain are generally positively related to undertaking more preparation activities. However, having experienced damage is the only statistically significant variable.

In terms of the deductible coverage, the Model 1 selection stage coefficient value of having a known deductible does not suggest this increases the likelihood of undertaking any preparation activities. From the Model 1 second stage results compared to those having an unknown deductible amount (the omitted category), coefficient signs generally indicate that knowing one's deductible increases the number of preparation activities undertaken, but only knowing that one has a deductible greater than $2,500 was statistically significant. Similarly, from Models 2 and 3, while most coefficient signs on the various deductible levels are positive, only knowing the deductible is $2,500 or greater had a statistically significant impact on the likelihood of undertaking window protection or long-term risk reduction. The lack of statistical significance for any of the deductible variables in the three models, other than for the highest deductible levels (> $2,500) is notable (Carson et al., 2013), especially since only 12% of respondents believe their deductible to be greater than $1,000, if they know it at all. These results indicate the deductible's relative lack of importance in incentivizing short-term preparation or longer-term risk reduction ahead of the hurricane for our insured respondent sample.

A second group of bivariate probit models estimated the joint relationship between a policyholder knowing their deductible and employing a risk-reducing measure (see appendix B, Table B3). The estimated values for *rho* are, for the most part, statistically insignificant, which implies that knowledge of the deductible has not influenced household risk reduction action. These findings suggest that the reasons for engaging in risk-reducing behavior emanate from the individual, and not from an external financial incentive like the deductible.

Summary of overall results

The results of each of the 4 sets of models across both countries indicate that moral hazard is not present in the investigated markets. Each set of model results individually (with the expectation of the propensity score matching set) produced findings that are both internally and externally consistent with the wider literature regarding natural disaster insurance. Each of these findings was reproduced across two countries, several different natural disaster insurance markets, and several statistical methods. Therefore, it does not appear that insured individuals are less likely to employ risk-reducing measures and that, due to our extensive testing, it can be concluded that the absence of moral hazard is a generalizable feature of natural disaster insurance markets. In fact, there is slight evidence for a higher tendency towards self-protection across insured individuals, while there was no systematic difference in the levels of self-insurance. Moreover, we also observed that individuals with flood insurance were more proactively informing themselves about the risk, which suggests that they are more risk-averse, as these households tended to score more highly on the subjective risk preference variables.

These findings taken together are not consistent with the theoretical predictions of Ehrlich and Becker (1972). Overall, there is no evidence for moral hazard. The higher degree of risk aversion may be what is preventing the predicted insurance disincentives from occurring. Moreover, our results confirm that the higher damage suffered during a flood by those with insurance (compared to those without) is a result of higher risk traits rather than al changes resulting in a greater susceptibility to flood damage.

These findings suggest that the reasons for engaging in risk risk-reducing emanate from the individual and not from residual risk incentives, such as the deductible that insurers often employ to prevent moral hazard. This supports the conclusions drawn from the models in the previous subsections.

V. Conclusion

It is often suggested natural disaster insurance can result in moral hazard when individuals with insurance take fewer measures to limit risks. Moral hazard increases the vulnerability of policyholders to natural disasters, and can create problems in establishing well-functioning natural disaster insurance markets. In this research we investigated the overall presence of moral hazard for natural disaster insurance markets in Germany and the U.S., utilizing field survey data.

Results indicate that flood insurance purchases in Germany appear to be insignificantly or positively related with flood preparation activities of households. In other words, a significant moral hazard effect was not observed. Moreover, propensity score matching (PSM) was applied to estimate the influence of adverse risk selection and behavioral changes as a result of having flood insurance on experienced flood damage by households in Germany, a novel approach to the best of our knowledge. The results show that adverse risk selection can occur since households with flood insurance experienced a worse hazard during past flood events in both the Elbe and Danube catchments.

However, flood damage did not differ significantly after controlling for this adverse risk selection effect, meaning that behavioral changes from insurance disincentives have not heightened the vulnerability of insured households to floods, the opposite finding to what the systematic presence of moral hazard would imply. In contrast, individuals with flood insurance in Germany were more likely to have undertaken one of the suggested flood coping measures than uninsured households. This suggests that households with flood insurance are more risk-averse, since they have collected more information about flood risk and are no worse prepared for flooding despite the disincentives emanating from insurance.

The evidence from Germany is complemented by a study of moral hazard in the markets for flood insurance and homeowner's policies that cover wind damage in the U.S. That analysis used real time data on hurricane risk reduction activity and shows that those households that engage in short- or long-term ex-ante property risk reducing behavior are more likely to have homeowner's or flood insurance. This also points towards the opposite of a moral hazard effect. Moreover, respondents have little specific knowledge of their deductible amount, or if they do, believe the amount to be relatively low despite the potentially large amounts due to separate hurricane and/or wind deductibles in these areas. The complementary statistical analysis shows that except for the known highest deductible levels, deductibles have no significant influence on undertaking short or long-term hurricane preparations. This finding extends previous work in this area by providing some evidence for the hypothesis that the positive correlation found in the U.S. between the use of risk reduction measures and having insurance is due to the intrinsic characteristics of the policyholder rather than external incentives.

The key novel finding of this study is that we find that decisions to reduce natural disaster risks and to buy insurance are jointly and mainly driven by internal (behavioral) characteristics of individuals who face low-probability/high-impact events, such as floods or hurricanes. Moreover, the strength of these internal characteristics can be seen through the consistency of the results across the different contexts in Germany and the U.S. The strong degree of consistency suggests that the absence of moral hazard is related to the nature of natural disasters as a low-probability/high-impact event. Such risks are commonly misperceived and individuals often do not use traditional economic rational decision-making models in preparing for low-probability disaster risk. This may imply that the disincentive to invest in risk reduction that emanates from insurance coverage is less important than standard economic theory predicts. Future research can examine whether similar findings hold in other natural disaster insurance markets.

The results of this study have implications for ongoing policy discussions about reforming natural disaster insurance markets in both countries (and further afield). An important finding is that adverse risk selection may be present, while moral hazard is not. Insurers should reflect this higher risk profile of households who demand natural disaster insurance in premiums that reflect the risk that a particular policyholder faces. This supports policy reforms such as recent flood insurance reform acts concerning the National Flood Insurance Program in the U.S. and moving toward risk-based rates, such as the Biggert-Waters Flood Insurance Reform Act of 2012 and the Homeowner Flood Insurance Affordability Act of 2014. Moreover, policies aimed at increasing the uptake of flood insurance among both low- and high-risk groups could be useful for creating a large risk pool and limiting problems with adverse selection.

Future research could examine the effectiveness of social psychological interventions that the government could undertake. Examples include public service announcements and mail campaigns that provide, in simple language, information or reminders about natural disaster risks and the benefit of purchasing natural disaster coverage (Box et al., 2016; Bolderdijk et al., 2012). For example, studies of the effectiveness of communication about flood risk show that communication messages can be effective in increasing risk awareness and demand (at least hypothetical demand) for flood risk reduction measures (Maidl and Buchecker, 2015; de Boer et al., 2015) and flood insurance (Botzen et al., 2013).

Taken together, our results suggest that the absence of moral hazard is an intrinsic trait of insured households. We conclude this on the basis of our findings of the positive joint decision process between risk reduction and insurance and the small influence of insurance policy deductibles (a residual risk incentive) on stimulating risk reduction. This implies that households with a different set of intrinsic traits compared to the insured, such as being less risk averse, would likely not prepare as extensively for natural disaster events.

Our findings support ongoing reforms and debates about using a greater range of incentives to stimulate risk reduction for households who are currently preparing insufficiently for natural disasters (Michel-Kerjan and Kunreuther, 2011; Surminski et al., 2015; Hudson et al., 2016). External (nonresidual risk) incentives may be useful for changing household motivations to prepare for natural disasters, if they do not already do so. For instance, in the U.S. the Disaster Savings and Resilient Construction Act would provide a tax incentive for building in a disaster resilient manner, which may encourage non-insured household to conduct risk-reduction activities. Moreover, policy interventions can also be based around the use of social network effects, such as normative feedbacks, social priming, and creating social norms to increase the level of self-protection before and after flood events (see e.g. Nolan et al., 2008; Parker et al., 2009; Becker, 2010; Eiser et al., 2012; Bolderdijk et al., 2012; van der Linden et al., 2015; Cheng et al., 2016). Studies of household flood risk reduction decisions in Germany (Bubeck et al., 2013) and Australia (Lo, 2013) have found that such social-psychological mechanisms significantly influence flood risk reduction. An important topic for future research can be to examine how government policies can make better use of such social network effects in improving individual risk reduction outcomes for natural disasters.

Another important finding for policy is that our results do not support concerns that broader natural disaster insurance coverage would result in fewer risk-reducing activities by policyholders. We find no evidence of moral hazard in the very different market contexts of the German and U.S. insurance markets. While the use of high deductibles by insurance companies in the U.S. aims to prevent moral hazard behavior, it appears that policyholders lack knowledge of the deductible amount. Only 12% believe it to be higher than $1,000, thus likely negating the high deductible’s intended effect of stimulating policyholder risk-reduction for disasters. This highlights the importance of informing policyholders about their deductible level or reminding them to check their deductible before the hurricane season starts.

Appendix A. Propensity Score Matching (PSM) and variables used in the PSM analysis

PSM provides unbiased evaluations of observational data, such as survey data that will be used here. In order to estimate the average effect (ATT) on damage suffered due to having a flood insurance policy, one can compare the average damage suffered between the control and treatment groups if selection into these groups is random. In the presence of non-random entry to the control and treatment groups, a mean comparison results in equation A1 holding:

$$E(y_1|\, T = 1) - E(y_0|\, T = 0) = ATT + SB \qquad (A1)$$

Equation A1 shows that in the presence of non-random entry the estimated effect consists of two elements disguising the ATT effect. In eq. 1 SB is the selection bias that occurs when the incorrect counterfactual observations are used. However, members of the non-treatment group can be used as the required counterfactual observation for treatment group members, if SB shown in Equation 1 can be removed. Removing this bias requires the following conditions to hold, where $\coprod$ represents independence, and $p(X)$ is the estimated propensity score (PS) as a function of the confounders X (Rosenbaum and Rubin, 1983; Hudson et al., 2014):

Condition 1: *Unconfoundedness* – $(y_0, y_1) \coprod T|\mathrm{p(X)}$

Condition 2: *Balancing* – $T \coprod X|\mathrm{p(X)}$

Condition 3: *Overlap* – The PS distributions for the control and treatment groups share a common support, i.e. only observation with a PS within the range: $[\max(PS_{\min}^{control}, PS_{\min}^{treatment}), \min(PS_{\max}^{control}, PS_{\max}^{treatment})]$.

PSM is able to remove the *SB* from a comparison of average damage, and estimate the ATT, which provides an indication of the presence or absence of moral hazard. PSM is most commonly used in cases where non-random entry into the control and treatment groups means that traits that affect both outcomes and treatment participation (confounders) can introduce bias into evaluation attempts. Important confounders in this application are the characteristics of the flood hazard faced by individuals and characteristics of their assets exposed to floods which have made them select into buying flood insurance (adverse risk selection). Both characteristics include factors that significantly influence the damage that individuals suffer when a flood occurs.

A list of the variables included in the PSM analysis is given below. The variables conditioned upon in the PSM follow the guidelines set out in Hudson et al. (2014). Therefore, the variables can be split into two categories. The first set are the direct confounders in that they can be argued to jointly influence insurance purchases and the damage suffered. These variables control for the influence of exposure, vulnerability and hazard. These variables must be used to estimate the propensity score in order to produce an unbiased estimate that mimics random assignment. The second set of variables consists of variables that can be argued to only affect damage outcomes. An example of such variables would be the perceived warning quality. This variable will not affect insurance usage, however, it may affect damage outcomes by allowing the household time to employ certain risk reducing measures or to prepare themselves for the event. The quality of the warning is used because a warning that is perceived to be uninformative may not promote a response from the household. This set of variables has been included because a strand of research has indicated that including these variables in the estimation of the propensity score reduce the variance of the ATT estimate (e.g. Brookhart et al., 2006). The data are trimmed in two respects. First, observations with over €100,000 (€300,000) of contents (building) damage are removed as these are outlying values. Second, sample is trimmed to only observations within the common support (Condition 3 for applying PSM).

List of variables included in the PSM analysis

1. Household contents damage: damage to household contents, where contents are all moveable items in the home (in € as replacement costs).
2. Household building damage: Damage to the building as repair costs (in €).
3. Household contents value: The value of all moveable items within the home (in €).
4. Flood duration: The number of hours the building was flooded.
5. Flow speed one: Dummy variable of low water speed (stationary water is the base group).
6. Flow speed two: Dummy variable of medium water speed (stationary water is the base group).
7. Elbe: Dummy variable of the respondent living along the Elbe River.
8. Urban area: Dummy variable of the respondent living in an urban area.
9. House age (1948): Dummy variable of the building being constructed between 1948-64.
10. House age (1964): Dummy variable of the building being constructed between 1964-90.
11. House age (1990): Dummy variable of the building being constructed between 1990-2000.
12. House age (2000): Dummy variable of the building being constructed after 2000.
13. House quality 2: Dummy variable of a building quality of 2 on a 6-point scale (1 is highest quality).
14. House quality 3: Dummy variable of a building quality of 3 on a 6-point scale (1 is highest quality).
15. House quality 3 plus: Dummy variable of a building quality of 4, 5 or 6 on a 6-point scale (1 is highest quality).
16. Flood risk 1: Dummy variable of being affected by a flood once.
17. Flood risk 2: Dummy variable of being affected by a flood twice.
18. Flood risk 3: Dummy variable of being affected by a flood thrice.
19. Flood risk 4: Dummy variable of being affected by a flood 4 times.
20. Flood risk 5: Dummy variable of being affected by a flood 5 times.
21. Water height: The height of floodwaters entering the house in meters.
22. Contaminated water: Dummy variable of contaminated flood waters
23. Warning duration: The length of time before a flood that a warning was issued in hours.
24. Return 1: Dummy variable of a recorded return period of 1 in 10 years to 1 in 50 years.
25. Return 2: Dummy variable of a recorded return period of 1 in 50 years to 1 in 200 years.
26. Return 3: Dummy variable of a recorded return period of over 1 in 200 years.
27. Cellar: Dummy variable of a cellar.
28. Floor size: The total floor space of the home, including the size of the cellar if present in m^2.
29. House price: An estimate of the house price based on the M1914 criteria (in €).
30. Warning quality 1: A dummy variable for if the perceived quality of the flood warning is given a value of 1, 2 or 3 on a scale of 0-11.
31. Warning quality 2: Dummy variable of the quality of the flood warning being 4, 5 or 6.
32. Warning quality 3: Dummy variable of the quality of the flood warning being larger than 7.
33. Detached house: Dummy variable of a detached house (this is the base category).
34. Semi-detached house: Dummy variable of a semi-detached house.
35. Town house: Dummy variable of a detached house.
36. Multi-family house: Dummy variable of a multi-family house.
37. Commercial building: Dummy variable of a commercial building.
38. Secured documents: Dummy variable of securing documents.
39. Move cars: Dummy variable of moving cars.
40. Turn off gas/electric: Dummy variable of turning off the mains electric and gas.
41. Evacuation: Dummy variable ofevacuating their building.

Appendix B. Sensitivity Analysis

We test the sensitivity of the PSM results for Germany by splitting the sample into two separate samples based on the catchment area an observation is located. The split sample results reported in Table B1 show that the overall results of the combined sample in Table 2 appear to be mainly driven by significant mean comparison estimates for contents damage by the Elbe catchment area and building damage by the Danube catchment area. Consistent with Table 2 is that within both catchment areas there is no conclusive evidence for the presence of moral hazard, because the ATT estimates are insignificant. There remains evidence for the presence of adverse risk selection from the results of the mean comparison: namely, for contents damage in the Elbe catchment and property damage in the Danube catchment. However, although building damage in the Elbe and content damage in the Danube appear to be higher for households with flood insurance, this difference compared with uninsured households is insignificant. Where the results are statistically significant we see a strong potential for adverse risk selection.

The difference in insurance culture between the two regions in Germany provides an opportunity for examining how this translates in different flood protection behavior. In particular, in the Elbe area insurance is acquired as a matter of habit, while in the Danube area it is more of a conscious decision to buy insurance. This allows investigating if the risk averse population has a higher tendency to buy insurance, which could be reflected by the more choice based insurance culture of the Danube catchment area displaying a higher portion of the insured population taking measures to protect themselves. While focusing on the Elbe catchment area on the other hand provides an opportunity to investigate if whether a more social consensus based reasoning behind insurance purchase encourages less personal risk reduction. Table B2 provides an indication of the difference in damage reduction attempts between the insured and non-insured population. On the whole, it appears that the insured group has a greater proportion of its population employing various damage reduction measures. In the Elbe catchment area this is a modest increase across all the measures investigated, while for the Danube catchment area especially large differences can be found in the use of water proofing and water barriers. This finding indicates that in general those who purchase insurance have also carried out more damage reduction actions, and that this effect is greater when the decision to buy insurance is more consciously made.

Table B3 presents the results of a bivariate probit model between a policyholder knowing their deductible and employing risk reducing measures. The purpose of these models is to provide a sensitivity analysis for Table 7 and the potential robustness of the (lack of) connection between the deductible and the use of risk reducing measures. Table B3 shows that there is not a statistically significant estimate for *rho*, implying no joint relationship between the two variables. This supports the findings presented in Table 7.

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Tables

Table 1: Probit model results of the relationship between any flood risk reducing behavior and flood insurance coverage for Germany

Variables	Parameter Estimates Insurance
Has water barriers	0.165* (0.095)
Has adapted building use	0.018 (0.088)
Has flood-proofed home	0.042 (0.077)
Has flood risk information	0.297*** (0.068)
Has flood awareness	0.156** (0.072)
A member of a flood coping network	0.186*** (0.068)
Risk culture proxy (Elbe catchment area)	0.822*** (0.081)
The respondent feels another flood will not occur	0.03 (0.068)
100 year flood zone	-0.09 (0.083)
Flooded Before	-0.087 (0.081)
Constant	-0.236* (0.139)

N	2143
Log-likelihood	-1315
LR chi2 (prob > chi2)	231 [0.000]
Pseudo R^2	0.08

Notes: *, **, *** stand for statistical significance at the 10 percent, 5 percent, and 1 percent levels respectively. The numbers in parentheses are standard errors. Values for the constant are not the marginal effect but the coefficient estimate from the probit model. Numbers in brackets are p-values.

Table 2: Probit model results of the relationship between any hurricane risk reducing behavior and insurance coverage for the U.S.

Risk reducing behavioral variable	Homeowners insurance estimated parameters (1)	Flood insurance estimated parameters (2)
Has preparation	0.231*** (0.047)	0.118** (0.042)
Has window protection	0.042** (0.0186)	0.111*** (0.027)
Has conducted risk reduction	0.023 (0.021)	0.122*** (0.031)
Has evacuation plans	-0.051** (0.022)	0.005 (0.028)
Safety	0.000 (0.000)	0.000 (0.000)
Hundred year floodplain	0.011 (0.022)	0.213*** (0.032)
Distance to Coast	0.017** (0.008)	-0.013 (0.009)
Experienced Damage	0.053*** (0.018)	0.083*** (0.026)
Hurricane Irene	-0.084*** (0.021)	-0.017 (0.028)
Hurricane Isaac	-0.057* (0.034)	0.198*** (0.041)
Constant	1.092*** (0.179)	-.301** (0.154)
N	1610	1610
Log-likelihood	-630.60	-869.73
LR chi2 (prob > chi2)	98.18 [0.00]	268.05 [0.00]
Pseudo R^2	0.07	0.13

Notes:*, **, *** stand for statistical significance at the 10 percent, 5 percent, and 1 percent levels respectively. The numbers in parentheses are standard errors. Values for the constant are not the marginal effect but the coefficient estimate from the probit model. Numbers in brackets are p-values.

Table 3: Bivariate Probit model results of the relationship between any flood risk reducing behavior and flood insurance coverage for Germany

	(1)		(2)	
	Have insurance	Employed a risk reducing measure	Have insurance	Employed a risk reducing measure
Has flood risk information	0.161** (0.073)	0.159** (0.076)		
Has flood awareness	0.324*** (0.064)	0.723*** (0.065)		
A member of a flood coping network	0.203*** (0.066)	0.479*** (0.069)		
Risk culture proxy (Elbe	0.816***	-0.06	0.81***	-0.049

catchment area)	(0.081)	(0.083)	(0.08)	(0.078)
The respondent feels another	0.033	0.157	-0.001	0.07
flood will not occur	(0.097)	(0.104)	(0.096)	(0.1)
100 year flood zone	-0.073	0.717***	-0.016	0.742***
	(0.08)	(0.082)	(0.079)	(0.078)
Flooded Before	-0.073	0.36***	0.125*	0.624***
	(0.08)	(0.082)	(0.066)	(0.065)
Constant	-0.369***	0.232**	-0.869***	-0.736
	(0.110)	(0.113)	(0.094)	(0.0821)
Rho	0.055		0.142	
	(0.04)		(0.038)	
Log-ratio test	1.9 [0.169]		13.92 [0.00]	
N	2143		2143	
Wald Test	725 [0.00]		542 [0.00]	

Notes: *, **, *** stand for statistical significance at the 10 percent, 5 percent, and 1 percent levels respectively. The numbers in parentheses are standard errors. Values for the constant are not the marginal effect but the coefficient estimate from the probit model. Numbers in brackets are p-values.

Table 4. Coefficient estimates of U.S. bivariate probit models

	(1)		*(2)*	
	General Insurance	*Risk Reduction*	*Flood Insurance*	*Risk Reduction*
Has evacuation plans	-0.194**	0.196*	0.074	0.2*
	(0.091)	(0.103)	(0.081)	(0.103)
Safety	0.002	0.002	0.00	0.002
	(0.002)	(0.002)	(0.001)	(0.002)
Hundred year floodplain	0.089	-0.033	0.587***	-0.029
	(0.101)	(0.107)	(0.084)	(0.107)
Distance to Coast	0.085**	-0.0811*	-0.043	-0.078*
	(0.038)	(0.045)	(0.028)	(0.044)
Experienced Damage	0.3***	0.36***	0.297***	0.366***
	(0.087)	(0.099)	(0.075)	(0.099)
Hurricane Irene	-0.4***	0.182	-0.029	0.177
	(0.093)	(0.117)	(0.081)	(0.117)
Hurricane Isaac	-0.159	0.8***	0.664***	0.79***
	(0.131)	(0.123)	(0.104)	(0.132)
Constant	-0.981***	-1.89***	-0.907**	
	(0.16)	(0.19)	(0.14)	
Rho	0.119* [0.097]		0.218*** [0.0001]	
N	1610		1610	
Log likelihood	-1147.77		1383.04	
LR chi2 (prob > chi2)	154.66 [0.00]		289.05 [0.00]	

Notes:*, **, *** stand for statistical significance at the 10 percent, 5 percent, and 1 percent levels respectively. The numbers in parentheses are standard errors. Values for the constant are not the marginal effect but the coefficient estimate from the probit model. Numbers in brackets are p-values.

Table 5: Estimates of the difference in average flood damages due to having a flood insurance policy (in EUR). The average treatment effect on the treated (ATT) is estimated using Propensity Score Matching with different matching methods.

	Contents damage	Building damage
Comparison of mean flood damage suffered by households with and without flood insurance	3458*** (928)	9514*** (2537)
ATT based on PSM using as matching method:	**Contents damage**	**Building damage**
-Nearest neighbor matching	2126	6337
	(2241)	(5852)
- Radius matching	1619	7016
	(1684)	(4490)
- Stratification matching	1395	6261
	(1874)	(4668)
- Kernel matching	1832	6196
(Gaussian)	(2075)	(4013)
- Kernel matching	1583	7266*
(Epanechnikov)	(1978)	(7266)
Average ATT estimate	1711	6615
No. Matches	270	255
Variables described in Appendix A	3-32,34-40	3-8,10-32,34-40

Notes: *, **, *** stand for statistical significance at the 10 percent, 5 percent and 1 percent levels. The numbers in parentheses are standard errors. Where analytical standard errors are not available, they have been calculated via bootstrapping with 2,000 repetitions. The ATT estimates above have been rounded to the nearest whole Euro. For a list of variables used in the PS function refer to Appendix A.

Table 6: Natural hazard summary statistics

	Panel A	
Indicator	**Insurance group**	**Non-insurance group**

Water level	100cm	78cm
Flood duration	192 hours	163 hours
Proportion of households suffering from contaminated water	0.63	0.55
Proportion of households who evacuated	0.63	0.48
Panel B		
Collected information regarding the flood hazard	0.43	0.32
Member of flood support group	0.33	0.23
Employing at least one reduction measure	0.35	0.35
Employed at least one of the above 3 flood coping measures	1	0.56

Table 7: For those with homeowners insurance the relationship between the likelihood and number of preparation activities undertaken and deductible coverage

Preparation outcome variable	Pre-event preparation – Coefficients (1)	Window protection – Estimated parameters (2)	Other risk reduction – estimated parameters (3)
Flood insurance	.276***	0.135***	0.119***
Experienced damage	.314***	0.0415	0.111***
Safety	-0.001	0.0003	0.000
Hundred year floodplain	0.055	0.036	-0.039
Distance to Coast	-0.0145	-0.023**	-0.007
$0 to $500 deductible	0.072	0.016	0.026
$501 to $1000 deductible	-0.037	-0.017	0.029
$1001 to $2500 deductible	0.106	0.046	0.063
> $2500 deductible	.326**	0.107*	0.087*
Hurricane Irene	0.019	0.123***	-0.034
Hurricane Isaac	.252**	0.326***	0.046
Constant	3.055***	-1.105***	-1.125***
Selection Stage			
Flood insurance	.245*		
Experienced damage	0.048		
Safety	-0.002		
Hurricane Irene	-0.148		
Hurricane Isaac	0.183		
Known deductible	-0.002		
Constant	1.769***		
Inverse Mills Ratio (lambda)	-1.152***		
N	1369	1369	1369
Censored observations	66		
Log likelihood	-2395.45	-769.14	-686.27

Wald/LR chi2 (prob > chi2)	76.44 [0.00]	180.97 [0.00]	87.19 [0.00]
AIC	4832.90	1562.28	1396.55

Notes: *, **, *** stand for statistical significance at the 10 percent, 5 percent and 1 percent levels. (1) are the Heckman sample selection model results, (2) and (3) are probit models; each model was estimated via maximum likelihood. For models (2) and (3) the values for the constant are not the marginal effect, but the coefficient estimate from the probit model. Numbers in brackets are p-values.

Table B1: Estimates of the difference in average flood damages due to having a flood insurance policy (in EUR) for households located in the Elbe and Danube River catchment areas separately. The average treatment effect on the treated (ATT) is estimated using Propensity Score Matching with different matching methods

	Elbe catchment – Historically compulsory insurance		Danube catchment – Historically voluntary insurance	
	Contents damage	Building damage	Contents damage	Building damage
Comparison of mean flood damage suffered by households with and without flood insurance	2838** (1149)	1253 (3411)	360 (1694)	6651** (2961)
ATT based on PSM using as matching method:	Contents damage	Building damage	Contents damage	Building damage
-Nearest neighbor matching	1073 (2772)	9571 (8629)	1573 (3355)	6763 (7460)
- Radius matching	1282 (2085)	8436 (6831)	1707 (3306)	5627 (5764)
- Stratification matching	1356 (2887)	8790 (5561)	1228 (3631)	5751 (6003)
- Kernel matching (Gaussian)	1380 (2074)	7956 (4970)	1465 (3005)	6315 (5964)
- Kernel matching (Epanechnikov)	1371 (2135)	9091* (4862)	1652 (3006)	5561 (6025)
Average ATT estimate	1292	8769	1525	6000
No. Matches	203	203	43	48
Variables described in Appendix A	3-32,34-41	3-8,10-32,34-40	3-32,34-40	3-8,10-32,34-40

Table B2: Difference in damage reduction measure usage between the insured and non-insured groups within the Elbe and Danube River catchment areas. Raw difference between the proportions of the insured and non-insured population who employ a specific damage reduction measure.

Damage reduction measure	Elbe catchment	Danube catchment
Flood adapted use	0.06	0.02
Flood adapted interior fitting	0.04	0.01
Waterproofing	0.04	0.15
Water barriers	0.02	0.09

Notes: See Kreibich et al. (2005) for definitions of the above damage reduction measures.

Table B3. Coefficient estimates of U.S. bivariate probit models between a known deductible and the employment of risk reducing measures.

Independent variable	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
	Any pre-event preparation		**Window protection**		**Other risk reduction**	
Flood insurance	0.173	0.137	0.377***	0.081	0.399***	0.085
Experienced damage	0.137	0.131	0.122	0.081	0.394***	0.086
Safety	-0.002	0.002	0.001	0.001	0.000	0.001
Hundred year floodplain	0.220	0.171	0.103	0.093	-0.139	0.100
Distance to coast	0.082	0.057	-0.068**	0.031	-0.026	0.032
Hurricane Irene	-0.306**	0.136	0.364***	0.088	-0.100	0.092
Hurricane Isaac	-0.043	0.210	0.895***	0.115	0.171	0.118
Constant	1.767***	0.245	-1.091***	0.143	-1.094***	0.150
	Known deductible		**Known deductible**		**Known deductible**	

Flood insurance	0.048	0.078	0.048	0.078	0.048	0.078
Experienced damage	0.319***	0.076	0.319***	0.076	0.319***	0.076
Safety	0.002	0.001	0.002	0.001	0.002	0.001
Hundred year floodplain	-0.031	0.091	-0.031	0.091	-0.031	0.091
Distance to Coast	-0.017	0.027	-0.017	0.027	-0.017	0.027
Hurricane Irene	0.236***	0.080	0.235***	0.080	0.235***	0.080
Hurricane Isaac	-0.002	0.111	-0.002	0.111	-0.002	0.111
Constant	-0.711***	0.136	-0.711***	0.136	-0.711***	0.136
Rho	-0.043	0.075	0.039	0.047	0.087*	0.048
LR Test rho = 0	0.322	0.570	0.700	0.402	3.173	0.074
N	1369		1369		1369	
Log-likelihood	-1152.18		-1666.78		-1582.77	
LR chi2 (prob > chi2)	47.95 [0.00]		206.71 [0.00]		112.49 [0.00]	

Notes:*, **, *** stand for stat

[i] The variables included in the probit regressions were guided by the Cutler et al. (2008) approach for the purpose of consistence between these two approaches.

[ii] Additionally, the statistical models employed in the current paper use additional explanatory variables to control for observable traits of households. In contrast, Thieken et al. (2006) presented and compared raw sample averages to generate their conclusions. Moreover, in contrast to Thieken (2006) the Kreibich et al. (2011) dataset included information on a later large scale flood (4 years later) affecting a separate region of Germany.

[iii] The 100-year A and V zones are areas with a 1% or greater annual chance of flooding, and coastal areas with a 1% or greater annual chance of flooding and an additional hazard associated with storm waves, respectively.

[iv] Reforms of the NFIP are ongoing since the Biggert-Waters Flood Insurance Reform Act was enacted in 2012. This act has been partly modified by the Homeowner Flood Insurance Affordability Act signed by President Obama on March 21, 2014. Reform discussions are likely to continue through the scheduled renewal of the NFIP in 2017.

[v] Irene respondents were from coastal counties in North Carolina and New York; Isaac respondents were from coastal counties in Florida, Alabama, Mississippi, and Louisiana; and Sandy respondents were from coastal counties in Virginia, Maryland, Delaware, and New Jersey.

[vi] The surveys were conducted in real-time and responses are as of the time of contact. It is possible that individual short-term behaviour in regard to questions could have changed after the survey contact. Responses were not ex-post verified. See Meyer et al. (2014) for more information on the survey application.

[vii] The related safety question for Hurricane Irene, an earlier version of the field survey, was slightly different, utilizing a scale of 0 to 10 and not specifically indicating the consideration of both wind and water. For the pooled dataset we multiplied these values by 10 to make them consistent with the 0 to 100 safety scale for Isaac and Sandy.

[viii] 57%, 62%, and 68% for Hurricanes Irene, Isaac, and Sandy, respectively.

[ix] Being located within the 100-year floodplain for Germany is based upon the return periods used in the PSM. The return periods of the hydrological event rather than occurrence probability are used. This is because the Zürs zones do not have a 100-year flood probability as a cut-off point for the zones. We made this choice to better match the US and German samples.

[x] As a sensitivity analysis, we checked whether the overall finding of this model is the same when employing a risk reduction measure is used as a dependent variable and having insurance as an independent variable. The results (not shown here) were indeed similar.

[xi] We estimated separate individual storm regression models with results similar to those presented here.

[xii] As a sensitivity analysis, we examined whether the overall finding of this model is the same if employing a risk reduction measure is used as a dependent variable and having insurance as an independent variable. The results (not shown here) were indeed similar.

[xiii] It could be argued that the group employing risk-reduction measures while being insured is wealthier than their non-insured counterparts. However, Hudson et al. (2014) indicate that no important differences appear to exist in income between the insured and non-insured groups.

[xiv] A possible concern is that the matching processes could result in a higher average variance driving the statistical insignificance. To investigate this a linear regression was also estimated. The overall results (not shown here) were the same.
[xv] We estimated separate individual storm regression models with results similar to those presented here.