Flood Vulnerability Curves and Household Flood Damage Mitigation Measures: an Econometric Analysis of Survey Data

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Key points

- Detailed survey data allows for the update and calibration of rarely estimated empirical vulnerability curves for buildings.
- Flood damage mitigation measures have the potential to reduce flood damage to both residential buildings and household contents by half.
- Updated input for flood risk models in the form of depth-damage functions that can be adjusted for flood damage mitigation measures.

Abstract

Flood events are expected to increase in their frequency and severity, which results in higher flood risk without additional adaptation measures. The information gained from flood risk models is essential in effective disaster risk management. However, vulnerability estimations are often a large driver of uncertainty and flood damage is rarely estimated due to a lack of empirical damage data from flood events. This study uses a unique dataset with experienced damages and the implementation of flood damage mitigation (FDM) measures on the household level, collected after the flood event in the Netherlands in 2021. Flood damage models that control for several hazard, exposure and vulnerability indicators are estimated and allow for an additional input in flood risk models. Previous estimates of the effectiveness of FDM measures are prone to a selection bias, as households that do, and do not implement FDM measures systematically differ in their risk profiles. By using an Instrumental Variable (IV)-estimation, this study overcomes this selection bias and finds significant reductions in flood damage due to FDM measures. These reductions can be incorporated in multivariate flood vulnerability estimations, which indicate that FDM measures significantly reduce flood damage. Highlighting the relevance of information provision on both of these FDM categories and early warning systems for effective flood risk management.

Index terms: 1807, 1821, 1986, 4330, 4336

Keywords: Flood vulnerability, IV-regression, Household survey, Flood damage mitigation

1. Introduction

Natural disasters caused approximately US$280 billion worth of losses in 2021, of which flood events accounted for 40% (Munich Re, 2022). In a changing climate, it is likely that the frequency and intensity of flooding increases, which results in higher flood risk without additional adaptation measures (IPCC, 2021). The assessment of potential flood damage and the effectiveness of adaptation measures is key information for flood risk management decisions (Huizinga et al., 2017). Flood damage is a commonly used measure of flood risk and often assessed by flood risk models that define risk as a function of hazard, exposure and vulnerability (Botzen et al., 2019; Kron, 2005). One of the drivers of uncertainty of estimated flood damage in these models is the input of vulnerability data (De Moel et al., 2012; Aerts et al., 2014), where exposure is also found to influence uncertainty (Sieg & Thieken, 2022). Vulnerability in flood risk models can be defined through depth-damage curves that denote a simple bivariate relationship between inundation depth and damage (De Moel et al., 2012). However, there is often a wide variation in flood risk, and flood damage cannot be fully explained by this depth-damage relationship (e.g., Merz et al., 2004; Thieken et al., 2005).

Moving beyond bivariate depth-damage curves, the inclusion of additional hazard indicators other than inundation depth (e.g., flow velocity, inundation duration) and socioeconomic factors make vulnerability estimates and flood risk models more reliable (Zhai et al., 2005). The studies that estimate multivariate flood damage models, are often limited in the inclusion of other hazard and exposure variables (e.g., Zhai et al., 2005; Poussin et al., 2015, Van Ootegem et al., 2015; Wagenaar et al., 2017). Hazard indicators, such as flow velocity and inundation duration, are often excluded from multivariate regression models, as detailed data from flood events are scarce (e.g., Zhai et al., 2005, Poussin et al., 2015; Van Ootegem et al., 2015). Exposure is frequently left out of depth-damage curves, as the value of damaged properties is often unknown (e.g., Merz et al., 2004, Hudson et al., 2014; Van Ootegem et al., 2015; Sultana et al., 2018). Exposure can be controlled for by using damage ratios instead of absolute damages in calibrating flood damage models. These damage ratios denote flood damage relative to actual property value, and their use in flood damage models facilitates their applicability in other regions with varying property values. As detailed empirical data from flood events is scarce, few studies have calibrated depth-damage models (e.g., Merz et al., 2004, 2013; Thieken et al., 2005, Sultana et al., 2018). Depth-damage curves are even less frequently calibrated in the Netherlands, where current estimates are based on flood damage records from the coastal flood of 1953 (Slager et al., 2013), A limitation of these flood vulnerability estimates is that they generally have limited transferability between different flood types (Wagenaar et al., 2018). Nevertheless, these models are still used to inform optimal safety standards for dikes (Kind, 2014), which makes additional empirical estimates of these curves essential.

An important expansion of multivariate flood damage models is the inclusion of flood damage mitigation (FDM) measures. These measures can be undertaken at the building level by households to reduce flood risk. It is important to evaluate the effectiveness of such measures, as they function as input in flood risk models, which helps guiding both households and policy makers in their flood risk management. Studies that do estimate the effectiveness of FDM measures frequently use a simple difference-in-means test to compare flood damage between the groups that do, and do not, implement these measures (e.g., Smith, 1981; Thieken et al., 2005, Kreibich et al., 2005, Thieken & Kreibich, 2009). However, such a method does not account for other factors than FDM that influence flood risk. Some studies also use multiple regression analysis and machine learning to assess flood damage (e.g., Van Ootegem et al., 2015; Wagenaar et al., 2018), and up to our knowledge only two others used these approaches for evaluating the effectiveness of FDM measures (Merz et al., 2013; Poussin et al., 2015).

Again, most previous literature on the effectiveness of FDM measures is based in Germany, with the exception of Poussin et al. (2015) who use French data, Van Ootegem et al. (2015) who use data from Flanders, Belgium and Wagenaar et al. (2017) who use Dutch data from the 1993 and 1995 Meuse floods, but did not evaluate the effectiveness of FDM measures.

However, these aforementioned studies on the effectiveness of FDM measures could be prone to a selection bias, as described by Hudson et al. (2014). This means that it is likely that both flood damage and the implementation of FDM measures are driven by individual characteristics, such as perceived flood risk prior to the flood event that relates to their actual flood risk profile. The reason is that households who face higher flood risk are more likely to take FDM measures before a flood event (Noll et al., 2022), which results in treatment (with FDM) and control (without FDM) groups that systematically differ in their risk profiles. In other words, it is likely that characteristics of households with FDM measures result in higher flood damage compared to households without these measures. Higher flood risk for the group with FDM measures results in an underestimation of the damage reduction when this selection bias is not controlled for in the analysis. Figure 1 visualizes the selection bias.

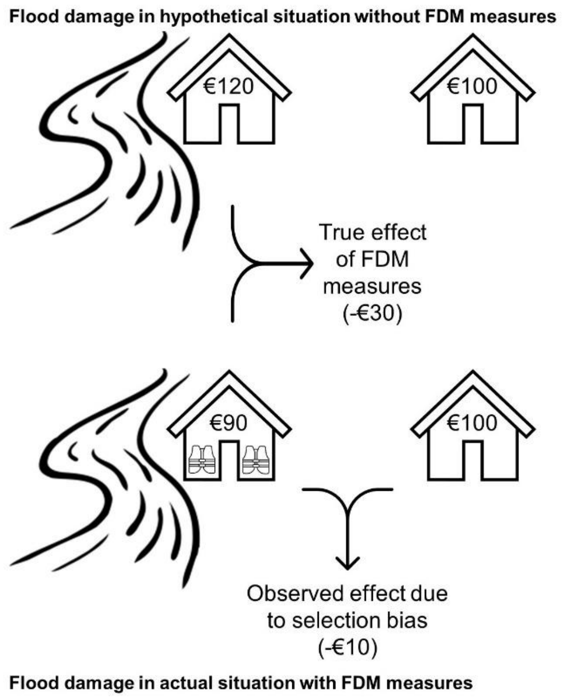

Figure 1. Selection bias that results in an underestimation of the true effect of FDM measures. Note: The building closest to the river faces higher flood risk (€120 vs. €100 in the top hypothetical situation without FDM measures) and is, therefore, more likely to take FDM measures (as shown in the actual situation below). However, we only observe the actual situation below where flood damage has occurred that implies an incorrect damage reduction of €10 (€100 vs. €90). The true effect of FDM measures is the difference between the counterfactual (hypothetical) situation without FDM measures (€120) and the observed situation (€90) with FDM measures: the damage reduction of FDM is €30. The buildings on the right are, therefore, not representative as control group, which results in an underestimation of the true effect of FDM measures.

Hudson et al. (2014) and Sairam et al. (2019) attempted to overcome this selection bias by using propensity score matching (PSM). In PSM each unit in the treatment group is matched with at least one member of the control group with a similar propensity score. This approach helps overcoming the selection bias, as the compared groups are similar based on their observable characteristics. However, PSM does not allow to estimate the separate effect of all confounding variables. As a consequence, only damage reductions are found, while these effects are not related to other indicators that explain flood damage, such as inundation depth or economic exposure. Moreover, flood exposure is excluded in both Hudson et al. (2014) and Sairam et al. (2019), as both studies only analyse absolute flood damages, making these results more difficult to implement in flood risk models.

The main objective of this study is to estimate flood damage vulnerability curves that account for the influence of FDM measures. A secondary aim is to illustrate how these curves and damage reduction estimates can be applied in flood risk models, to allow for a broad applicability in various case study areas by other researchers. The contribution of this study to the existing literature is that we overcome the selection bias present in previous estimates of the effectiveness of FDM measures. This is done by introducing an econometric Instrumental Variable (IV)-regression approach (Angrist et al., 1996) to this literature on empirical flood damage assessments. Moreover, we express the effectiveness of these measures in damage ratios instead of absolute damage to control for exposure. This enables a wider applicability of our estimates to other contexts. Our study makes use of unique survey data on experienced flood damages during a recent flood event in the Netherlands in 2021, and various FDM measures in place at the building level. Thereby, we add to the scarce empirical estimates of determinants of flood damage in general, and FDM measures as explanatory variables in particular.

The remainder of this paper is structured as follows. Section 2 describes the case study and the data that has been collected with the survey. Section 3 outlines the statistical methods. Section 4 presents the results for flood damages to residential buildings and home contents. Section 5 discusses the predictive power of our models, the findings in relation to the existing literature, and the broader applicability of our estimates in flood risk models. Section 6 concludes and gives recommendations for policy makers and future research.

2. Data

2.1. Case study area

In July 2021, parts of Belgium, Germany and the Netherlands experienced severe precipitation and flooding, which caused fatalities, health problems and large financial damage. The peak discharge was the highest ever measured at several gauging stations along the Meuse and its tributaries. Discharge return periods along the Meuse reached 200 years and even 100 to 1000 years along the rivers Geul, Geleenbeek and Roer (*Expertise Netwerk Waterveiligheid* (ENW), 2021). The area of interest in this study is the part of the Netherlands that was affected by this flood event. It is estimated that approximately 2500 households and 600 firms have experienced flood damage and almost 50,000 people have been evacuated in the Netherlands alone (ENW, 2021). Flood damage to households can be covered by either the homeowner's insurance or home contents insurance, depending on the type of insurance contract. In 2018, following the advice of the Dutch Association of Insurers (2021), most national insurers included compensation for local flooding in their homeowner's and household contents insurance policies. This compensation applies to damage resulting from flooding in regional waterways, including tributaries of the Geul, Geleenbeek and Roer, but not to main waterways (e.g., Meuse). Almost all households in the Netherlands are now insured for flooding from regional waterways (Dutch Association of Insurers, 2021). Dutch insurers have received approximately 25,000 damage claims, with the total insured damage estimate between €160 and €250 million (Dutch Association of Insurers, 2021). Since not all flood damage is insured, ENW (2021) estimated that total damage was between €350 and €600 million. Although it is likely that economic exposure has increased since the 1993 and 1995 flood events of the Meuse, flood losses are significantly higher with respectively €201 million and €126 million (converted to euros and corrected for inflation) of economic damage (ENW, 2021).

2.2. Survey

The purpose of the survey is to collect information on individual flood damage amounts and its determinants that are unknown in the aggregate damage estimates. The questionnaires were distributed in December 2021. Letters by postal mail were sent to 10,143 household addresses with a request to complete the online survey. Half of these addresses were located in the flooded area. This flood area was determined by using helicopter images and flood simulation models for the Meuse and its tributaries (Geul, Roer and Geleenbeek). The other half was randomly sampled from the households located in areas in which an evacuation order was issued during the flood event. It is useful to sample these latter areas, as some flood impacts may have occurred at these locations due to potential inaccuracies in the initially defined flood extents. Households who did not respond to the survey received a reminder in February 2022. 1509 (14.9%) households responded to the survey. 40% of all households are located near the Meuse river and 20% along the Geul river. For about a third of the respondents, the geographical location is unknown, as respondents were given the option to refuse to share their home location. The remainder is located along the Geleenbeek or Roer. One third of all households in the survey experienced water intrusion. Data on flood damage as well as several hazard, exposure and vulnerability characteristics were collected, as explained in more detail below.

2.3. Damage ratios

When a property has a higher value, potential damage is larger as well. For this reason, we control for economic exposure by using damage ratios for both building structure and household contents as dependent variables of interest in this study. These are ratios of the absolute damage to the building and household contents compared to their objectively estimated replacement value, as is common practice to correct for exposure in flood risk models (Merz et al., 2010). Estimated damage ratios for both structure and household contents larger than 1 are capped at 1, which implies total destruction of the building or contents. We use estimates of the objective building and content values instead of estimates of these values made by individuals, as individuals may assess these values with errors. Moreover, market values estimated by individuals may not well reflect reconstruction values. Reasons for this difference are that home values may have decreased due to the flood event or market values are very location dependent. For example, homes in attractive cities sell at higher prices than in more remote areas whilst reconstruction costs may be very similar.

For the objective building value, two contractors are contacted to give an estimation of the rebuilding value, which gives a representation of costs faced by the homeowner or insurer. The first approach, proposed by iTX Bouwconsult (2022) allows for more differentiation between building types, as building values are determined based on building type, the number of floors, roof type and the presence of a garage (e.g., buildings with multiple floors have a higher reconstruction value compared to single-floor buildings). These reconstruction values range between €1,610/m^2 and €2,911/m^2 However, these characteristics are not known for the entire database, as not all respondents answered these questions. For this reason the estimates for the known values are compared with the more homogeneous approach of BMVV (2022), that determines reconstruction values only based on building area (€1,806/m^2). A Two-sample t-test has shown that the mean reconstruction values of both approaches do not significantly differ for the known values. For this reason, the BMVV approach is used, as it requires fewer restrictive assumptions.

The replacement value for household contents has been determined using the same approach as insurance companies commonly apply in the Netherlands (e.g., Dutch Association of Insurers, 2023; Independer, 2023). It is assumed that a household owns less than €12,000 worth of audio and computer equipment, less than €6,000 worth of jewelry and less than €15,000 of remarkable possessions. This approach is based on a point system, where points are attributed to household contents based on the respondent's age, dwelling size, household income, homeownership and home living area. One point equals a value of €1,094, where mean replacement value for household contents in our sample is €78,787. This mean value is substantially higher than the mean value of €45,000 in the Netherlands (Dutch Consumer Association, 2023), which can be attributed to the fact that we use replacement values instead of depreciated values for household contents. Moreover, more points are attributed to homeowners and older people, groups that have a higher representation in our sample.

2.4. Explanatory variables in the risk framework

Flood risk, and thus flood damage, can be expressed as a function of hazard, exposure and vulnerability (Kron, 2005; Koks et al., 2015). For this reason, the variables used to explain flood damage in this study all fall within these three categories. Table 1 gives an overview of the explanatory variables included in this study.

First, hazard denotes the severity and probability of a flood event (Kron, 2005). We capture hazard characteristics by including inundation depth, water rise rate, water withdrawal rate and flow velocity. We define inundation depth as the water level at the ground floor of the building to compose depth-damage functions. The rate of water rise is determined by the time it takes for water to enter a building and reach its maximum level. Similarly, the rate of water withdrawal refers to the period between water entering and leaving the building. However, estimating these rates can be challenging for individuals during a flood, particularly when they evacuated during the event. Therefore, respondents were asked to provide estimates for these periods using categorical time steps. While this approach may enable more respondents to answer the question, it may result in less reliable estimates. To estimate flow velocity, we adopted the reference categories used in previous studies by Thieken et al. (2005) and Merz et al. (2013). Although this approach relies on the respondent's perception of an average person and is not entirely precise, we believe it provides more dependable results than asking for flow velocity in m^3/s, which can be difficult for individuals to assess based on their own experiences. Our flow velocity indicator in Table 1 may reflect inundation depth as well, but this does not correspond to inundation depth at the ground floor. While water levels on the street were generally below 1.5 meters, water levels in buildings were influenced by their elevation relative to the street level (ENW, 2021). As a result, the indicator that captures velocity at the street does not correspond to inundation depth. The variable on prior flood experience will be discussed in more detail in Section 3.1 and 3.2.

Next, we include economic exposure in the flood damage model, as objects with higher economic value are likely to incur higher economic damage (Kron, 2005). Exposure is primarily accounted for by expressing flood damage in terms of damage ratio rather than absolute values. Moreover, we include dwelling size and homeownership, as these variables tend to be associated with higher building and content values (Drakes et al., 2019). Moreover, the Dutch flood event was characterized by heterogeneous impacts along the Geul river relative to the Meuse. To address this, we introduce a dummy variable for the Geul river as the most impacted area, which is compared to all other less disrupted areas.

Table 1

Overview of the included explanatory variables in this study. Standard deviations in parentheses (N=312).

Variable	Description	Mean
Hazard		
Inundation depth	Inundation depth at the ground floor in centimetres	50.97 (62.55)
Water rise rate	Hours until the water has reached its highest level in the building	6.76 (10.01)
Water withdrawal rate	Hours until the water has left the building	22.42 (6.60)
Flow velocity	Ordinal variable describing flow velocity in the area of the respondent's home (1=average man could easily stand up, 2=average man could barely stand, 3=average man would have been swept away)	2.14 (0.93)
Prior flood experience	Dummy variable with the value 1 if the respondent has experienced a flood event before	0.35 (0.48)
Exposure		
Dwelling size	Number of people in the household	2.34 (1.09)
Geul river	Dummy variable with the value 1 if the respondent is flooded by the river Geul	0.60 (0.49)
Homeowner	Dummy variable with the value 1 if the household owns their home.	0.88 (0.33)
Vulnerability		
Building year home	Building year home	1938.13 (61.63)
Farmhouse home	Dummy variable with the value 1 if the respondent lives in a farmhouse	0.12 (0.33)
Detached home	Dummy variable with the value 1 if the respondent lives in a detached house	0.42 (0.49)
Terraced home	Dummy variable with the value 1 if the respondent lives in a terraced house	0.14 (0.35)
Semi-detached home	Dummy variable with the value 1 if the respondent lives in a semidetached house	0.25 (0.44)
Apartment	Dummy variable with the value 1 if the respondent lives in an apartment	0.07 (0.26)
FDM x	Dummy variable with the value 1 for the specific FDM measure (Table 2)	Tables 3 and 5

The last category of variables that explain flood damage are the vulnerability indicators. Where older buildings are found to be associated with higher flood damage, caused by outdated construction or poor maintenance (Merz et al., 2010). Next, building types differ in their susceptibility to flooding due to variations in their design, materials and construction (Merz et al., 2013; Huizinga et al., 2017). Finally, it is relevant to assess the impact of FDM measures on flood damage (Table 2). The literature often makes a distinction between wet- and dry flood-proofing measures (e.g., Kreibich et al., 2005; Poussin et al., 2012; De Moel et al., 2012). Dry-proofing refers to sealing a building in such a way that water is not able to enter the building. Specific dry-proofing measures are placing barriers or elevating the building. The drawback of dry-proofing is that it often fails during extreme floods with high inundation depths (Kreibich et al., 2015; Poussin et al., 2012). In contrast to dry-proofing, wet-proofing is targeted at reducing the water's destructive capacity once it has entered the building. Examples include using waterproof materials, placing a water pump and elevating electronic devices and power sockets. We do not include insurance as vulnerability-reducing factor, as prior research has demonstrated that flood insurance is not a significant factor in the adoption of FDM measures in the Netherlands. Mol et al. (2020a, 2020b) conducted an experimental study that found no evidence of moral hazard arising from flood insurance leading to reduced FDM uptake in the Netherlands. Furthermore, flood insurers do not actively incentivize the uptake of these measures (Dutch Association of Insurers, 2021).

Table 2

Overview of how specific FDM measures are grouped in different categories of FDM measures (N=312).

FDM measure	Emergency	Structural	Dry-proofing	Wet-proofing
Barriers	X		X	
Elevating building above street level		X	X	
Water pump	X			X
Water-resistant floor		X		X
Water-resistant walls		X		X
Other water-resistant materials		X		X
Strengthening foundation		X		X
Elevating electrical appliances		X		X
Elevating personal possessions	X			X

Note: Water-resistant walls and strengthening the foundation are only applicable for damage to building structure; elevating personal possessions is only applicable to damage to household contents.

Furthermore, a distinction between emergency and structural FDM measures is relevant from a policy perspective. Emergency measures refer to FDM measures taken shortly before a flood event is almost certain to occur (e.g., placing barriers, moving personal possessions to higher floors). Early warning systems play an essential role in facilitating emergency measures, through risk communication and insights in effective emergency response (Merz et al., 2013; Lendering et al., 2016; Kreibich et al., 2021). Structural FDM measures are taken as a precautionary preparation for a potential future flood event (e.g., strengthening the building foundation, placing a waterproof floor). By estimating the effect of both wet- and dry-proofing as well as emergency and structural FDM measures, the results of this study can be of use in different types of flood risk models, depending on the goal and scope of the modelling study.

3. Methodology

3.1. Estimation technique

Depth-damage functions are estimated using two different approaches arising from the literature. First, the median flood damage ratio at every inundation depth is plotted, using the 25th and 75th percentile of the data as confidence intervals (Thieken et al., 2005, Wagenaar et al., 2017). This approach will not result in a smooth curve, but will give a relationship between inundation depth and flood damage. Next, a root function is used to describe the nonlinear effect inundation depth has on flood damage in regression models (Wagenaar et al., 2017; Sultana et al., 2018; Sieg & Thieken, 2022). When estimating the effect of inundation depth and multiple FDM measures, a regression equation in Ordinary Least Squares (OLS) would be as follows:

$$Damage\ ratio_i = \beta_0 + \beta_1\sqrt{inundation\ depth_i} + \beta_2 FDM_i + \beta_k X'_i + \varepsilon_i \qquad (1)$$

The damage ratio for either building structure or household contents for individual *i* is a function of the square root of inundation depth, FDM measures and the additional control variables ($\beta_k X'_i$) (Section 2.4). FDM measures are designed to reduce flood damage. However, households that perceive higher flood risk are more likely to take FDM measures (Noll et al., 2022), This can result in a selection bias where households with FDM measures seem to have high damages, thus blurring the damage reducing effect of these measures. In econometrics, this selection bias manifests itself as a problem of endogeneity with the error term ε_i, where the variable *FDM* is positively correlated with both the dependent variable *damage ratio* and the unobserved household characteristics in error term ε_i. As a consequence, an OLS-estimation will give an underestimation of the true effect of FDM measures on flood damage. A Hausman-Wu test (Wu, 1973; Hausman, 1978) on our data confirmed that there is indeed endogeneity present when estimating the effect of FDM measures using an OLS regression. For this reason, an approach that deals with endogeneity has to be chosen. An IV-regression is an approach to overcome the issue of endogeneity in regression analysis caused by selection bias that originates from unobserved individual characteristics (Angrist & Pischke, 2008). This method is also referred to as two-stage-least-squares (2SLS) and has been applied in this study as follows:

$$\widehat{FDM}_i = \delta_0 + \delta_1\sqrt{inundation\ depth_i} + \delta_2 Prior\ flood\ experience_i + \delta_k X'_i + u_i \quad \textit{(first stage)}\ (2)$$

$$Damage\ ratio_i = \beta_0 + \beta_1\sqrt{inundation\ depth_i} + \beta_2\widehat{FDM}_i + \beta_k X'_i + e_i \qquad \textit{(second stage)}\ (3)$$

In an IV-regression, an exogenous variable functions as an instrument for the endogenous variable, in this case *FDM*. In the survey, respondents were asked whether they had experienced a flood event before. 35% of the flooded households in the survey have experienced a flood event at their home before July 2021. Prior flood experience can function as an exogenous instrumental variable in this case. The reason is that prior flood experience has been shown to increase the probability that a household adopts FDM measures (e.g., Bubeck et al., 2012; Koerth et al., 2017; Van Valkengoed & Steg, 2019). In the first stage, prior flood experience is used to predict whether a household takes FDM measures or not. In the second stage these predicted values are used instead of the actual values of *FDM*. Unobserved characteristics in the second stage are now no longer a predictor of adopting FDM measures, resolving the issue of endogeneity by removing the correlation with the error term e_i. The first and second stage are performed for each individual FDM measure category separately. A Breusch-Pagan test has shown the need to apply robust standard errors (Woolridge, 2014), as we do in our study. There is not an issue of multicollinearity in our data, as the confounding variables in the regression models are not strongly correlated.

3.2. Assumptions of an Instrumental Variable (IV) regression

Including prior flood experience as an instrumental variable means that it is one of the relevant drivers of FDM uptake, while also being exogenous to actual flood damage. There are two assumptions that need to be met to use a variable as instrument (Woolridge, 2014):

1. Relevance: Cov(*Prior flood experience*, *FDM*) ≠ 0

The first assumption is instrument relevance, which means that there should be a correlation between the instrumented variable (i.e. *FDM*) and the instrumental variable (i.e. *Prior flood experience*). The instrument should be able to explain variation of the endogenous variable. Without sufficient correlation between these two variables, it is not possible to make accurate predictions for the second stage of the 2SLS. This approach does not imply that prior flood experience is the main driver of FDM uptake, just that it is one of the drivers, and thus relevant to include in an IV-regression (Angrist & Pischke, 2008). In several review papers of individual flood preparedness, it has been found that prior flood experience does positively influence the adoption of FDM measures, which already implies that the instrument is relevant (e.g., Bubeck et al., 2012; Koerth et al., 2017; Van Valkengoed & Steg, 2019). The relevance assumption can be tested by rejecting the null-hypothesis of no correlation with a sufficiently small level of significance (i.e. 1% or 5%) (Woolridge, 2014). Staiger and Stock (1997) propose a rule-of-thumb that the F-value of the first stage should be larger than 10. By performing these tests, it is found that the relevance assumption holds and these results are provided below for every regression model in Tables 4 and 6.

2. Exogeneity: Cov(*Prior flood experience*, ε_i) = 0

The second assumption is exogeneity, which means that the instrument cannot affect the dependent variable in any other way than through the endogenous (instrumented) variable (Woolridge, 2014). This assumption cannot be tested, but should be discussed using knowledge of the system. Although there are various relevant indicators that drive the uptake of FDM measures (e.g., homeownership, coping appraisal, risk appraisal), these indicators are often not exogenous to flood damage. It is key that the instrument that explains the uptake of FDM measures is not associated with flood damage. In this context, prior flood experience should not influence current flood damage in other ways than through adopting more FDM measures.

Prior flood experience is plausibly exogenous and not directly correlated with the error term in the regression equation. Specific hazard characteristics of the 2021 flood are not impacted by the fact that there has been a flood before. Prior flood experience is expected to only be correlated with flood damage through its impact on households' decisions to invest in flood protection measures, as has been shown in the literature (e.g., Wind et al., 1999; Kreibich & Thieken, 2009). Prior flood experience and damage is therefore unlikely to affect flood damage to affect flood damage after a future flood event in any other way than through higher FDM uptake. It is, therefore, likely that the exogeneity assumption holds, which allows for an IV-regression using prior flood experience as instrumental variable.

3.3. Implications of 2SLS

A limitation of an IV-approach is that it is not possible to include more instrumented variables than there are instruments available (Hansen et al., 2008). The implication of this limitation, is that multiple FDM measures cannot be incorporated in the model at the same time, although it is possible that some households adopt multiple FDM measures at once. Neither is it possible to include an interaction term of the water level and the FDM measures, although some FDM measures differ in effectiveness at different inundation levels (Merz et al., 2013, Poussin et al., 2014). In an attempt to overcome this, an additional analysis with separate regressions for different inundation depths has been included in the discussion and appendix. Finally, an IV-regression produces larger standard errors compared to the same model in OLS, as the fitted values of the instrumented variables are used compared to its actual values, which increases uncertainty. For this reason, it may be more difficult to detect significant effects of FDM measures (Woolridge, 2014).

4. Results

4.1. Building structure: depth-damage relationship

Figure 2 shows a bivariate depth-damage relationship, as frequently composed in the literature (e.g., Thieken et al., 2005; Wagenaar et al., 2017). The y-axis gives the building damage ratio and the x-axis water level at the ground floor during the flood, divided in several classes. Where the median damage and the 25th and 75th percentile per inundation depth is given for the group that did implement FDM measures (in green) and the group that did not (in blue). The category labelled as '0 cm' includes the group that faced water accumulation against the exterior wall of the building but prevented water from entering the building, as well as the group that experienced flooding only in the basement of the building.

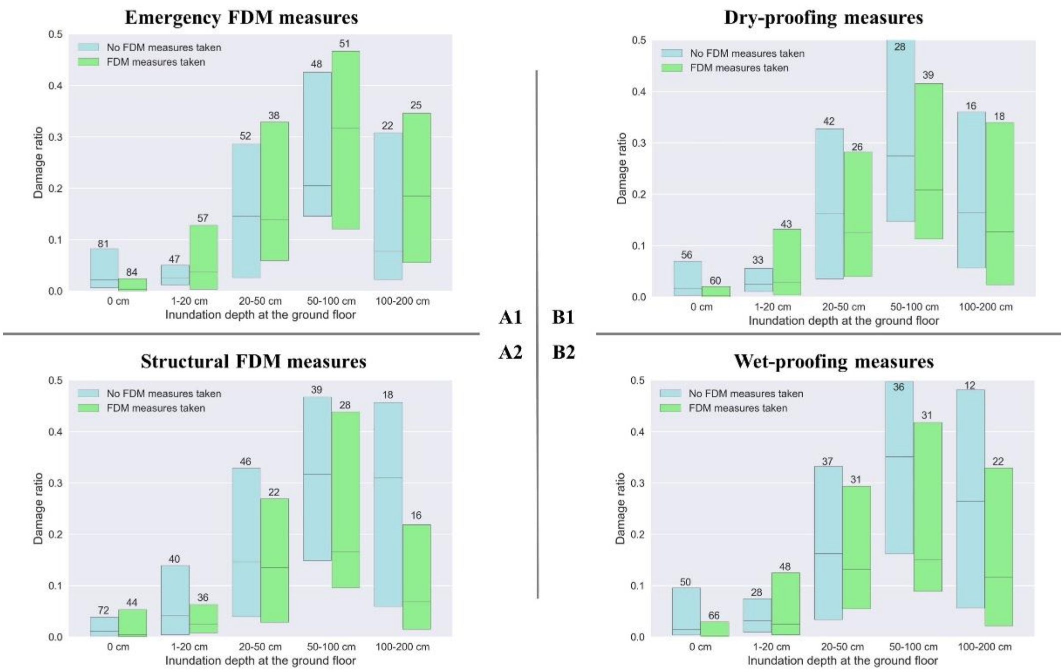

Figure 2. Depth-damage relationship for building structure, differentiated for the groups without FDM (blue) and with FDM (green) divided into emergency (A1) versus structural (A2) and dry- (B1) and wet-proofing (B2) FDM categories. The lower and upper part of the boxes represent the 25th and 75th percentile of flood damage ratios, with the median in between. Number of observations on top of the boxes.

Note: The group with FDM measures (green) only reflects the group that has taken FDM measures reflected in the figure. The group without FDM (blue) did not take that specific measure, but may have taken other FDM measures.

In Figure 2, it is visible that the flood damage seems to follow a non-linear path, with a relatively large increase in damage ratios going from inundation depths below 20 cm to 20-50 cm. Flood damage slightly decreases at inundation depths higher than 1 meter, while the confidence intervals increase. Wagenaar et al. (2017) offer an explanation for this phenomenon, as households with the largest inundation depths may have been flooded before. Consequently, these households may be better prepared for future flood events, based on their prior flood experience. It is, therefore, important to note that the estimated effect of FDM measures is still prone to the selection bias as described before, as both groups (i.e., those with and without FDM measures) systematically differ from each other in their risk profiles. The size of the effect of FDM measures can, therefore, not be quantified as this effect will be underestimated. Nevertheless, the direction of the effect remains clear and it is possible to observe at which inundation depth certain FDM categories are more effective. However, it should be noted that even the group without FDM measures from Figure 2 experiences a decline in damage ratios above 1 meter for emergency and dry-proofing FDM measures. This observation can be attributed to some households having implemented multiple FDM measures. For instance, some households in the group that has not taken emergency FDM measures may have employed structural FDM measures, leading to a slight reduction in damage ratios for the group without emergency FDM as well. To determine the exact effect of FDM measures, an IV-regression will be conducted.

Panel A1 shows no visual evidence for any effect of emergency measures at inundation depths below 20 cm. Additionally, lower damage ratios are observed for the ‘0 cm’ group (i.e., the group that managed to keep the water out of the building and where only the basement has been flooded) for all measures. We observe a larger difference in means between the group that has and has not taken structural FDM measures at inundation depths above 20 cm (Panel A2). Panel B2 shows that wet-proofing becomes more effective in reducing damage as inundation depth increases. At high inundation depths, it becomes increasingly difficult to keep the water out, where wet-proofing is observed to be more effective than dry-proofing (De Moel et al., 2012).

4.2. Building structure: difference-in-means

Table 3 gives the difference-in-means between the group that has taken FDM measures and the group that has not taken FDM measures. The group that has taken adaptation measures does have a lower mean absolute damage and damage ratio for each FDM category. When comparing absolute flood damage to buildings, a significant reduction for structural FDM measures and wet-proofing can be observed. When controlling for exposure by relating flood damages to building values, also emergency measures significantly ($p<0.1$) reduce flood damage. Moreover, using damage ratios instead of absolute damages also results in less uncertainty around the estimates of structural FDM measures. This highlights the importance of controlling for exposure in flood damage estimates, as it reduces errors in the estimates. We observe that wet-proofing buildings results in the largest damage reduction compared to the other FDM categories.

Table 3

Damage reduction in absolute euro amounts and damage ratio for building structure by comparing the means of the group that has not taken FDM measures (A) and the group that has (B) of which the group sizes are shown in the columns by N.

FDM measure	N (A)	N (B)	Difference in absolute building damage (€)	Difference in damage ratio building
Emergency FDM	123	191	-10,032	-0.10*
Structural FDM	184	130	-23,451**	-0.14***
Dry-proofing	156	158	-6,276	-0.07
Wet-proofing	142	172	-31,687***	-0.15***

*** p<0.01, ** p<0.05, * p<0.1

These results should be interpreted with caution, as the aforementioned selection bias is still present in the data. This does mean that we do observe the damage reducing capacity of these measures, although the estimates are likely to be an underestimation of the damage-reducing effect of the measures if people with FDM measures face higher flood risk. For this reason, an IV-regression will be applied in Table 4.

4.3. Building structure: IV-regression for depth-damage curves and FDM measures

Table 4 gives several regression specifications with the damage ratio for building structure as dependent variable. Models 1 and 4 give an OLS-specification, where Models 2,3,5,6 are computed using an IV-approach. Model 1 in Table 4 shows the OLS estimation as described in equation (1) in the methodology Section 3.1. The specification in OLS (Model 1) shows a smaller negative effect for all FDM measure categories compared to the IV-specifications (Models 2 and 3), which shows that there was endogeneity present in the OLS specification, as the effect of FDM measures was underestimated compared to the IV-specification that overcomes the selection bias.

Adopting emergency measures significantly ($p<0.05$) reduces the damage ratio for building structure with 0.29, ceteris paribus. The F-value of the instrument confirms that the relevance assumption holds, as the value is larger than 10 (Staiger & Stock, 1997). It is found that having prior flood experience increases the likelihood of adopting emergency measures with 23%, keeping all the other variables constant. The instrument is significant at the 1% level in all models, which again confirms the relevance assumption. Model 3 shows that the effect of structural FDM measures is smaller compared to emergency measures, although still of an important size. The effect sizes of FDM measures in Table 4 are larger compared to the 0.10 and 0.14 percentage point reduction in damage ratios observed using a difference-in-means test in Table 3. Moreover, the bias correction shows that the effect of dry-proofing is larger than the effect of wet-proofing on building damage, which is different from the relative effects from Table 3.

Similar results are visible in Models 4-6, as OLS still underestimates the effectiveness of wet-proofing and dry-proofing measures in Model 4 compared with the IV Models 5-6. The coefficient of dry-proofing is of similar size as that of emergency measures. This result makes sense as a large share of the measures within these categories are similar for the mitigation of building damage. The coefficients of structural FDM measures and wet-proofing are of similar size as well, although the effect of wet-proofing measures is significant at the 1% level.

The coefficient for inundation depth gives the shape of the depth-damage curve. It is confirmed that inundation depth is the most important hazard indicator for explaining flood damage, as this variable has the highest coefficient of all hazard indicators and remains significant between different specifications. The coefficient of the square root of inundation depth ranges between 0.014 and 0.017 between the models and is significant at the 1% level. This confirms the relationship between inundation depth and flood damage as described in the literature (Thieken et al., 2005, Wagenaar et al., 2017; Sultana et al., 2018; Sieg & Thieken, 2022).

All models consistently show that homeownership is associated with higher flood damage ratios. Homeowners are more susceptible to economic damage from flooding compared to tenants, as they have a greater financial investment in the property (Drakes et al., 2019). In this study, we used uniform maximum damage values for both homeowners and tenants. Homeowners have higher economic exposure compared to tenants, resulting in higher damage and thus, higher damage ratios because of the same property value baseline used in this study. The next significant variable in the models is the Geul river dummy, which is a dummy for the most disrupted area. It is shown that residents living along the Geul on average have a 0.10 higher damage ratio compared to residents living in less disrupted areas.

Table 4

Estimated coefficients using an OLS regression (Model 1 & 4) and an IV-regression (Model 2,3,5,6) that explain building damage ratios in models including emergency (1 and 2), structural (1 and 3), and dry- (4 and 5) and wet-proofing (4 and 6).

VARIABLES	(1) OLS	(2) IV	(3) IV	(4) OLS	(5) IV	(6) IV
$\sqrt{\text{Inundation depth}}$	0.016***	0.015***	0.015***	0.016***	0.017***	0.014***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)
Homeowner	0.090***	0.107**	0.109***	0.093***	0.106**	0.115***
	(0.034)	(0.044)	(0.039)	(0.034)	(0.041)	(0.040)
Dwelling size	0.019	0.030*	0.024*	0.020	0.028*	0.025*
	(0.013)	(0.017)	(0.014)	(0.014)	(0.016)	(0.014)
Building year home	-0.000	-0.000	-0.000*	-0.000	-0.000	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Geul river	0.104***	0.102***	0.093***	0.102***	0.106***	0.087***
	(0.024)	(0.030)	(0.025)	(0.024)	(0.029)	(0.024)
Water rise rate	-0.001	-0.001	-0.000	-0.001	-0.000	-0.001
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Water withdrawal rate	0.001	0.000	0.000	0.002	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Flow velocity	0.017	0.019	0.026*	0.017	0.014	0.025
	(0.015)	(0.019)	(0.016)	(0.015)	(0.018)	(0.016)
FDM Emergency	0.013	-0.289**				
	(0.027)	(0.128)				
FDM Structural	-0.076***		-0.222**			
	(0.026)		(0.087)			
FDM Dry-proofing				0.003	-0.284**	
				(0.026)	(0.125)	
FDM Wet-proofing				-0.069***		-0.203***
				(0.027)		(0.077)
Constant	0.458	0.727	0.757*	0.468	0.592	0.748*
	(0.437)	(0.491)	(0.453)	(0.427)	(0.478)	(0.421)
Observations	311	311	311	311	311	311
Adjusted R-squared	0.196			0.193		
Building FE	X	X	X	X	X	X
F-value instrument		14.44	26.03		14.24	30.78
β instrument		0.23***	0.30***		0.23***	0.32***
		(0.06)	(0.06)		(0.06)	(0.06)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.4. Household contents: depth-damage relationship

Figure 3 gives a relationship between inundation depth and flood damage to household contents. We observe that flood damage to household contents follows the same pattern as for building structure, where there is a rapid increase in damage ratios from 1-20 cm to 20-50 cm. Note that these results are still prone to the selection bias, although the direction of the effect can be interpreted. It stands out that emergency measures seem to result in lower damage ratios until 50 cm, where this difference is smaller at higher inundation depths (Panel A1). The damage reducing effect of structural FDM measures seems to be larger for water levels above 20 cm (Panel A2). Dry-proofing shows a larger damage reducing effect at inundation depths below one meter, where the largest damage reduction for wet-proofing is observed for inundation depths larger than 20 cm (Panels B1 and B2).

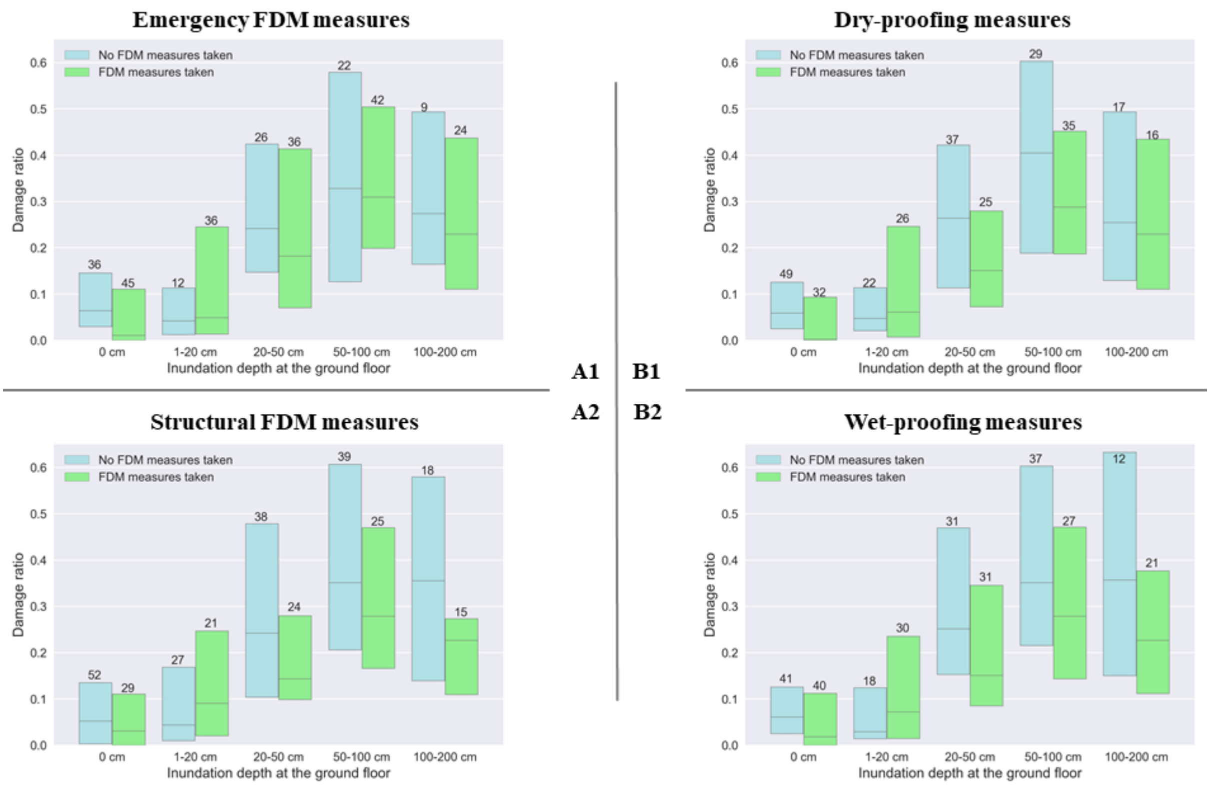

Figure 3. Depth-damage relationship for household contents, differentiated for the groups without FDM (blue) and with FDM (green) divided into emergency (A1) versus structural (A2) and dry- (B1) and wet-proofing (B2) FDM categories. The lower and upper part of the boxes represent the 25th and 75th percentile of flood damage ratios, with the median in between. Number of observations on top of the boxes.

Note: The group with FDM measures (green) only reflects the group that has taken FDM measures reflected in the figure. The group without FDM (blue) did not take that specific measure, but may have taken other FDM measures.

4.5. Household contents: difference-in-means

Similar to Table 3 for building damage, Table 5 gives the difference-in-means for household contents damage for the groups that have, and have not, taken FDM measures. All groups that have taken FDM measures experienced lower damage to household contents compared to the group that has not taken these measures. The difference between these groups is significant for absolute contents damage for structural FDM measures and wet-proofing. When controlling for exposure, we can also distinguish a significant effect for emergency FDM measures (p<0.1). To overcome the selection bias and to make more precise estimates, a multivariate IV-regression will be applied to the data.

Table 5

Damage reduction in absolute euro amounts and damage ratio for household contents by comparing the means of the group that has not taken FDM measures (A) and the group that has (B) of which the group sizes are shown in the columns by N.

FDM measure	N (A)	N (B)	Difference in absolute contents damage (€)	Difference in damage ratio household contents
Emergency FDM	97	175	-8,498	-0.13*
Structural FDM	160	112	-11,412**	-0.16**
Dry-proofing	147	125	-3,141	-0.04
Wet-proofing	129	143	-15,605**	-0.34**

*** p<0.01, ** p<0.05, * p<0.1

4.6. Household contents: IV-regression for depth-damage curves and FDM measures

Table 6 presents the results of both an OLS and an IV-approach to explain the damage ratio of household contents. The depth-damage function for household contents follows the same path as for building structure, as the coefficient are of similar size and significance for inundation depth. Also the amount of time the water has been in the building significantly increases damage to household contents, where one additional hour of the flood water being in the house is associated with a 0.01 increase in the household contents damage ratio. Again, the coefficient for homeownership is significant and positive, which can be explained by homeowners having on average higher household contents values (Drakes et al., 2021), while we use the same baseline for homeowners and tenants.

Emergency measures are shown to be more effective than structural FDM measures in reducing flood damage to household contents. These findings are similar to the findings for building damage in Table 4. The intuition behind this, is that moving personal possessions to higher floors is included in the category of emergency measures for household contents, which seems to be highly effective in reducing flood damage. The instrument in the IV-regressions is relevant for all models, except model 5. Although the instrument is still significantly correlated, the F-value is below the threshold of relevance proposed by Staiger and Stock (1997), which indicates that the instrument is not strong enough to reliably estimate the effect of dry-proofing FDM measures on building damage. Wet-proofing is again significant at the 1% level and shows a 0.38 reduction in the damage ratio when applied, keeping all other variables constant.

Table 6

Estimated coefficients using an OLS regression (Model 1 & 4) and an IV-regression (Model 2,3,5,6) that explain household contents damage ratios in models including emergency (1 and 2), structural (1 and 3), and dry- (4 and 5) and wet-proofing (4 and 6).

VARIABLES	(1) OLS	(2) IV	(3) IV	(4) OLS	(5) IV	(6) IV
$\sqrt{\text{Inundation depth}}$	0.017***	0.017***	0.014***	0.017***	0.018***	0.013***
	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)
Homeowner	0.161***	0.191***	0.183***	0.164***	0.180**	0.200***
	(0.049)	(0.065)	(0.057)	(0.050)	(0.072)	(0.063)
Dwelling size	0.023	0.027	0.035*	0.025	0.027	0.041**
	(0.017)	(0.019)	(0.020)	(0.017)	(0.020)	(0.019)
Building year home	0.000	-0.000	-0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Geul river	0.108***	0.097**	0.069	0.101***	0.110**	0.044
	(0.035)	(0.046)	(0.048)	(0.035)	(0.052)	(0.050)
Water rise rate	-0.001	0.001	-0.001	-0.002	0.004	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Water withdrawal rate	0.007***	0.004	0.005*	0.007***	0.008**	0.006**
	(0.001)	(0.003)	(0.003)	(0.001)	(0.003)	(0.003)
Flow velocity	0.019	0.031	0.035	0.021	0.013	0.043*
	(0.019)	(0.026)	(0.023)	(0.020)	(0.029)	(0.025)
FDM Emergency	-0.005	-0.437**				
	(0.040)	(0.171)				
FDM Structural	-0.042		-0.375**			
	(0.035)		(0.150)			
FDM Dry-proofing				0.005	-0.539**	
				(0.035)	(0.266)	
FDM Wet-proofing				-0.062*		-0.382**
				(0.035)		(0.149)
Constant	-0.421	0.554	0.068	-0.397	0.387	0.168
	(0.389)	(0.588)	(0.561)	(0.374)	(0.764)	(0.524)
Observations	251	251	251	251	251	251
Adjusted R-squared	0.222			0.228		
Building FE	X	X	X	X	X	X
F-value instrument		12.76	16.44		6.90	16.24
β instrument		0.23***	0.27***		0.18***	0.27***
		(0.06)	(0.07)		(0.07)	(0.07)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5. Discussion

5.1. Spatial fit of the model

The purpose of Figure 4 is to detect a potential spatial pattern of the damage model. This is achieved by showing the root mean squared error (RMSE) of the predictions of Model 3 of Table 4 for each individual case. The Figure shows the RMSEs for this model, as this is the model with the most accurate predictions. The other IV-models from Table 4 and 6 are supplied in the appendix. It should be noted that these cases were also used to derive the model, indicating that this is not a validation exercise, but aimed at investigating and identifying any potential spatial patterns in the predictions of the model.

It stands out that the model is able to predict flood damage fairly well, as the majority of observations show a RMSE below 0.15. The RMSE is larger than 0.3 for 39 out of 244 households of which the geographical location is known. Approximately 90% of these households are located along the Geul. A closer look to this group shows that more than two-third experienced large flood damage with building damage ratios larger than 0.4. For these cases, the model generally underpredicts flood damage. A potential explanation for this underprediction is the destructive capacity of high flood velocities and quickly rising flood water in these areas. In addition, households in this tributary river were caught by surprise and probably had less time to follow up early warning signals as compared to downstream communities (ENW, 2021). The model performs better further downstream, where slopes are less steep and flood damage is mainly caused by inundation depth.

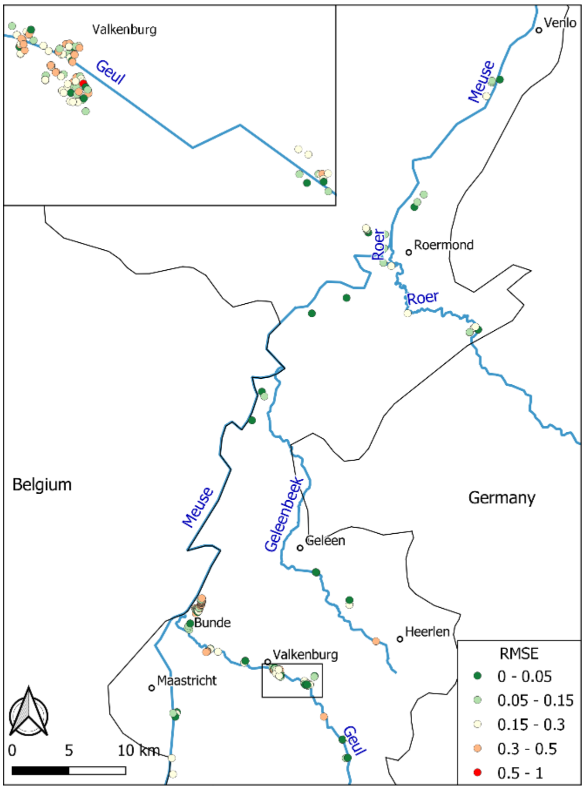

Figure 4. Root mean squared error (RMSE) of the model's predicted structural flood damage ratio (Based on Table 4, Model 3).

5.2. Application in flood risk models

The IV-regression outcomes presented in Tables 4 and 6 can serve as inputs for flood risk modeling, particularly for riverine flooding in unembanked areas, in the form of depth-damage curves. These curves are valuable for assessing flood risk, and the addition of FDM measures can enable household flood adaptation. However, empirical flood vulnerability estimates can vary between different types of floods and regions (Jongman et al., 2012; Wagenaar et al., 2018). As our flood damage model is based on a specific flood event in the Netherlands with relatively low inundation depths and Dutch building types, they may not necessarily be representative for other flood events with different characteristics, such as higher stream velocities or water pollution. Therefore, it is necessary to exercise caution when using these models in other contexts. Table 7 gives the formulas that are the outcomes of Table 4 and 6.

To apply these formulas in flood risk model, all known variables should be filled in the equation. To apply a FDM measure, the measure can have the value 1 in the formulas above to incorporate its damage-reducing potential. Note that the model can predict negative damage ratios, which implies no flood damage. Although it is more difficult to include the other explanatory variables due to a lack of information on input data, it is possible to include these to add more precision to the flood risk model. If some variables are unknown, one can account for this by simply filling in the sample mean from Table 1 to compose the damage function.

Table 7

Flood damage formulas for building and contents damage to insert in flood risk models.

	Damage ratio building structure	**Damage ratio household contents**
Emergency FDM measures	0.727 + 0.015× $\sqrt{inundation\ depth}$ – 0.289×*FDM Emergency* + 0.107×*Homeowner* + 0.024×*Dwelling size* – 0.0004×*Building year home* + 0.102 ×*Geul river* - 0.001×*Water rise rate* + 0.00002×*Water withdrawal rate*+ 0.026×*Flow velocity* +0.033×*BT_D* + 0.019×*BT_T* + 0.028×*BT_SD* – 0.025×*BT_A*	0.554 + 0.017× $\sqrt{inundation\ depth}$ – 0.437×*FDM Emergency* + 0.191× *Homeowner* + 0.027×*Dwelling size* – 0.0003×*Building year home* + 0.097 ×*Geul river* - 0.001×*Water rise rate* + 0.004×*Water withdrawal rate* + 0.031×*Flow velocity* + 0.102×*BT_D* + 0.084×*BT_T* + 0.155×*BT_SD* + 0.048×*BT_A*
Structural FDM measures	0.757 + 0.015× $\sqrt{inundation\ depth}$ – 0.222×*FDM Structural* + 0.109× *Homeowner* + 0.024×*Dwelling size* – 0.0004×*Building year home* + 0.093 ×*Geul river* - 0.0004×*Water rise rate* + 0.0003×*Water withdrawal rate* + 0.03×*Flow velocity* - 0.003×*BT_D* + 0.004×*BT_T* – 0.011×*BT_SD* – 0.041×*BT_A*	0.068 + 0.017× $\sqrt{inundation\ depth}$ – 0.375×*FDM Structural* + 0.183× *Homeowner* + 0.035×*Dwelling size*– 0.0001×*Building year home* + 0.069 ×*Geul river* - 0.001×*Water rise rate* + 0.005×*Water withdrawal rate* + 0.035×*Flow velocity* +0.016×*BT_D* + 0.043×*BT_T* + 0.061×*BT_SD* + 0.046×*BT_A*
Dry-proofing	0.592 + 0.017× $\sqrt{inundation\ depth}$ – 0.284×*FDM Dryproofing* + 0.106× *Homeowner* + 0.028×*Dwelling size* – 0.0003×*Building year home* + 0.106 ×*Geul river* – 0.00007×*Water rise rate* + 0.001×*Water withdrawal rate* + 0.014× *Flow velocity* + 0.009×*BT_D* + 0.009×*BT_T* – 0.003×*BT_SD* – 0.06×*BT_A*	0.387 + 0.018× $\sqrt{inundation\ depth}$ – 0.539×*FDM Dryproofing* + 0.180× *Homeowner* + 0.027×*Dwelling size* – 0.0003×*Building year home* + 0.110 ×*Geul river* – 0.004×*Water rise rate* + 0.008×*Water withdrawal rate* + 0.013×*Flow velocity* + 0.156×*BT_D* + 0.202×*BT_T* + 0.183×*BT_SD* + 0.131×*BT_A*
Wet-proofing	0.748 + 0.014× $\sqrt{inundation\ depth}$ – 0.203×*FDM Wetproofing* + 0.115× *Homeowner* + 0.025×*Dwelling size* – 0.0004×*Building year home* + 0.087 ×*Geul river* - 0.001×*Water rise rate* + 0.001×*Water withdrawal rate* + 0.025×*Flow velocity* + 0.024×*BT_D* + 0.027×*BT_T* + 0.027×*BT_SD* – 0.017×*BT_A*	0.168 + 0.013× $\sqrt{inundation\ depth}$ – 0.382×*FDM Wetproofing* + 0.200× *Homeowner* + 0.041×*Dwelling size* – 0.0002×*Building year home* + 0.044 ×*Geul river* - 0.002×*Water rise rate* + 0.006×*Water withdrawal rate* + 0.043×*Flow velocity* +0.079×*BT_D* + 0.060×*BT_T* + 0.152×*BT_SD* + 0.079×*BT_A*

Note: for building types: BT_D=detached, BT_T=terraced, BT_SD=semi-detached, BT_A=apartment, farmhouses function as the reference category. These models are based on the outcomes of Table 4 and 6 for the IV-regression model where the respective FDM measure has been included. Building specific differences were included as fixed effects in the regression models, but are shown in Table 7 below (the full regression with visible building fixed effects can be found in the supplementary materials).

Figure 5 shows how the formulas from Table 7 can be transferred into bivariate depth-damage curves by using the sample means for all variables except inundation depth and FDM measures. Table 7 shows how the original depth-damage curve can be shifted by structural and emergency FDM measures. The depth-damage curve without FDM can be drafted as the average of the

Models from Table 7, with the value of the FDM dummy being 0. Wet- and dry-proofing measures are excluded from the figure for more clarity, but can be inserted in the same way. Figure 5 shows the average of the coefficients with Model 2 and 3 from Tables 4 and 6 functioning as an upper and lower bound of the estimates. It stands out that the average of the coefficients for structural and emergency FDM measures overlap for household contents, although the latter generally shows a larger damage reduction.

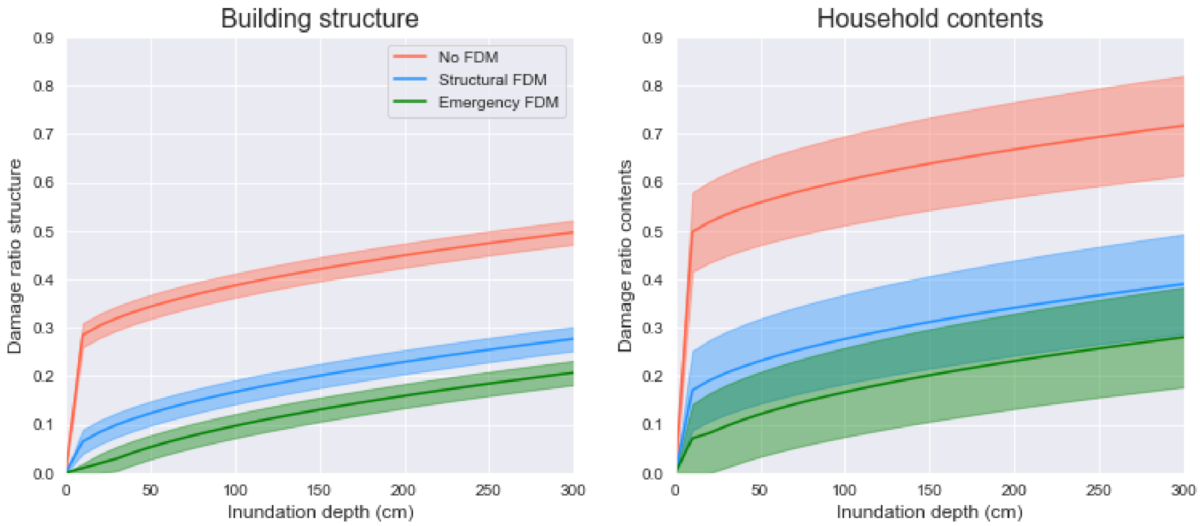

Figure 5. Depth damage functions for no FDM measures (red), structural FDM measures (blue) and emergency FDM measures (green).

Note: Curves are estimated by using the average coefficients from Models 2 and 3 from Table 4 (Building structure) and Table 6 (Household contents) the sample averages from Table 1 for the other model covariates than inundation depth and FDM measures.

5.3. Comparison with previous literature

This study adds additional knowledge on both building structure and household contents vulnerability, which is essential for the flood risk model performance (Wagenaar et al., 2018). Our proposed approach in the supplementary materials also allows for the inclusion of other hazard, exposure and vulnerability indicators in depth damage curves, which allows to reduce the error in these vulnerability estimates even further. Merz et al. (2004) find a large scatter in their estimates of depth-damage curves, which can be attributed by the lack of control for exposure and vulnerability and additional hazard characteristics beside inundation depth. Thieken et al. (2005) are already more capable of reducing noise in their vulnerability estimates, as they control for building value.

Comparing our depth-damage curves from Table 4 and Figure 5 to the German estimates (Merz et al., 2004; Thieken et al., 2005; Sultana et al., 2018), we observe that these curves follow a similar root function. Thieken et al. (2005) presented curves that illustrate the correlation between inundation depth and building damage ratios. Interestingly, their curves fall within the range of our estimated curves for households with and without FDM, indicating that Thieken et al. (2005) did not distinguish between these two groups, resulting in an average curve. In contrast, both Thieken et al. (2005) and Merz et al. (2004) operationalize inundation depths as water level above the top ground surface, while we define it as above the ground floor. Measuring the water level above the ground floor allows for the incorporation of a more specific building setting, as some buildings may be elevated above or below street level.

Building and contents vulnerability curves commonly used in Dutch flood risk assessments (SSM2017) are based on the 1953 coastal flood and the 1993 and 1995 riverine floods in the Netherlands, with some comparison with international studies (Slager et al., 2013; Slager & Wagenaar, 2017). We do observe that our vulnerability curves are higher compared to the original Dutch estimates for building structure below 150 cm. A potential explanation for this is that the Dutch curves are mostly based on the 1953 coastal flood, as there were relatively few observations available after the 1993 and 1995 riverine floods (Vrouwenvelder, 1997). The original Dutch estimates are therefore mostly based on a coastal flood event with high water levels, resulting in total destruction of buildings due to high flow velocities. In addition, in 1953 some homes still had single brick walls, which can collapse much sooner than homes nowadays (de Bruijn et al., 2015). The SSM2017 functions therefore describe a total collapse of the home. As a consequence, the SSM2017 functions for both structure and contents follow an exponential path, with low economic damage at low inundation depth and a very steep increase in economic damage at higher inundation depths (Slager & Wagenaar, 2017). In contrast, our curves follow a root-function, with a relatively large increase in flood damage at lower inundation depths, to stabilize at higher inundation depths. These functions are more in line with other global estimates (Huizinga et al., 2017).

Previous studies that have estimated the effectiveness of FDM measures may underestimate the effect due to a selection bias. We find that FDM measures are more effective in reducing flood damage than the literature shows. By comparing means, Kreibich et al. (2005) find a damage ratio reduction of approximately 0.07 due to wet-proofing for building structure. Using a similar database, Thieken et al. (2005) only find a significant effect for emergency measures. These FDM measures reduce this damage ratio with 0.08 to 0.23. As predicted, that found effect is smaller compared to our findings of 0.22 to 0.29 from Table 4, as the estimates from Thieken et al. (2005) do not control for endogeneity. Using a regression analysis Poussin et al. (2014) find an effect for several wet-proofing measures on structure building damage between -0.03 and -0.07. These measures reduce household contents damage with -0.04 to -0.18, which again shows a lower value compared to our IV-estimates.

Kreibich et al. (2005) and Thieken et al. (2005) do find that wet-proofing buildings is more effective than dry-proofing. These findings are in contrast with the findings of this study, where dry-proofing buildings is found to be more effective than wet-proofing (Tables 4 and 6). A potential explanation is that these studies studied the 2002 flood event in the river Elbe in Germany, which has shown much larger inundation depths compared to the July 2021 flood in the Netherlands. Literature has shown that dry-proofing fails with extreme inundation depths (Kreibich et al., 2015; Poussin et al., 2012). The inundation depths in the case study of the Netherlands were lower at many places, which implies that dry-proofing measures may have performed better.

The mean building and contents damage of our sample are €53,070 and €25,626 respectively, which can be used to calculate the absolute damage reduction by multiplying this with the damage ratios from the results. This allows us to approximately compare the average outcomes of our study with studies that report flood damage reduction in absolute terms. Both Hudson et al. (2014) and Sairam et al. (2019) apply PSM to overcome the selection bias. Sairam et al. (2019) group all types of FDM measures together and find that these reduce flood damage with €11,238 to €15,053 (€12,185 to €16,322 when adjusted for inflation). Although our study distinguished multiple types of FDM measures, the lowest estimate for a category gives damage reduction of €10,614 and €14,860. Damage reductions are, therefore, of comparable magnitude. Similar rebuilding values between Germany and the Netherlands may be the reason for this.

Hudson et al. (2014) use different FDM categories compared to the distinction made in our regression models. It is, therefore, not possible to compare the effect of separate FDM measures, as these specific measures within the categories of Hudson et al. (2014) and our study frequently overlap. For all categories, Hudson et al. (2014) find an average damage reduction for building damage between €2,976 and €14,385 (€3,227 to €15,598 when adjusted for inflation), while the average outcomes in our study range between €10.614 and €15,390. These sets of outcomes mostly fall into the same range, although our estimates show more accuracy with a smaller interval. For contents damage, Hudson et al. (2014) report structurally lower damage to household contents compared with our estimates.

Although the outcomes of Sairam et al. (2019) and Hudson et al. (2014) are of similar magnitude as the average effect found in our study, the results of these PSM studies are less applicable in flood risk models. Regardless of actual property value, damage reductions are reported in absolute amounts in the PSM studies based in Germany. As a consequence, there is no differentiation in the effect of FDM measures possible for flood risk between different regions, neighbourhoods or households. Reporting flood damage reductions in terms of damage ratios allows for more differentiation with respect to exposure and vulnerability, resulting in more accurate flood risk predictions.

5.4. Uncertainty and limitations

A limitation of this study is the exclusion of the impact of water contamination on flood damage, despite its significant role as shown in the literature (Thieken et al., 2005; Merz et al., 2013). The literature suggests that water contamination increases flood damage, mainly through the destruction of oil and septic tanks by floodwater (Thieken et al., 2005). Although these tanks are rarely used in the Dutch context, the exclusion of contamination does result in a lower explanatory power of our models. However, it does not bias our estimates of inundation depth and FDM estimates, as previous research found no correlation between contamination and these variables (Sultana et al., 2018), indicating no risk omitted variable bias (Woolridge, 2014).

Uncertainty in vulnerability for flood risk models can be introduced by adjusting the FDM coefficients using the 95% confidence intervals presented in Figure 6. All FDM measures significantly reduce flood damage for both building structure and household contents. Standard errors, and therefore, confidence intervals, are larger when using an IV-regression compared to OLS. Notably, the estimates for household contents have wider confidence intervals than those for building structures, likely due to the smaller sample size for damage to household contents. There are particularly large confidence intervals for dry-proofing. This may be due to the weak instrument observed in Model 5 of Table 6. Additionally, dry-proofing occasionally failed for respondents. Roughly two-thirds of all barriers placed were found to be too weak or too low to keep the water out of the building. Dry-proofing is either very effective or completely ineffective, resulting in larger confidence intervals around the avoided damage estimate. Additionally, the regression analysis did not explicitly include inundation depth in the basement, despite residents reporting flood damage there. Additionally, inundation depth in the basement has not been explicitly included in the regression analysis. Although residents have experienced flood damage in their basement, the inclusion of inundation depth in the basement did not result in a larger explanatory power of the model.

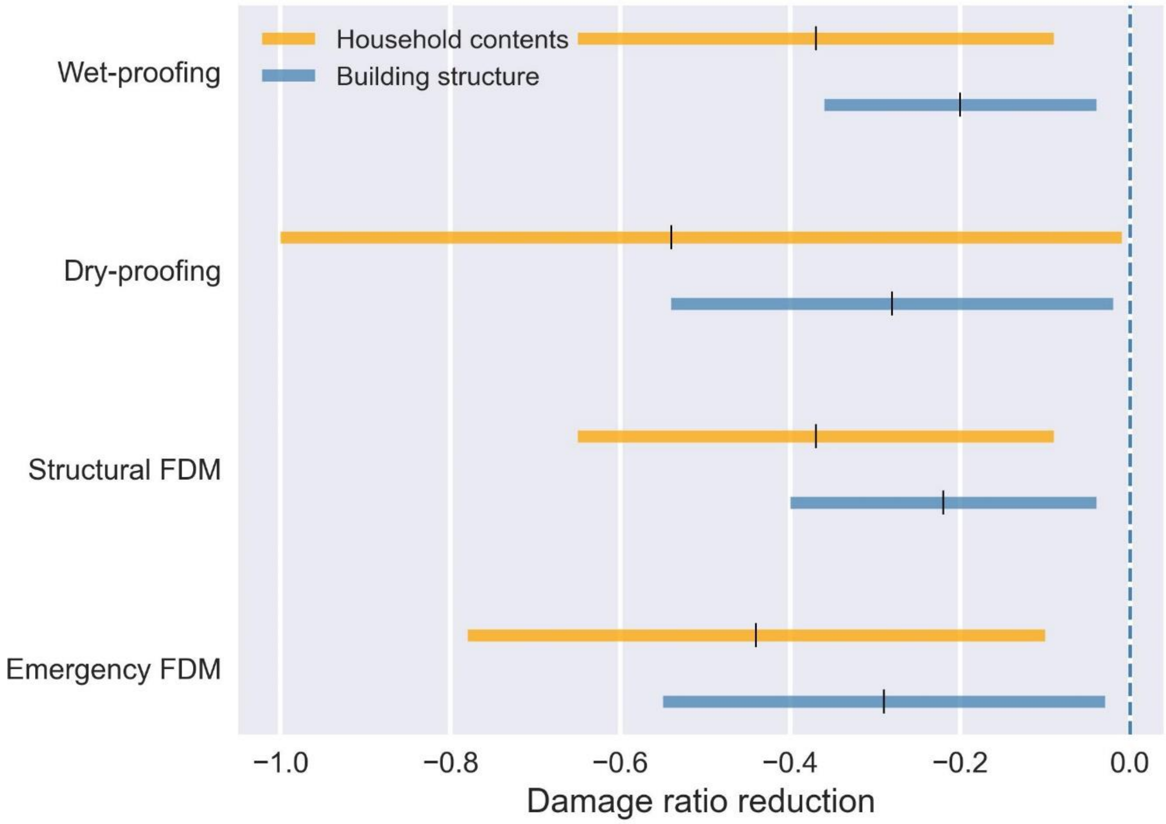

Figure 6. 95% confidence intervals for the effectiveness of FDM measures in reducing the damage ratio for buildings (in blue) and contents (in orange).

A limitation of the IV-approach is that it is not possible to include more instrumented variables than there are instruments available (Hansen et al., 2008). As a consequence, it is not possible to distinguish distinctive effects of FDM measures at different inundation depths, as an interaction term between the FDM measure and inundation depth cannot be included, as this variable will be endogenous as well. However, the literature has shown that most FDM measures in fact show different effectiveness at different inundation levels (Merz et al., 2013, Poussin et al., 2015).

To address this limitation, an additional analysis with separate building damage regressions for inundation depths below and above 50 centimetres has been performed in Table A1 in the appendix, as this is a turning point also observed in Figures 2 and 3. By splitting our sample in two, the number of observations becomes smaller for these models. As a consequence, it becomes challenging to distinguish significant effects for both the instrument as FDM measures, especially with the already larger standard errors in an IV-regression (Woolridge, 2014). Therefore, the effects in Table A1 in the appendix should be interpreted as exploratory analysis that could be updated with future research if larger datasets become available.

The only models where there are significant results ($p<0.1$) with sufficient instrument relevance are the models for dry-proofing at inundation depths above 50 centimetres and wet-proofing below 50 centimetres. However, it is notable that the observed effect in Table 4 always falls between the coefficients of the models with lower and higher inundation depths. Emergency FDM measures are an exception, where the coefficient of both the <50 cm and >50 cm models are only 0.01 lower compared to the original specification. The size of the coefficient is smaller at higher inundation depths for dry-proofing, and higher for wet-proofing, which is in line with the findings of Merz et al. (2013) and Poussin et al. (2014). To fully distinguish the effect of FDM measures on flood damage, more damage cases should be included in the analysis, or an additional relevant and exogenous instrument needs to be found in future studies.

A recommendation for future research is to look into an instrument that is both relevant for FDM uptake and exogenous to flood damage. Although there are many variables that are known to influence FDM uptake (e.g., Bubeck et al., 2012; Koerth et al., 2017; Van Valkengoed & Steg, 2019), these variables are often associated with actual flood damage. For instance, homeownership does increase the probability of FDM uptake (Dillenardt et al., 2022). However, homeownership is not exogenous to flood damage, as homeowners typically experience higher flood damage as shown by both our outcomes and the literature (Thieken et al., 2005; Merz et al., 2013). Using homeownership as instrumental variable would thus still result in biased estimates. A future study could account for homeownership in FDM uptake by using PSM, an approach that has other restrictive assumptions compared to an IV-regression (Hudson et al., 2014; Sairam et al., 2019).

6. Conclusion

The assessment of potential flood damage and the effectiveness of adaptation measures is key information for flood risk management decisions. However, vulnerability inputs in flood risk models are often a large driver of uncertainty. Empirical data to estimate these vulnerability curves is rarely collected, where previous assessments of riverine flood risk vulnerability in the Netherlands are partially based on a coastal flood event in 1953. Still, these curves are used to inform decision optimal safety levels for dikes. Our study uses a unique and detailed dataset on experienced flood damage after the flood event in the Netherlands in 2021 to create and update empirical vulnerability estimates and to include FDM measures. The effectiveness of FDM measures is often underestimated due to a selection bias. This selection bias has been overcome by using prior flood experience as an instrumental variable to estimate the effectiveness of FDM measures. This resulted in flood damage vulnerability curves that account for the influence of FDM measures. By controlling for exposure, relative depth-damage functions offer a wider applicability to flood risk models.

This study gives concrete recommendations for the implementation of vulnerability curves and the effectiveness of FDM measures in flood risk models. Multivariate damage models are composed that can function as vulnerability input in flood risk models, allowing for more differentiation by incorporating several hazard, exposure and vulnerability indicators. It is found that both emergency and structural FDM measures significantly reduce flood damage for both building structure and household contents, highlighting the importance of both information provision and early warning systems in effective flood risk management. Emergency FDM measures are generally more effective in reducing flood losses compared to structural FDM measures. Furthermore, dry-proofing is generally more effective than wet-proofing in reducing flood damage to buildings, which may be an implication of the relatively low inundation depths observed compared to other flood events. Future research may search for another relevant and exogenous instrument for FDM measures, where the instrument should influence FDM uptake, but should not be related to the amount of flood damage. Additional instruments or a larger sample size will allow for the estimation of the effect of FDM measures at different inundation depths. Moreover, more observational data should be collected to allow for the assessment of the effectiveness of FDM for different water levels.

Data availability statement

The flood damage data used for this study have been stored at 4TU.ResearchData via https://doi.org/10.4121/21603348.

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Appendix

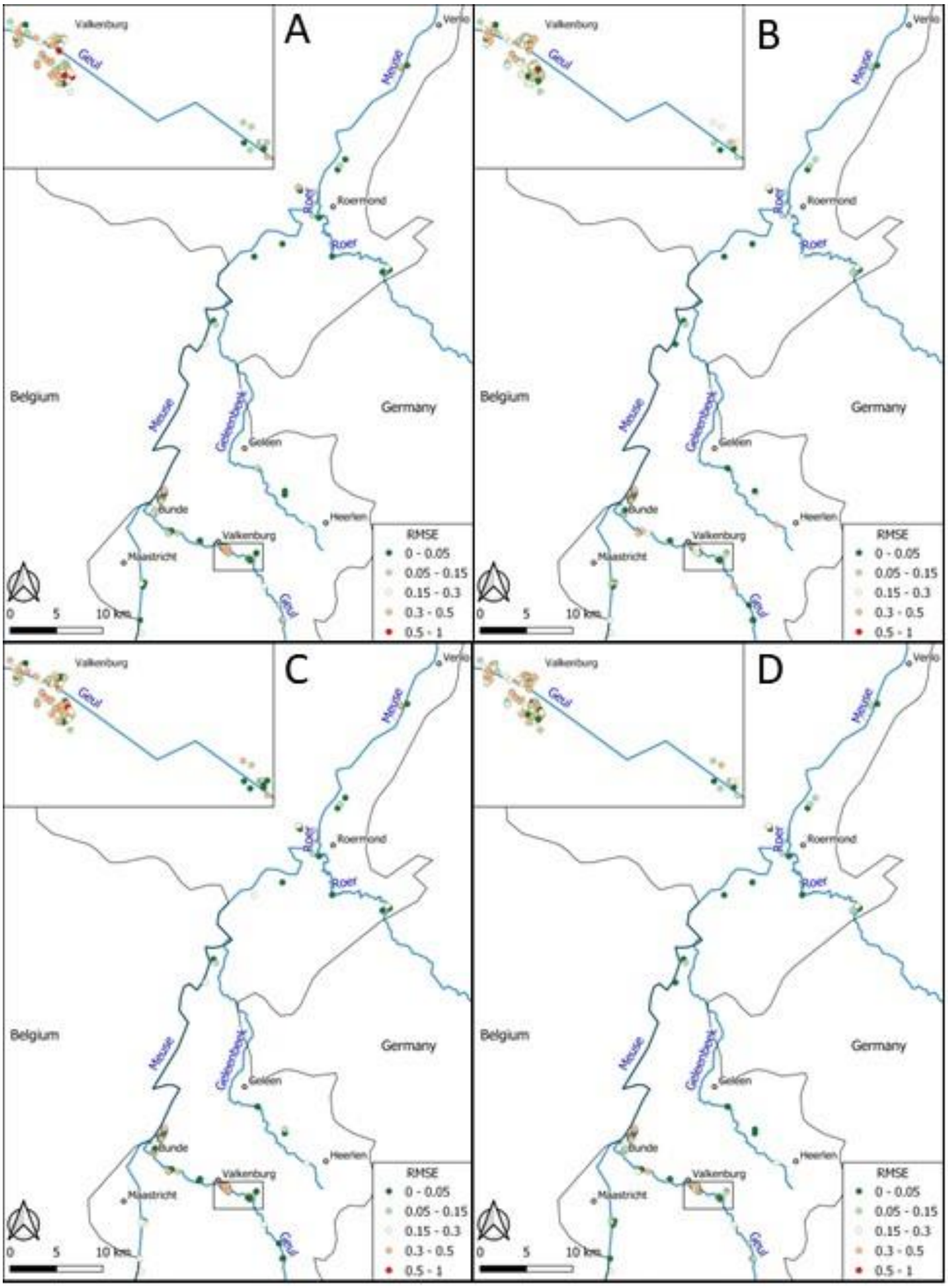

Figure A1. Root mean squared error (RMSE) of the model's predicted structural flood damage ratio for Table 4, Model 2 (Panel A), Model 3 (Panel B), Model 5 (Panel C) and Model 6 (Panel D)

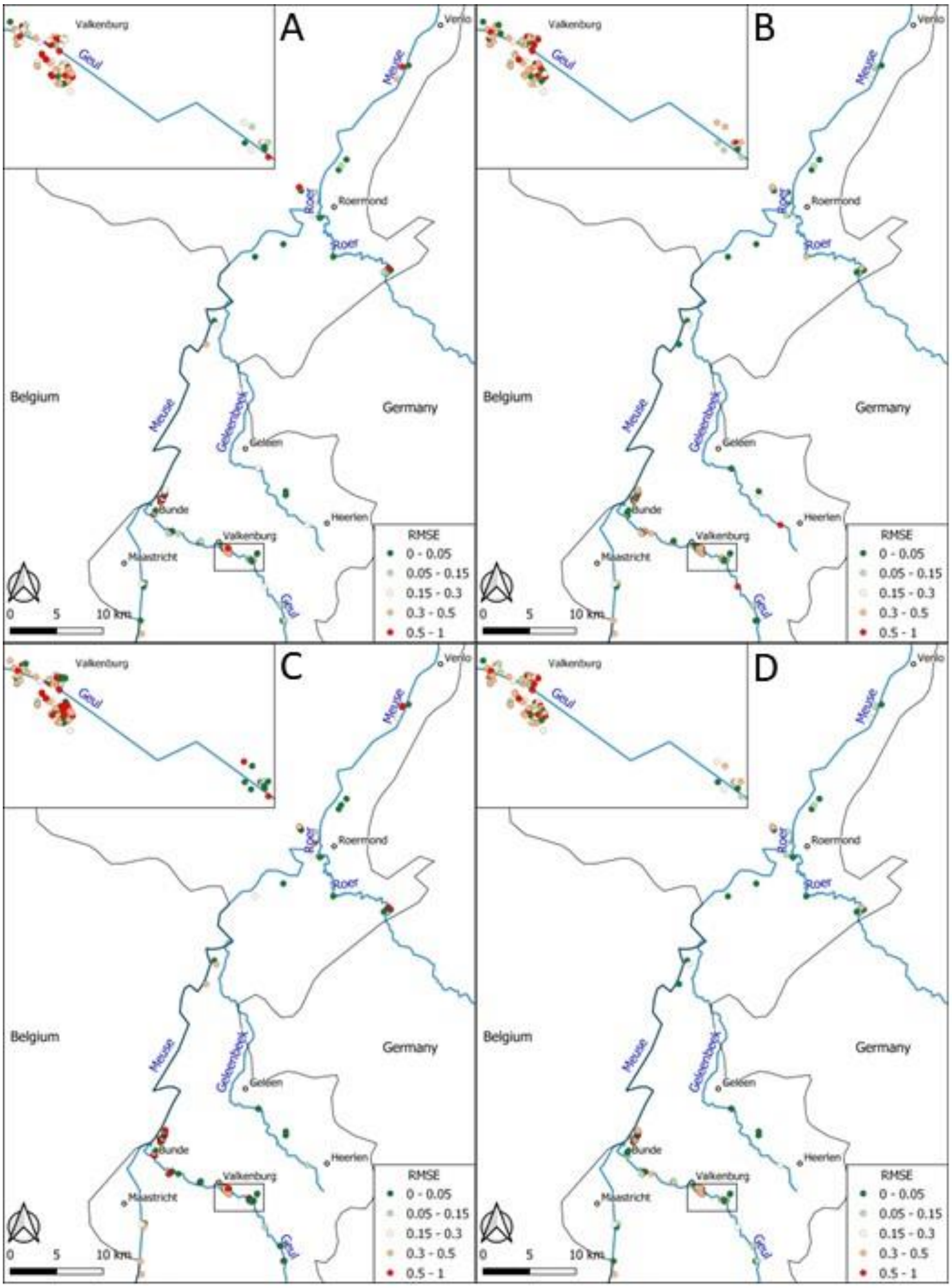

Figure A2. Root mean squared error (RMSE) of the model's predicted flood damage ratio for household contents for Table 4, Model 2 (Panel A), Model 3 (Panel B), Model 5 (Panel C) and Model 6 (Panel D)

Table A1

Estimated coefficients using an IV regression that explain building structure damage ratios in models that only use observations with the stated inundation depths including emergency (1 and 2), structural (3 and 4), and dry- (5 and 6) and wet-proofing (7 and 8)

VARIABLES	(1) <50 cm	(2) >50 cm	(3) <50 cm	(4) >50 cm	(5) <50 cm	(6) >50 cm	(7) <50 cm	(8) >50 cm
$\sqrt{\text{Inundation depth}}$	0.02	-0.00	0.02***	-0.01	0.02	-0.01	0.02***	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Homeowner	0.09*	0.14	0.07**	0.23**	0.10	0.12	0.08**	0.24**
	(0.05)	(0.09)	(0.03)	(0.09)	(0.06)	(0.09)	(0.03)	(0.10)
Dwelling size	0.04*	-0.00	0.03**	0.00	0.06	-0.01	0.03**	-0.00
	(0.02)	(0.03)	(0.01)	(0.03)	(0.04)	(0.03)	(0.01)	(0.03)
Building year home	0.00	0.00	0.00	0.00	-0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Geul river	0.08***	0.08	0.09***	0.02	0.06	0.10	0.09***	-0.02
	(0.03)	(0.06)	(0.03)	(0.08)	(0.04)	(0.06)	(0.03)	(0.09)
Water rise rate	0.00	-0.00	0.00	-0.00	0.00	0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Water withdrawal rate	-0.00	0.00	-0.00	0.00	-0.00	0.01*	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Flow velocity	0.06***	-0.07**	0.06***	-0.04	0.05**	-0.06**	0.06***	-0.04
	(0.02)	(0.03)	(0.02)	(0.04)	(0.02)	(0.03)	(0.02)	(0.04)
FDM Emergency	-0.28	-0.28						
	(0.22)	(0.18)						
FDM Structural			-0.15	-0.30*				
			(0.10)	(0.18)				
FDM Dry-proofing					-0.39	-0.20*		
					(0.38)	(0.11)		
FDM Wet-proofing							-0.14*	-0.32
							(0.09)	(0.20)
Constant	-0.09	0.37	-0.20*	0.32*	-0.02	0.28	-0.22**	-0.32
	(0.18)	(0.23)	(0.11)	(0.18)	(0.28)	(0.19)	(0.10)	(0.20)
Observations	202	109	202	109	202	109	202	109
Building FE	X	X	X	X	X	X	X	X
F-value instrument	3.53	7.59	11.53	7.82	1.67	16.40	13.46	7.19
β instrument	0.14*	0.31***	0.25***	0.29***	0.10	0.44***	0.27***	0.27***
	(0.07)	(0.11)	(0.07)	(0.10)	(0.08)	(0.11)	(0.07)	(0.10)

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$