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Investigating moral hazard and property-level flood resilience measures through panel data from Germany

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ABSTRACT

Property-level flood resilience is an important element of managing current and future flood risk. Government-provided flood protection infrastructure alone cannot fully prevent flood impacts. Property-level flood resilience can aid in the management of risk through two interconnected avenues of individual action. The first is through risk transfer (insurance), which provides post-disaster compensation so that the recovery process is enhanced. The second is through property-level resilience measures, which are strategies aimed at limiting flood damage. Well-designed insurance schemes could incentivise insurance policyholders to employ additional property-level flood resilience measures. However, insurance can equally be argued to disincentivise the employment of property-level flood resilience measures, as the policyholder's losses will be compensated by an insurance company. This latter impact has been referred to as moral hazard, and its systematic presence in disaster insurance markets jeopardizes the industry's sustainability. However, the presence of moral hazard is context dependent. Therefore, it is necessary to study whether moral hazard is present to understand how resilient society is. We study the presence of moral hazard in Germany using a panel dataset, resulting from a longitudinal survey following a flood in 2013. The panel provides insights into dynamic mechanisms concerning moral hazard that would remain hidden in a cross-sectional survey, a dataset that is more widely used in the current literature. We did not find indications for the presence of moral hazard in Germany overall, but a continuing positive association between insurance purchases and the employment of flood resilience measures despite the overall increasing coverage rates.

1. Introduction

1.1. Research context of moral hazard

Munich Re estimated global monetary losses due to natural hazards of $119bn between 1980 and 2019, a value reflecting the severity that these pose to human society [1]. Flooding in particular accounts for 40% of all natural hazard losses [1]. Flood risk, or impact, is generated through three core elements: hazard (the probability and magnitude of potential floods), exposure (what can be affected/lost in terms of assets or people, elements at risk), and vulnerability (susceptibility to loss of what is exposed). In the future, flood risk is expected to further change due to a combination of factors: Climate change is likely to increase flood hazards, while socio-economic development is likely to increase exposure and alter vulnerability [2]. Human behaviour and social constructs influence

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all core elements, as e.g. changing river courses or creating retention areas has an impact on river regimes [3,4]. Protective behaviours, however, might also decrease the vulnerability of flood-prone people and assets [5,6].

It is for this reason that the role of human behaviour is focused on in flood risk management [7] through concepts such as integrated flood risk management [8] and risk governance [9]. These concepts account for the complexity of flood risks, as no single actor alone can combat all aspects of the threat posed by flooding. Therefore, all stakeholders contributing towards flood risk should act within their capabilities to limit or mitigate flood impacts. This includes property-level flood resilience measures [10–13]. A prominent example is the elevation of buildings above a reference inundation depth (e.g., that of a 100-year flood), as is employed by the National Flood Insurance Program in the USA [14,15]. Other property-level flood resilience measures can be described as dry flood-proofing, which includes measures that aim to limit flood damage by keeping floodwaters out of a building, or wet flood-proofing, which refers to measures that aim to limit damage once water has entered a building [16]. These measures reduce risk directly by acting on either the expected probability of suffering a loss or the expected impact when flooded. An alternative avenue is risk transfer. Risk transfer mechanisms do not seek to directly lower the impact of floods, but provide the resources necessary for a rapid recovery [17]. The preeminent example of a risk transfer mechanism is insurance. A flood insurance policy converts incurred flood loss into a smaller fixed loss through the premium charged. A successful insurance mechanism allows people to successfully absorb losses that are beyond their normal financial capacity, promoting a faster recovery process and limiting further indirect impacts, such as resources being redirected or everyday activities being restricted by floodwater [18]. However, this requires a rapid and effective insurance mechanism, as otherwise the problems with accessing this compensation can be worse than receiving no help at all, since such problems add an additional layer of stress and anxiety for the policyholder [19].

Risk reduction and risk transfer are argued to have great potential for risk management if linked together [20]. This is because insurance policies can be used to incentivise additional risk reduction or management by the policyholder. For example, if risk-based premiums are employed, premiums change in line with the disaster risk faced.[1] Therefore, a policyholder who actively lowers risk can be rewarded with premium discounts. Additionally, if insurance is not risk-based, insurers can impose minimum requirements on the level of vulnerability of a property to be able to buy insurance. This can involve regulations or expectations that only certain building materials are used, or certain risk reduction measures that are integrated into the property, e.g., backflow preventers. Similarly, insurers can also require that policyholders have a deductible in place, which means they must bear a certain proportion of the impacts suffered before the insurance policy becomes effective. Insurers can also alter the size of the deductible in relation to proactive risk management and disaster experiences. France is an example of such a procedure [21]. These strategies can generate benefits from disaggregated or decentralised adaptation, as only those who will benefit from undertaking such additional risk-reducing actions will employ them. This generates a higher net increase in social welfare than could otherwise be possible if all actors were expected to reach the same level of proactive risk management. However, these avenues for promoting proactive risk management can be limited if there are information asymmetries between the insurer and the insured. Both sets of actors (i.e., the insurer and the insured) are aware of different aspects of the risk faced and the behaviours undertaken to limit risk, and how much room there is to manoeuvre therein. Information asymmetries can lead to the collapse of insurance markets due to different perspectives between actors, as insurability conditions are no longer met [22].

In disaster risk research, the main information asymmetries often considered are the concepts of adverse selection, moral hazard, and charity hazard.[2] Charity hazard is where there is an expectation that the government will provide compensation in the aftermath of a flood event, which reduces the incentive to buy insurance [23–25]. Adverse selection is where only the highest at risk wish to buy the insurance, forcing premiums to grow very rapidly given the problems with insuring flood risk and the geographically clustered nature of demand [22]. The other main information asymmetry is moral hazard. Moral hazard is where the purchasing of insurance causes a behavioural change in the policyholder. It is believed that with the purchase of an insurance policy, the level of risk increases, because more risky activities are undertaken or policyholders become laxer with their degree of risk management. In disaster risk research, this lesser degree of risk management as an expression of moral hazard can be measured through fewer individual risk reducing measures being employed or intended after the purchase of insurance compared to before the purchase. Moral hazard limits the capability of insurance to be used as a tool for integrated flood risk management. While it addresses one problem (post-flood recovery), it could worsen another (the degree of risk faced). The wide-scale presence of these information asymmetries undermines the conditions needed for disaster risk insurability [22], which in turn threatens the long-run sustainability of the industry.

1.2. Previous research findings regarding moral hazard

It has been observed that the occurrence of moral hazard across different types of insurance depends on specific market structures and conditions to determine its systematic presence [26]. Research on the presence of moral hazard in flood insurance markets has been impeded by several factors. First, it requires the ability to observe people with and without insurance. This can be problematic in countries such as France, with a formal mandate to purchase flood insurance, or countries such as the UK, with informal mandates [27]. This creates a high coverage rate and an insufficient sample size of the control group, i.e., people without insurance. Previous research linking insurance coverage and property-level resilience measures has been conducted in Germany [25,28–31] and the United States [32–34], both countries with (effectively) voluntary disaster risk insurance markets. For instance, the German flood insurance market provides coverage against flooding as an optional extra available for residential buildings, contents, and private property

[1] Risk being the weighted sum of the probability of potential impacts. Therefore, protective actions can aim to limit either the probability of an event or the potential impacts of an event should one occur.

[2] It is important to note that these terms do not imply a normative judgement (i.e., that behaviour is “wrong”). Rather, they are used as idiomatic expressions for a hypothesised relationship (i.e., that insurance coverage lowers the incentive for self-protective behaviour). A deeper discussion can be found in Rowell and Connelly (2012).

[35]. While coverage against events such as storms is high, the market penetration of the voluntary flood insurance extension is much lower, reaching about 44% in 2019 (GDV 2020). The degree to which risk premiums are risk-based depends on the insurance company. However, in principle, premiums increase in line with the risk faced to the point where buildings located in areas with a flooding probability of at least once in 10 years are often excluded from coverage [35].

There is a further body of literature investigating moral hazard in disaster risk research using cross-sectional datasets. Collectively, the results of these studies indicate that the presence of moral hazard has not been systematically detected. For instance, Thieken et al. [28]; Osberghaus [29]; Hudson et al. [30]; Andor et al. [25], and Petrolia et al. [33] do not detect a moral hazard effect using survey data of observed behaviour, while Carson et al. [32]; Botzen et al. [34] and Mol et al. [36,37] find more mixed results. Carson et al. [32] did not find a moral hazard effect when looking at the precautionary decisions of those surveyed, but found moral hazard regarding the level of provision. Botzen et al. [12,18,34] found a moral hazard impact regarding the level of provision, too, as well as for flood preparedness, but none for proactive mitigation efforts. The economic experiments presented in Mol et al. [36,37] find that moral hazard depends on the conditions of the market. They find none with high deductibles [36,37], but rather that lower deductibles promote moral hazard. The same was true of the hazard context, in which Mol et al. [36,37] find that the lower the probability of damage the less likely that moral hazard would be observed, but as the probability of damage increased so did the chance of observing moral hazard.

1.3. Research gap

Ehrlich and Becker (1972), in a seminal paper on the development of individual protective actions and insurance coverage, implies a simple negative relation between insurance coverage and flood protective behaviours if the policyholder is not rewarded with lower insurance premiums. In this case, insurance coverage and self-protection become substitutes for one another. We believe that this assumption is likely to hold, as across Europe, despite the call for an increased interlinkage between insurance policies and proactive policyholder adaptation, such a link is not systematically present (Surminski et al., 2015), even though there are expectations (Hanger et al., 2018). Moreover, a substitutive pressure can be easily imagined between insurance coverage and proactive self-protection. This is because insurance reduces the negative consequences of a risky event by converting a large uncertain loss (e.g., flood damage) into a smaller fixed loss (e.g., the premium) [38]. If individuals alter their behaviour unbeknownst to the insurer, the insurer bears additional negative costs of this risk transfer, e.g. increased flood damage [38]; Krugman, 2009). Therefore, when insured, individuals have a smaller opportunity cost of lowering their level of self-protection, and therefore have an incentive to employ fewer protective measures. Nonetheless, previous studies in Germany have not detected effects of moral hazard in private flood-prone households.

One hindering factor in the previous research on moral hazard is the dynamic nature of insurance coverage and moral hazard, i.e., that an impact may take time to manifest. Studies on moral hazard within disaster risk research have mainly been using cross-sectional datasets [39–43]. These datasets only provide a (temporal) snapshot of individual behaviour and trends, and dynamics cannot always be reliably reconstructed (e.g., the downward trend in adaptive behaviour that occurs a year after insurance has been purchased could not be observed). Repeated cross-sectional datasets, as used in Hudson and Thieken [31] to explore moral hazard for German SMEs (Small and Medium Enterprises), provide a more detailed insight at this point. Repeated cross-sectional data can detect changes in population-level trends over time, but the dynamics of behaviour cannot be traced back to the individual level at which moral hazard operates.

1.4. Research questions and added value to the literature

In our study, we use a unique panel dataset of households collected between 2013 and 2017 in Germany to explore the potential presence of moral hazard. We achieve this via three avenues: (1) detecting temporally dynamic changes in observed behaviour, (2) observing stated intentions of future behaviour, and (3) studying the behaviour intention gap regarding how well a stated behavioural intention is converted into tangible action.

We argue that each of these three avenues can reveal an avenue for moral hazard to occur because insurance coverage can be expected to change the set of incentives a person acts upon. Hence, we base our investigation on the following the research objectives:

1) Do insured respondents display a slower rate of increasing their level of protective behaviour over time as compared to the uninsured?
2) Do insured respondents display fewer intentions to employ additional measures when insured as compared to the uninsured?
3) Do insured respondents display a larger behaviour intention gap as compared to the uninsured?

Our research objectives cannot be studied using (repeated) cross-sectional datasets, which were predominantly used in previous studies on moral hazard. We address this knowledge gap directly by using a panel dataset. Therefore, our addition to the scientific literature is our study's ability to explore the temporal dynamics of moral hazard and flood risk management at the property level. We address the research gap by directly studying whether buying insurance changed a person's behaviour over time rather than trying to isolate the outcome of a dynamic process from a single snapshot.

A second contribution is that we can investigate whether the current failure to observe (strong) moral hazard impacts in the German flood insurance market [28–31] holds when using panel datasets. As introduced in this study, moral hazard is a dynamic impact and as such should use panel data to account for this dynamic process.

2. Data and methods

2.1. The panel dataset

The panel dataset originated from a cross-sectional survey of 1652 households that were impacted by the flood event of May/June 2013 in Germany, i.e., households reported damage to the building structure or household contents. The sample was selected based on flood-affected streets, allowing for the targeted identification of landline phone numbers to conduct computer-aided telephone interviews (CATI). This original survey was followed by two later survey waves attempting to follow the original respondents. Altogether, three survey waves were conducted 9, 18, and 45 months after the flood event. Participation in each survey wave was voluntary and therefore participation decreased in each wave. All in all, 227 respondents could be considered as constructing a balanced panel of people who partook in all three survey waves. A potential problem associated with panel surveys is attrition bias, which relates to respondents dropping out of the panel non-randomly. This could result in findings that reflect underlying changes in the sample composition rather than those related to temporal changes. Hudson et al. [40] indicate that there is little concern regarding attrition bias for the panel data, indicating that on average there are no significant changes in the composition of the panel dataset over time.

The CATIs employed were based on a standardised questionnaire. In the first wave, the questionnaire was focused on flood damage and event characteristics, while the later waves focused on the recovery process, adaptation against flooding, and intangible impacts over time to gain insights into the dynamics of human behaviour in the flood risk domain. The questions included were derived from the scientific literature that has been used in other studies [7,28,44–51]. Therefore, some variables (e.g., income, flood impacts) are static because they were only asked in one survey wave, while others (e.g., risk perception, responsibility appraisal) are fully dynamic as they were asked in all three waves.

Respondents were mainly located in the federal states of Saxony-Anhalt (41%) and Saxony (27%). These two states were the most severely impacted by the 2013 flood event [46]. Bavaria (16%) and Thuringia (10%) followed, while the remaining respondents were drawn from Baden-Wurttemberg, Brandenburg, Lower-Saxony, and Schleswig-Holstein. Respondents tended to be property owners, and the average age in wave one was 62 years. The average age is higher than the German national average of 44 in 2016. Part of this difference is because children were excluded from the survey and only households with landlines were sampled.

We present limited additional information on the sample, as it has been further described in Bubeck et al. [45] and Hudson et al. [27,40]. Hudson et al. [27,40] study the sample of 227 respondents in terms of its potential for attrition bias (i.e., that the results no longer reflect the underlying population because of a changing sample composition) and retention bias (i.e., bias introduced due to respondents dropping out of the survey). Of these two issues, retention bias was deemed to be the more significant issue, as about 60% of respondents did not move to the next wave. Hence, only 227 respondents remain out of the initial sample of ~1600 respondents. In terms of attrition bias, Hudson et al. [27,40] find that the starting and ending samples have roughly the same average sample characteristics, and therefore conclude that overall attrition bias is not an overly significant issue. Therefore, overall, we are confident that the sample of 227 respondents remains suitable to focus on, so that we have maintained a suitable set of respondents. However, the dataset is limited by the number of final respondents, which indicates that future panel studies in this area need to consider more seriously how to promote sample retention.

2.2. Methods

To capture the relevant linkages between insurance coverage and proactive risk management by the respondents, we employ three different modelling approaches. The first two are regression–based, considering the number of property-level flood resilience measures that were employed at the time of the survey or were intended to be employed within the following six months, as connected to insurance coverage. The third approach is a more qualitative approach considering the size of the implementation gap (i.e., how well intentions to employ additional property-level flood resilience measures stated in earlier survey waves were converted into observable action in a later survey wave) between the group that was insured at the time of the first survey wave and the group of respondents that were not.

However, while the survey contained many different types of precautionary behaviour the surveyed household could have implemented,[3] not all measures can be put on the same level regarding their ease of employment. It can be argued that some of the measures cannot be readily reversed without substantial effort (e.g., a sealed cellar, a backflow preventer, oil tank protection, etc.), while other measures are more readily changeable or require continuous maintenance and efforts to maximise their effectiveness (e.g., flood-adapted use or no storage of chemicals in the cellar). Therefore, to account for these differences, we further refine the three potential dependent variables by separating them into those corresponding to "low-cost", "medium-cost", and "high-cost" measures following the classification scheme presented in Bubeck et al. [45]. This classification follows the logic that "low-cost" measures are relatively easy to implement and require upkeep, while "high-cost" measures are those that must be planned for and, once implemented, cannot be easily undone. These measure categories will be studied separately.

The dependent variables are operationalised as follows: first is (1) the first-order difference between the number of measures implemented across survey waves (i.e., the number of measures employed in wave 2 against those reported in wave 1). This is selected rather than the level (or number) of measures implemented due to the way the question in the survey was asked. It allows only for inferring static or increasing levels of property-level flood resilience measure employment, not potential reductions. Second is (2) the number of stated intentions to employ measures within an adaptation measure category, which can more readily vary across survey

[3] See the supplementary information presented in Bubeck et al. [45] for a full list. Moreover, the modelling framework is selected to be in line with the preceding research on this topic.

waves. Third is (3) the sum of measures per measure category (low cost, medium cost, or high cost) that had successfully converted an intention into an action for the following survey wave.

2.2.1. Regression modelling approach

We estimated two sets of regression models, both designed similarly. A regression-based analysis was selected as the methodological approach to answer research questions 1 and 2 for the following reasons. The first is that it is in line with the methodological choice of studies investigating moral hazard in disaster insurance markets (e.g., Refs. [12,18,29,30,34]. A pooled model was selected to reconstruct the temporal dynamics of insurance purchase and changes in adaptive behaviour while allowing the sample size to be increased using all viable survey wave data. The use of a panel data model such as a fixed-effects model could possibly reduce the sample size further, enhancing the likelihood of the potentially small sample of individual respondents. The small sample of respondents is the reason why the behaviour-intentions gap is studied qualitatively through a graphical analysis and descriptive statistics, as otherwise the sample would be too small for a viable regression analysis.

The first statistical model is a pool panel data regression model as shown in eq. (1). In this equation, ${M_{i,t,c}}^1$ represents the change in number of measures employed by observation i observed at time t for measure category c, as compared to the value observed at time t-1. This is then supposed to be a function of insurance coverage (I) at time t and t-1, a series of important psychological variables that can be used to explain the employment of risk management measures ($\boldsymbol{x_{i,t}}$). The beta terms represent coefficients (**vectors**) to be estimated. The error term is represented by $u_{i,t}$.

$$ {M_{i,t,c}}^1 = \beta_0 + I_{i,t}\beta_2 + I_{i,t-1}\beta_3 + \boldsymbol{x_{i,t}\beta} + u_{i,t} \tag{1} $$

The explanatory variables selected are the respondents' level of subjective recovery, their stated level of protective motivation, the perceived probability of a future flood, and the avoidance of thinking about future flooding, as well as to what extent the respondent trusts the federal government and to what extent the respondent trusts insurers. A summary of these variables can be found in Table 1. These variables have been selected from the behavioural factors studied in Bubeck et al. [45] that were found to be dynamic over time. Moreover, given the relatively small number of panel respondents (N = 227), we must prioritise the variables that we can include in our model. We focus on the variables identified as "dynamic" in Bubeck et al. [45]; because these variables are known to be important in explaining adaptive behaviour and are more likely to vary at each survey wave. In taking this approach, the variation between observations increases in comparison to using static variables, and the pooled regression model benefits from the increased variation in observation values.[4]

The second statistical model used is like model 1 in construction, except that in eq. (2) the dependent variable is now the sum of stated intentions to employ additional measures within the next 6 months for each measure category. There is only one new explanatory variable added, which is ${M_{i,t-1,c}}^{1,all}$. This variable indicates the total number of measures the respondent has employed at time t-1. The logic for the inclusion of this variable is that there is an upper limit to the number of measures a respondent can physically employ, on top of diminishing returns to each additional measure employed. Therefore, a household that perceives itself to be well protected has a smaller incentive to employ additional new measures.

$$ {M_{i,t,c}}^2 = \beta_0 + I_{i,t}\beta_2 + I_{i,t-1}\beta_3 + {M_{i,t,c}}^{1,all}\beta_4 + \boldsymbol{x_{i,t}\beta} + u_{i,t} \tag{2} $$

For both models, we also explore whether or not all the variables should be expanded into a fully dynamic model (i.e., each variable has its first lagged term included). This is tested by estimating a regression model where each term does have its first lagged value added as an additional explanatory variable (other than insurance). We then conduct an F-test where all the newly introduced lagged variables are tested to see if they are jointly statistically insignificant. The results of this test indicate that, in all cases, except for medium-cost measure intentions, we fail to reject the null hypothesis that the additional lagged terms are jointly equal to zero. Therefore, in this paper we focus only on the models where there are no additional lagged terms. The extended model can be seen in the appendix. The results are in line with those presented in the main text, and as such are not discussed further in the main manuscript.

2.2.2. Behaviour intention gap

The final approach used for studying moral hazard is to examine the behaviour intention gap. The behaviour intention gap investigates how people's stated intention to employ property-level flood resilience measures are acted upon. The behaviour intention gap is explored in a similar way as in Bubeck et al. [45]. Bubeck et al. [45] take a qualitative approach by recording when survey respondents implemented a property-level flood resilience measure that they stated they would employ in an earlier survey wave. The approach employed by Bubeck et al. [45] is modified by dividing the survey respondents into two groups: those insured and those not insured. Moral hazard is assessed by examining how behaviour intention differs across these two groups. Moral hazard is expected to strengthen the behaviour intention gap for those who are insured. This is a simplification, as we only divide the groups based on their insured status in wave 1, whereas respondents also bought insurance in later survey waves. We elect for this simplification to counteract the fact that the potential sample size for this analysis is much smaller compared to the previous steps. We can only follow those who had stated intentions to employ a property-level flood resilience measure. Therefore, we elect for simplicity rather than the complexity of further sub-dividing groups of respondents.

[4] Additionally, most of the static variables are observed in wave 1, several of which (e.g., income) are plausibly temporally dynamic. Therefore, by excluding these variables we aim to reduce potential measurement error due to creating artificial temporal dynamics.

Table 1
Summary table of regression model variables.

Name	Description	Summary statistics
Dependent variables		
Change in number of measures employed (eq. (1))	The reported change in the number of low-cost property-level resilience measures between survey waves.	Mean: 4.87 Median:5 Standard deviation: 2.84
	The reported change in the number of medium-cost property-level resilience measures between survey waves.	Mean: 3 Median:3 Standard deviation: 2.28
	The reported change in the number of high-cost property-level resilience measures between survey waves.	Mean: 1.79 Median:1 Standard deviation: 1.69
Level of intentions to employ extra measures within the next 6 months (eq. (2))	The level of intentions to employ additional low-cost property-level resilience measures within the next 6 months.	Mean: 0.17 Median:0 Standard deviation: 0.65
	The level of intentions to employ additional medium-cost property-level resilience measures within the next 6 months.	Mean: 0.22 Median:0 Standard deviation: 0.6
	The level of intentions to employ additional high-cost property-level resilience measures within the next 6 months.	Mean: 0.18 Median:0 Standard deviation: 0.6
Explanatory variables		
Insured	A binary variable indicating whether the respondent is insured (=1) or not (=0). Once insured it is assumed that the respondent remains insured for later periods.	Mean: 0.55 Median:1 Standard deviation: 0.5
Lagged insured	The value for "Insured" in the previous survey wave.	
Total measures implemented	A variable presenting the total number of property-level resilience measures employed.	Mean: 12.5 Median:10 Standard deviation:8.2
Self-stated recovery from the 2013 flood event	The respondent's response to the following question: "How much does the flood event of May or June 2013 still affect you today?". Values are on a 6-point Likert scale from 1 (it does not bother me at all/I feel the same as before the event) to 6 (it bothers me a lot).	Mean: 3.4 Median:3 Standard deviation:1.8
Self-stated protective motivation	The respondent's response to the following statement: "Personally, I will do everything I can to protect the house I live in from flooding". The answers have been converted so that they are on a 6-point Likert scale from 1 (completely disagree) to 6 (completely agree).	Mean: 4.5 Median:5 Standard deviation:1.9
Perceived probability of a future flood	The respondent's response to the following question: "How likely do you think it is that your apartment or house will be affected by a flood again?". The answers are provided on a 6-point Likert scale where 1 is 'completely unlikely' and 6 is 'completely likely'.	Mean: 4.3 Median:5 Standard deviation:1.6
Avoids thinking about flooding	The respondent's response to the following statement: "I don't even want to think about future flood damage!". The answers have been converted so that they are on a 6-point Likert scale from 1 (completely disagree) to 6 (completely agree).	Mean: 3.2 Median:3 Standard deviation:1.8
Trust in the federal government	The respondent's response to the following question: "How much do you trust the federal government in relation to flood management?". The answers have been converted so that they are on a 6-point Likert scale from 1 (do not trust at all) to 6 (completely trust).	Mean: 3.5 Median:3 Standard deviation:1.5
Trust in insurance	The respondent's response to the following question: "How much do you trust insurers in relation to flood management?". The answers have been converted so that they are on a 6-point Likert scale from 1 (do not trust at all) to 6 (completely trust).	Mean: 3.2 Median:3 Standard deviation:1.6

2.2.3. Proposed hypothesis to be tested

Expected relationship 1 can be observed by estimating eq. (1), where the potential moral hazard impact will be identified through the two *I* variables capturing the impacts of contemporaneous insurance coverage and historical insurance coverage, as there could be a temporal aspect to moral hazard becoming enacted. The presence of moral hazard dynamics should be represented by negative coefficient values, which would represent a smaller increase in the number of measures employed per measure category. Therefore, we will investigate whether β_2 and β_3 in eq. (1) are statistically significant and display a negative coefficient.

Expected relationship 2 can be observed by estimating eq. (2). In eq. (2), a potential moral hazard would be detected through a negative coefficient on the insurance variables, as this would indicate that the insured may be less willing to increase their level of protective behaviours. Therefore, we will investigate whether β_2 and β_3 are statistically significant and display a negative coefficient in eq. (2).

Expected relationship 3 will be studied through a graphical and descriptive analysis of the rate at which a respondent converts a behavioural intention into tangible action by the end of the survey wave. Therefore, we would expect fewer behavioural intentions to have been converted into increased protective behaviours by the policyholder respondent sub-set as compared to the non-policyholder sub-set of respondents.

3. Results and discussion

3.1. Results

3.1.1. Low-cost measures

Table 2 presents the results for changes in the observed number of measures employed and the level of intentions for future adaptation.

Starting with the insurance variables in model 1 of Table 2 looking at implemented measures, we see that there is an overall positive association with being insured in the current period and an increase in the number of low-cost measures being employed (nearly 1.6 additional low-cost measures as compared to the uninsured group). On the other hand, being insured in the previous period is negatively associated with the change in the number of new low-cost measures employed (about 1/3rd of a low-cost measure less as compared to the uninsured group) but is statistically insignificant. Therefore, being insured tends towards an overall increase in the low-cost measures being employed. For the remaining variables, we see that individuals with a higher perceived probability of flooding tend to employ more low-cost measures, as do people who still feel burdened by their flood experiences.

3.1.2. Medium-cost measures

Table 3 presents changes in the observed number of measures employed and their level of intentions for future adaptation in reference to medium-cost measures.

Starting with the insurance variables in model 1 of Table 3, we see that there is an overall positive association with being insured in the current period and an increase in the number of medium-cost measures being employed (nearly 1.4 additional medium-cost measures). On the other hand, being insured in the previous period is negatively associated with the number of new medium-cost measures employed (about 0.6 of a medium-cost measure less). Therefore, being insured tends towards an overall increase in the

Table 2
Regression model output for low-cost property-level resilience measures.

	(Model 1) Change in number of measures employed	(Model 2) Level of intentions to employ extra measures within the next 6 months
Insured	1.57*** (0.2)	0.03 (0.08)
Lagged insured	−0.31 (0.21)	0.1 (0.09)
Total measures implemented		−0.02* (0.01)
Self-stated recovery from the 2013 flood event	0.15*** (0.05)	−0.03 (0.03)
Self-stated protective motivation	0.17*** (0.07)	−0.01 (0.03)
Perceived probability of a future flood	0.14** (0.06)	−0.03 (0.03)
Avoids thinking about flooding	0.05 (0.05)	0.04 (0.03)
Trust in the federal government	−0.05 (0.08)	−0.005 (0.04)
Trust in insurance	−0.09 (0.07)	−0.03 (0.03)
Constant	0.86 (0.57)	0.71** (0.3)
Observations	318	318

Table 3
Regression model output for medium-cost property-level resilience measures.

	(Model 1) Change in number of measures employed	(Model 2) Level of intentions to employ extra measures within the next 6 months
Insured	1.42*** (0.18)	0.17** (0.07)
Lagged insured	−0.59*** (0.19)	0.18** (0.09)
Total measures implemented		−0.02*** (0.01)
Self-stated recovery from the 2013 flood event	0.18***	−0.03 (0.02)
Self-stated protective motivation	0.13** (0.06)	0.04* (0.02)
Perceived probability of a future flood	−.1* (0.05)	−0.01 (0.02)
Avoids thinking about flooding	0.08** (0.04)	0.05*** (0.02)
Trust in the federal government	−0.08 (0.07)	0.03 (0.03)
Trust in insurance	−0.04 (0.06)	−0.01 (0.01)
Constant	−0.20 (0.52)	0.03 (0.21)
Observations	318	318

medium-cost measures. However, while the initial purchase of insurance is associated with a large increase in the number of measures employed, the growth in later years is nearly halved in size (i.e., in the year in which you purchase insurance you will be associated with a 1.42 increase in measures as compared to the uninsured group, while in the following years the increase falls to about 1 additional measure overall as compared to the uninsured group).

For the remaining variables, we see that individuals who report a lower level of self-stated recovery (i.e., a score of 6) tend to display a higher change in the number of medium-cost measures employed. Similarly, people who display a high sense of protective motivation are also associated with a higher change in the number of medium-cost measures employed. On the other hand, a high perceived flood probability is associated with a reduction in the number of measures employed. This is a different relationship than that presented in either Table 2 (low-cost measures) or Table 4 (high-cost measures). We would argue that this is because medium-cost measures are in a potentially unfortunate middle ground where they are not seen to be effective enough (as compared to high-cost measures) or easy enough to employ (as compared to low-cost measures). We advise additional research into this avenue.

The results of model 2 presented in Table 3 show that both insured variables are positively associated with the level of intentions to employ more medium-cost measures within the next six months, which is not the case with the annual change in medium-cost measures employed. Part of this difference could be explained through the correlation associated with the "Total measures implemented" variable, which is negatively associated with the level of adaptation intentions. The more measures employed, thus the greater protection against flooding, means that the marginal benefit of employing an additional medium-cost measure is smaller and so there is a smaller chance that employing a new additional medium-cost measure is a sensible choice.

3.1.3. High-cost measures

Results for the high-cost measures are displayed in Table 4, analogous to 3.1.1 and 3.1.2.

For the insurance variables in model 1, we see that there is an overall positive association with being insured in the current period and an increase in the number of high-cost measures being employed (nearly 0.9 additional high-cost measures, Table 4). On the other hand, being insured in the previous period is negatively associated with the change in the number of new high-cost measures employed (about 0.45 of a high-cost measure less as compared to the uninsured group). Therefore, being insured tends towards an overall increase in the high-cost measures being employed.

However, while the initial purchase of insurance is associated with a large increase in the number of measures employed, the growth in later years is nearly halved in size (i.e., in the year in which you purchase insurance you will be associated with a ~1 measure increase, while in the following year the increase falls to about ~0.5).

For the remaining variables, we see that individuals who report a lower level of self-stated recovery (i.e., a score of 6) tend to display a higher change in the number of high-cost measures employed. Similarly, people who display a high sense of protective motivation are also associated with a higher change in the number of high-cost measures employed, as is having a high perceived flood probability. On the other hand, avoiding thinking about floods or trusting in the federal government (a perceived provider of flood protection and post-disaster compensation) are associated with a smaller change in the number of new high-cost measures employed.

Turning to model 2 presented in Table 4, an overall similar but weaker relationship was detected, as the insurance variable overall is still positively correlated with the stated level of intentions. However, in model 2 a statistically significant relationship is observed regarding the lagged insurance variable (while the insured variable still displays a positive correlation).

3.1.4. Behaviour intention gap

In this stage of the analysis, the presence of moral hazard is expected to be detected through a larger behaviour intention gap in the insured group as compared to the uninsured group (i.e., fewer people in the insured group should convert their intentions into action).

Fig. 1 presents the comparison between the respondents who were and were not insured at the first survey wave. The barplots are separated into low, medium, and high-cost measures following the previous steps of the analysis. The bars in the panels in Fig. 1 show whether the stated intentions in survey wave 1 were acted upon and implementated in one of the later survey waves. The figure uses percentages refering to the respective sample sizes of both groups to faciliate a direct comparison.

Table 4
Regression model output for high-cost property-level resilience measures.

	(Model 1) Change in number of measures employed	(Model 2) Level of intentions to employ extra measures within the next 6 months
Insured	0.89*** (0.14)	0.07 (0.06)
Lagged insured	−0.45** (0.15)	0.13* (0.06)
Total measures implemented		−0.02*** (0.006)
Self-stated recovery from the 2013 flood event	0.12*** (0.04)	−0.02 (0.02)
Self-stated protective motivation	0.18*** (0.05)	0.03 (0.02)
Perceived probability of a future flood	0.11*** (0.04)	−0.02 (0.03)
Avoids thinking about flooding	0.1*** (0.03)	0.05** (0.02)
Trust in the federal government	−0.12** (0.06)	+0.01 (0.03)
Trust in insurance	0.02 (0.05)	−0.03 (0.02)
Constant	−0.75* (0.39)	0.21 (0.21)
Observations	318	318

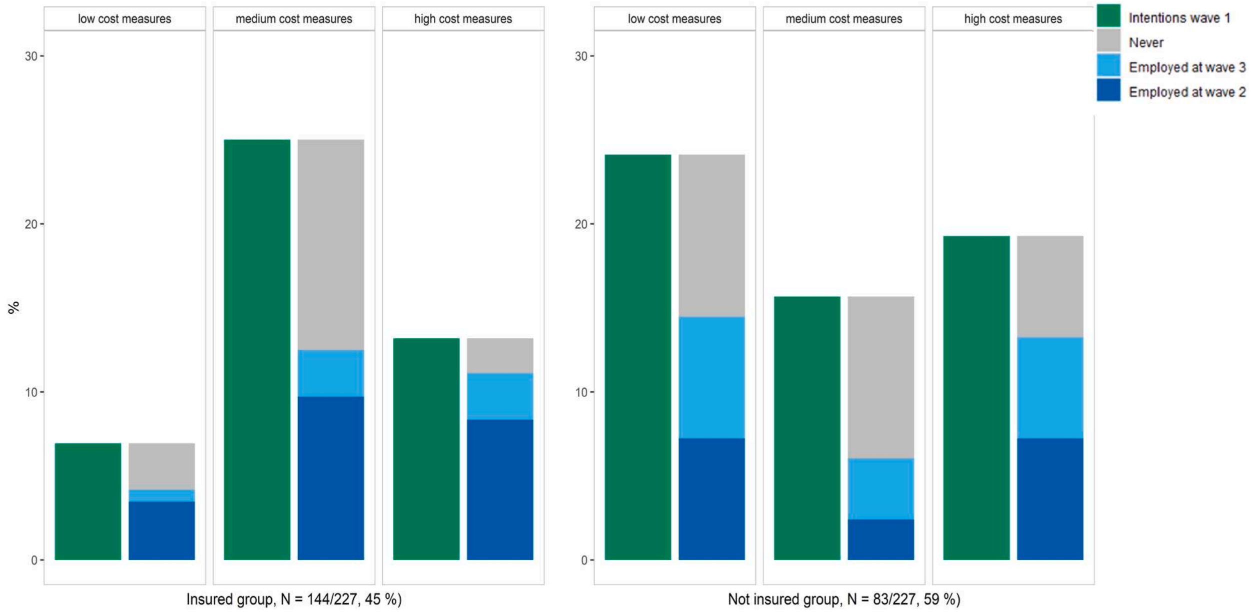

Fig. 1. Stated intentions and follow-up actions of implementations by the respondents, sorted into the insured group, which was already insured at survey wave 1, and the non-insured group, which was not insured at survey wave 1. Histograms shows the percentages, 100% referring to the total sample of each respective group.

Panel 1 of Fig. 1 shows that about a quarter of already insured respondents planned to implement medium-cost measures in the future (N = 36, 25%). However, only 50% followed their intention and implemented medium-cost property-level resilience measures. High-cost measures were planned by 13% of the already insured sample. Most followed their intentions to adopt high-cost measures at a later survey wave (84% had acted upon their intention by wave 3). In comparing the intentions to implement high-cost measures across both groups, i.e. the panels of Fig. 1, we see that there is a higher ratio stating such an implementation in the uninsured sample (19%). However, fewer uninsured respondents followed their intention with action in comparison to the insured respondents (69% vs. 84%, a gap of 15% points).

The least planned category of property-level flood resilience measures to implement were the low-cost measures (7%) – in contrast to the uninsured respondents, where 24% stated an intention to implement low-cost property-level flood resilience measures within the next six months.

Overall, from the data presented in Fig. 1, we do not find evidence in favour of moral hazard, as overall there was a lower behaviour intention gap for the insured group as compared to the uninsured group. In particular, this gap was lower in the insured group for the high and medium-cost property-level flood resilience measures.

Therefore, overall we take this as not presenting evidence in favour of moral hazard, as there is slight evidence in favour of a smaller behaviour intention gap in the insured group as compared to the uninsured group.

3.2. Limitations

A common limitation to discuss in a regression-based analysis is endogeneity or the identification assumptions employed. In terms of identification assumptions, our paper draws upon the identification logics presented in Osberghaus [29] and Hudson et al. [30]; who explored moral hazard in Germany and the United States using cross-sectional data. Collectively, these two studies argue that the presence of moral hazard overall can be detected via the overall correlation between risk reduction measure indicators and the insurance variable as a combined indicator. Osberghaus [29] and Hudson et al. [30] argue, therefore, that the aggregated correlation indicated by the coefficient combines the relevant observable and unobservable influences that contribute to the joint decision process of being insured and employing risk management techniques. Thereby, it allows for the detection of an overall signal for the presence of moral hazard, or the conditions that give rise to it based on how strongly moral hazard incentives systematically outweigh moral hazard-inhibiting incentives across the sample population. Additionally, Ehrlich and Becker (1972), in a seminal paper on the development of individual protective actions and insurance coverage, imply a simple negative relation if insurance coverage and flood protective behaviours are truly substitutes. With this in mind, the main impetus of this paper was to explore the most dynamic variables in the underlying dataset to maximise the variation in the data and help minimise the impacts of the relatively small sample size. Therefore, there is room for future work to employ causal or quasi-experimental statistical techniques (e.g., randomised controlled trials in collaboration with insurers) to provide additional insights and increased certainty in the findings of moral hazard now that longitudinal datasets are slowly becoming more common in disaster risk research.

Secondly, due to how the questions of property-level resilience measures were constructed in the questionnaire, it is only possible to establish whether the respondent had employed additional measures since the last survey wave. This poses a limitation to potential decreases in the measures. To deal with that, we make the same methodological choice as in Bubeck et al. [45]. Bubeck et al. [45] responds to this issue by focusing on measures which, once employed, are unlikely to be undone. It should be noted that this did create a boundary regarding the extent of moral hazard that could be studied. This is because if moral hazard depends on market circumstances and features, it is also sensible to consider whether this is also the case across different types of property-level resilience measures. Therefore, we attempt to mitigate this issue by investigating different measure categories including those studied by Bubeck et al. [45].

There is a similar concern with how insurance coverage was recorded. We were able to reliably identify whether a respondent had acquired insurance in between survey waves, not whether the insurance status changed. This is a significant limitation, as insurance coverage is an annual business and thus a person or insurer may decide to cancel an insurance policy. Further, it must be noted that the insurance coverage rate in the panel is relatively high in comparison to the average German insurance penetration rate at the time. Therefore, it is possible that the respondents of the sample are more intrinsically interested in being proactive against flooding, as was argued in Hudson et al. [30].

The data used for this study were generated between 2013 and 2017. The data used and questions presented are still timely for the following reasons. The first is that panel data take time to collect over a length of time sufficient to explore behavioural dynamics, and the employed dataset represents the most recent we have access to, allowing the researchers to answer a question that to the best of our knowledge has not been explored with panel data. The second is that this study is the first to attempt studying the presence of moral hazard using a panel rather than a cross-sectional dataset, filling a research gap in the current scientific literature. This forms a basis from which later studies can develop. The third reason is that to the best of our knowledge there have been no fundamental shifts in the German flood insurance market. The fourth reason is that such a dataset also ends relatively soon before the onset of the COVID-19 pandemic. Therefore, it represents a period without a major external driver of behavioural change (e.g., national lockdowns).

A final limitation is that we do not fully know whether the respondents were correctly aware of the details of their insurance policy. For instance, the insured respondents believed that the voluntary extension was included in their insurance policy when they did not purchase the coverage extension. Data from insurers would be beneficial when dealing with this limitation, as both sides of the information asymmetry could be observed. This would also help with another potential limitation, because the details of the insurance policy itself such as whether the insurer offered any incentives for policy holders to increase their level of resilience is unknown to us as well. Correctly addressing the issue in future questionnaires would require a deeper dive into this aspect of the survey. Doing so would be a trade-off within the overall survey design, which was aimed at achieving multiple different objectives relating to flood experiences. While misinformation is a potential problem to investigate regarding moral hazard, it could also be mitigated through the observation that moral hazard depends on what individuals believe that they know. Therefore, it is an open question whether it matters if people are suitably insured or just think that they are.

3.3. Discussion

In exploring moral hazard with our unique panel dataset, we find a nuanced view of moral hazard. Within our sample of individuals impacted by the major 2013 flood, insurance coverage was positively associated with both a greater positive change in the number of medium and high-cost property-level flood resilience measures observed and the stated intentions to employ more of these measures in the next six months. This could be argued to represent advantageous selection. Advantageous selection is the opposite of moral hazard, referring to the intrinsic characteristics and behaviours of the purchaser, meaning that people who are proactive in one area of disaster risk management are proactive in others [30,52]. This would follow the current scientific literature investigating moral hazard in Germany [30,31,53] and the argument that a high risk aversion can limit the occurrence of moral hazard [30].

However, the nuance appears that in the case of moral hazard, impacts do potentially occur dynamically regarding the number of medium and high-cost measures implemented. Insurance coverage in the previous period was associated with a reduction in the change in the number of new medium and high-cost measures that are employed in later periods. This is an additional nuance compared to the findings of the existing scientific literature, as it has only been possible to detect with a panel dataset. Therefore, this can be considered a type of (weak) moral hazard impact because, while there is an initial advantageous selection impact, later periods grow at a slower rate. Additionally, the relative gap between the coefficients of the contemporaneous and lagged variables also shrinks the more expensive property-level flood resilience measures become. For instance, the lagged coefficient associated with low-cost measures (see Table 1) is 20% that of the contemporaneous correlation, while it is 41% for medium-cost measures, and 51% for high-cost measures. This implies that prolonged insurance coverage may lower the incentive to employ further self-protection, implying dynamic moral hazard, and in certain respects it may be stronger for certain measures rather than others. However, identifying this avenue for moral hazard also requires further research with external data, as there could be multiple effects taking place. For instance, the model studying property-level flood resilience measure intentions consistently finds a negative relationship between the number of measures currently employed and intentions to employ more measures in the future. The regression models investigating the change in medium and high-cost measures employed cannot include this variable in their model, because it could display aspects of "double counting" with the dependent variable. Therefore, future research could investigate whether the moral hazard effect detected is truly moral hazard or a reflection of a better standard of property-level protection. This could involve (quasi-)experimental techniques, but for this to be successful such techniques would have to be integrated into the survey design.

A wider discussion point that can be raised from this viewpoint of moral hazard is the nature of how the flood insurance penetration rate has developed. Over the years, the German national flood insurance penetration rate has increased from around 10% in 2002 to just under 50% in 2019 (GDV, 2020). The current findings of the absence of moral hazard in the German flood insurance market are based on a relative minority of individuals voluntarily buying insurance coverage. The existing scientific literature argues that these individuals tend to display features that could lead to advantageous selection, completely (or mostly, in the case of the current study) offsetting this result. However, as insurance coverage expands in Germany there are potentially different directions in which flood insurance may evolve. The first is that there could be a market saturation point of the relatively proactive individuals, meaning that the insurance penetration rate could converge to a fixed level whereby most market participants display traits that prevent moral hazard. The other direction that the market may take is where insurance purchasers come from outside of this group of relatively proactive individuals. Therefore, the market may become more dominated or influenced by individuals who do not display traits leading to advantageous selection and instead strengthen the conditions that could give rise to moral hazard. Therefore, we would argue that further research is required to actively monitor this situation. Moreover, more research into the dynamics of moral hazard should take place outside of active floodplains and areas where flooding is relatively rare to further investigate the geographical locus of potential moral hazard occurrence. It may be that facing a higher tangibility of flood risk inhibits the negative incentives that would give rise to moral hazard, and less tangibly threatened areas would not have the same pre-existing conditions. However, this may be in contradiction of the laboratory experiment results presented in Mol et al. [36,37].

Moreover, it must also be noted that both the insured and uninsured groups display a significant intention behaviour gap, as about 50% followed their intentions in later survey waves to implement low-cost measures, as well as medium-cost measures, although we observed that the insured group had a lower behaviour intention gap. This is an area that requires additional research to understand how to convert intentions into tangible actions. To do this, a larger panel dataset designed as a longer long-term study would be useful. This would allow for a more successful analysis controlling for respondent-specific traits through fixed-effects regression models, for example. This is because of the argument that the current lack of overall observable moral hazard is due to the overall instrinic traits of voluntary insurance purchasers. Moreover, a more temporally diverse panel would be able to account for major life events that may cause these intrinsic traits to change (e.g. parenthood), exploring the true stability of these results and whether or not they are time-invariant. Understanding these traits may also aid in determining how the behaviour intention gap manifests and how it can be successfully overcome. An additional line of research connected to this would be to understand how peoples' insurance contracts are constructed and how their perceptions of such might differ from what they actually contain, as noted in Osberghaus [29].

We also observed the lowest intention behaviour gap in the high-cost measures of the insured respondents group. High-cost property-level flood resilience measures, in particular, are expected to require more planning and comitment. When this expectation is put into the context of existing studies on moral hazard in Germany, in particular Hudson et al. [30] and Osberghaus [54]; this may be because those who are insured tend to be more proactive in their overall risk management activities. The panel dataset offers further evidence in favour of this idea. When asked about their stated willingness to buy insurance, 83% of the uninsured sample stated no intention to buy insurance in the future.

4. Conclusion

Insurance coverage is an important part of disaster risk management for its potential to achieve multiple disaster resilience objectives simultaneously if well designed. For instance, well-designed insurance mechanisms can provide a timely influx of resources to help kick-start the post-disaster recovery process, while providing incentives for additional risk management activities by the policyholders. It is for this reason that the European Commission has placed improving disaster insurance coverage as one of the key objectives under the current European Climate Change Adaptation Strategy. There are similar efforts to expand disaster insurance coverage in developing countries for similar reasons. However, while increased insurance can provide many positives to disaster management, increased insurance coverage could also have negative impacts. One of the main avenues that these negative impacts could take effect could be through moral hazard. Moral hazard in the field of disaster risk research is used to refer to an overall reduction in the employment of property-level flood resilience measures. The systematic presence of moral hazard would in the long run undermine the expected increase in disaster resilience.

Therefore, moral hazard is an important topic to study within disaster risk research. We contribute to this literature by investigating the presence of moral hazard using panel data to examine the unexplored temporal dynamics of moral hazard. Previous research in this area has focused on the use of cross-sectional datasets that cannot accurately follow the behaviour over time. Panel data can understand these dynamics, as they record the behaviour of individuals at multiple time steps, rather than the single snapshot that is provided by cross-sectional data.

There is no strong evidence in favour of moral hazard being present through the avenues of the change in property-level flood resilience measures employed, the strength of intentions to employ additional property-level flood resilience measures, and the behaviour intention gap in the panel dataset from Germany. None of these avenues show strong evidence of moral hazard (i.e., an overall reduction in the level of protection). The only avenue of potential moral hazard occurred when a respondent was insured for multiple consecutive years, which was negatively associated with protective behavioural outcomes. However, the association between insurance and property-level resilience measures was positive overall. Therefore, this relationship may have developed because the respondents increase their level of adaptation over time and thus see less need for additional property-level resilience measures. Overall, this paper's central finding remains positive for risk management in our study context.

We argue that future panel datasets should include details on the respondents' insurance policy itself, or at least how the respondents perceive their insurance policy and its details. This would go beyond the common questions used to explore disaster insurance purchase. Such detailed information on disaster insurance policy properties could further be used in countries where insurance coverage is mandatory (e.g., such as in France or Spain). This is because most studies on moral hazard have been in countries where there is, effectively, voluntary insurance coverage. Therefore, we cannot directly extrapolate these results to countries where insurance coverage is compulsory. This is because the failure to find evidence in favour of the systematic presence of moral hazard is driven by the fact that individuals purchasing insurance tend to be proactive in their protection. The impact of this driver might decrease as more individuals purchase insurance. However, in countries where insurance coverage is voluntary, this point may not be reached if there is a limit to how far the insurance penetration rate can increase when it involves a voluntary purchase decision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix 1. Additional regression model results

Table A1
Additional regression model output for medium-cost property-level resilience measures

	Level of intentions to employ extra measures within the next 6 months
Insured	0.18** (0.09)
Lagged insured	0.22** (0.01)
Total measures implemented	−0.02*** (0.01)
Self-stated recovery from the 2013 flood event	−0.06** (0.02)
Lagged self-stated recovery from the 2013 flood event	0.09** (0.03)
Self-stated protective motivation	0.04 (0.03)
Lagged self-stated protective motivation	−0.04** (0.02)
Perceived probability of a future flood	−0.03 (0.03)
Lagged perceived probability of a future flood	0.02 (0.03)
Avoids thinking about flooding	0.06** (0.03)
Lagged avoids thinking about flooding	0.02 (0.02)
Trust in the federal government	−0.001 (0.03)
Lagged trust in the federal government	−0.01 (0.04)
Trust in insurance	0.02 (0.03)
Lagged trust in insurance	−0.05 (0.03)
Constant	0.03 (0.35)
Observations	244

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