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Enhancing resilience

Understanding the impact of flood hazard and vulnerability on business interruption and losses

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Enhancing resilience: Understanding the impact of flood hazard and vulnerability on business interruption and losses

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ABSTRACT

Without taking additional measures, flooding is becoming more likely and intense in a changing climate, which causes large economic damage. Households and firms are directly impacted by physical flood damage, but further ripple effects on society occur through business disruptions. By using post-disaster survey data from the 2021 flood event in the Netherlands, this study adds to the literature on business interruption duration and losses after flooding. The current empirical literature on flood impacts on firms is often unable to distinguish separate effects for flooded and non-flooded firms and does not incorporate flood severity and the influence of risk reduction measures. Here, we use multivariate regression models to determine depth-duration functions that describe the relationship between flood hazard characteristics and business interruption duration. This relationship can be used to calibrate flood damage models that capture indirect firm impacts. The prediction of business interruption after flooding allows for differentiation in business interruption between firms within a flooded area, reducing the reliance of these macroeconomic models on restrictive assumptions. Our results indicate that a day of business interruption duration costs a firm on average 0.5 % of their annual revenue; an effect that is stronger for firms with a weaker connection to their region. Flood damage mitigation (FDM) measures taken at the building level do not significantly affect business interruption duration, although further research on this is required. Finally, quick damage compensation is found to reduce business interruption duration and thus revenue losses, calling for higher insurance uptake and rapid and streamlined post-disaster insurance and government compensation.

1. Introduction

In a changing climate, the intensity and frequency of natural disasters will likely increase [1]. Flooding is the costliest among natural disasters, causing over €70 billion of economic losses globally in 2021 alone [2]. Floods directly impact households and companies through the destruction of their assets [3]. Further indirect ripple effects for society occur due to infrastructure destruction

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and interruption of business processes and financial markets [4,5]. It is expected that business interruption losses[1] exceed direct flood damage to companies, but little research has been conducted on this topic [6,7]. Understanding the impact of floods on firms is essential for effective disaster risk management.

Business interruption is a major driver of post-disaster revenue losses [8]. Current literature that assesses the effect of flood-induced business interruption on firms is dominated by Input-Output (IO) and Computable General Equilibrium (CGE) models [9]. These models heavily rely on assumptions on business interruption duration and recovery paths, with little empirical evidence for recovery processes, which in turn increases uncertainty in their estimations [10]. Moreover, these indirect loss models often assume that business interruption duration is the same across all firms in the flooded area, regardless of the magnitude of direct flood impacts [10]. However, large heterogeneity in business interruption has been observed in the few existing empirical studies [11]. Currently, studies that attempt to explain variation in business interruption only focus on pluvial flooding [12] or assess variable importance, but do not quantify the exact impact of flooding on recovery time [13].

The main objective of this study is to explain the role of flooding on business interruption duration and business interruption losses using firm-level survey data from the floods in the Netherlands in the summer of 2021. This is done by applying multivariate regression analyses to find the relationship between several detailed hazard and vulnerability indicators and business interruption duration. Next, firm-specific business interruption duration is used as an explanatory variable to identify revenue losses in the wake of the flood event. A secondary goal is to identify the risk-reducing effect of flood damage mitigation (FDM) measures taken at the firm level. Generally, firms take fewer precautionary adaptation measures compared to households [14]. More information on the effectiveness of these measures may thus stimulate additional resilience for businesses. To our knowledge, no study has as of yet identified whether FDM measures have the potential to reduce business interruption duration. However, the estimation of the impact of adaptation actions is prone to a selection bias, as individuals and firms that face higher flood risk are more likely to adapt [15]. To address this bias, our study applies propensity score matching (PSM) to compare adapted and non-adapted groups that are similar based on other background characteristics. This approach is in line with other studies that analyzed the role of FDM measures on residential flood damage [16,17].

Empirical evidence on the impacts of flooding at the firm level is relatively scarce [18,19]. The available studies find mixed evidence. In the assessment of the firm's post-disaster capital, labor, and productivity, both Leiter et al. [20] and Zhou & Botzen [19] find that flooding stimulates capital and labor growth up to three years after flooding. The same studies find that the firm's added value decreases after a flood event, implying that productivity decreases. Noth and Rehbein [21] find that flooding increases a firm's revenues within two years after flooding using firm-level data from Germany. Disasters allow firms to invest in new capital, which may not have been possible prior to the flood event [21]. In contrast, Hu et al. [22] and Pan and Qiu [23] find negative impacts of flooding on firm performance.

Additionally, these aforementioned studies are heterogeneous in the used time scale and spatial extent of the flooded area. Concerning the spatial extent of the flood, Leiter et al. [20], Zhou & Botzen [19], and Noth & Rehbein [21] define a firm as flooded if a flood has occurred within a specific region, whereas Hu et al. [22] and Pan and Qiu [23] identify flooding on the city-level. A similarity between all these studies is that they do not identify whether a single firm is hit by flood water or not, let alone the severity of flooding. Consequently, the effect these studies find is the average impact of being located in a flooded region on a firm's activities, regardless of whether the firm experienced water intrusion or not. This average effect contains both the impact on flooded firms as well as positive and negative spillovers to firms that did not experience direct flooding. Negative spillovers are mainly demand-driven, as customers may temporarily avoid the flooded area [24]. Positive spillovers can occur due to the substitution of production processes to nearby non-affected areas and increased demand for reconstruction. Additionally, these studies also cannot identify differences in flood magnitude and firm vulnerability between firms in the flooded area, and thus assume that flood impacts are the same across all firms in the flooded area. However, flood hazard characteristics such as inundation depth and flow velocity differ within a flooded region, resulting in heterogeneous impacts across firms during the same flood event [11].

Studies that do identify whether a firm is flooded, use survey data [11–13,25]. Wijayanti et al. [25] exclusively focus on direct physical damage incurred by businesses without examining the associated indirect losses. Yang et al. [12] estimate business interruption losses using data from pluvial flooding in Japan and identify different business interruption losses at different flood hazard levels. Sultana et al. [13] apply machine learning to identify the most important indicators that explain both business interruption and business interruption losses. It is found that longer business interruption is associated with higher revenue losses. However, they use absolute revenue losses as the outcome variable. Absolute damage numbers reduce the comparability between different firms and economic sectors, where there is large heterogeneity in exposed capital and activities. Consequently, this reduces the predictive power of their models. Our study addresses this challenge by relating revenue losses to the firm's annual revenue to get a standardized indicator for flood impacts across firms.

The remainder of this paper is structured as follows. Section 2 describes the data used in this study, including the case study area, the survey, and the operationalization of the variables. This section also gives some descriptive statistics on the firm-level impacts of flooding. In Section 3, the statistical methods are outlined. Section 4 presents the results on business interruption duration, the role of FDM measures, and business interruption losses. Section 5 discusses the main findings in relation to the existing literature and gives pathways for future research. Section 6 concludes and gives policy recommendations.

[1] We refer to business interruption losses as the losses in revenue caused by disruptions in production, consumption, and/or supply chains during and after the flood event. The scope of the distributed survey considers losses up until eight months after flooding.

2. Data

2.1. Case study area

In July 2021, parts of Germany, Belgium, and the Netherlands were affected by flooding due to extreme precipitation over a two-day period. This flood event resulted in fatalities, health problems, large economic damages, and business interruption. In the Netherlands, most economic damage occurred along the Meuse River, along with its tributaries the Geul, Geleenbeek, and Roer [26]. Return periods of peak discharges in these tributaries ranged between 1/100 and 1/1000 years [27]. This study focuses on the part of the Netherlands that was affected by this flood event, which is the province of Limburg in particular. It is estimated that approximately 600 companies and non-profit organizations and 2500 households have experienced flood damage in this area [28]. Dutch insurance companies have received around 10,000 damage claims from households and 1250 from companies, where total damage has been estimated to range between €400 and €500 million [29]. The flooding in the Netherlands was relatively minor in comparison with the same flood event in Germany and Belgium, with €7 billion and €1 billion of economic damage, respectively [30,31].

The Dutch flood insurance system differentiates between flooding from different water systems. Dutch insurers cannot insure against failure of primary water defense systems (i.e., the sea, the Meuse, Scheldt, Rhine Rivers, and the large lakes),[2] because they cannot attract sufficient capital to make flood insurance premiums affordable for low-probability high-impact flood events (Dutch Association of Insurers, 2018). It is possible to insure against flooding from non-primary rivers, which is often included in the homeowner- and contents insurance (Dutch Association of Insurers, 2018). However, a share of the firms affected by the flood was insured through stock exchange policies,[3] where pluvial flooding is insured and riverine flooding is part of an additional insurance package [32]. Many businesses did not purchase this additional package, as they assumed that they would be insured against all types of flooding [32]. Insurers considered this particular flood event in the Netherlands as a riverine flood event, which resulted in a share of businesses not receiving any insurance compensation. The Dutch government supported some of these firms by partly compensating uninsured physical economic damage and revenue losses through the Calamities and Compensation Act[4] (CCA) [33]. The CCA usually only activates for disasters that cannot be insured, such as the failure of the main water defense systems. Although this insurance against this particular type of flooding was possible, the government still decided to partially compensate uninsured firms.

2.2. Survey

The goal of the survey is to collect detailed information on individual firm's physical flood damages, business interruption duration, and revenue losses caused by this particular flood event. Companies were also asked about flood characteristics near their location and to what extent they had taken FDM measures before flooding. The questionnaires were distributed by postal mail in three different waves to small and medium-sized companies. The first wave took place in December 2021 and targeted all 857 firms located in the flooded area and areas in which an evacuation order was issued during the flood event. The flooded area has been determined by using helicopter images complemented by flood simulation models for the Meuse Rivers and its tributaries Geul, Roer, and Geleenbeek [28]. The evacuation areas have been sampled to reach more affected firms, as there may have been some inaccuracies in the determined flood extent. The second wave started in February 2022, when a reminder was sent to the firms that did not complete the questionnaire. To account for potential inaccuracies in the originally determined flood extent and evacuation order area, the third wave sampled 606 firms in addition to the 857 firms that were already contacted for the survey. These 606 additional businesses were located in the same postal code area as households that experienced flood damage in the household survey of Endendijk et al. [26]. This means that all firms in the sample are either flooded or a near-miss, which makes them relevant to include in this study. Near-miss firms may also experience indirect losses, for example through supply chain and accessibility disruptions [3].

These three waves eventually resulted in a total response of 215 companies (response rate of 15 %). 42 % of all surveyed firms are located near the Meuse River and 18 % along the Geul River. For 33 % of all companies, the geographical location is unknown, as respondents were given the option to refuse to share their addresses. The remainder of the respondents (7 %) were located along the Geleenbeek or Roer. 83 (39 %) of 215 respondents experienced water intrusion to their assets and 33 % of the total sample experienced physical flood damage. 60 % of all surveyed firms experienced business interruption, which indicates that business interruption even occurs when the firm's properties have not been flooded. This is supported by Fig. 1, which gives insight into the distribution of the self-reported absolute direct damage and revenue losses after flooding. More firms experienced revenue losses than direct damage, where revenue losses are in most cases larger than physical damage to properties. Non-flooded firms also experienced revenue losses, although the flooded firms show a larger variety in their impacts. Flood impacts on firms strongly differ per economic sector [34,35]. Fig. 2 shows that there is a large variety of included firms, where most surveyed firms are active in the hospitality sector (e.g., hotels, restaurants, campsites).

[2] Dutch laws determine the definition of primary water bodies, all other rivers and lakes are classified as non-primary [67].

[3] Stock exchange policies are a type of insurance where risk is pooled on the international insurance market [32].

[4] The Calamities Compensation Act (CCA) [*Wet Tegemoetkoming Schade bij Rampen, in Dutch]* is a compensation scheme from the Dutch government to partially compensate for otherwise uninsurable flood damages. The government compensates firms and households for physical damage that is uninsurable, unavoidable, and cannot be recovered elsewhere.

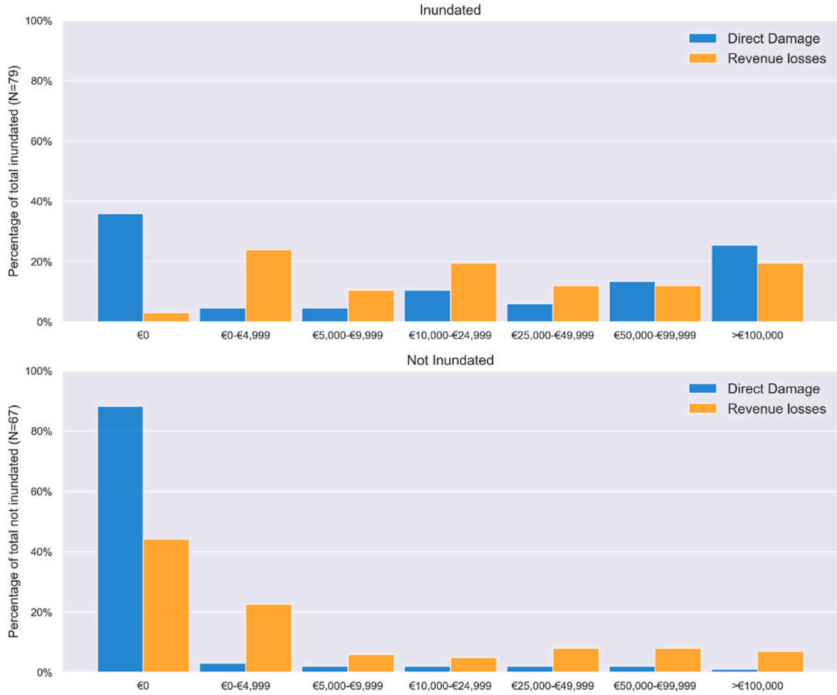

Fig. 1. Distribution of the direct physical damage (blue) and revenue losses (orange) of firms in the sample that reported their revenue losses. Separated into firms that were inundated (top) and firms that were not inundated (bottom). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

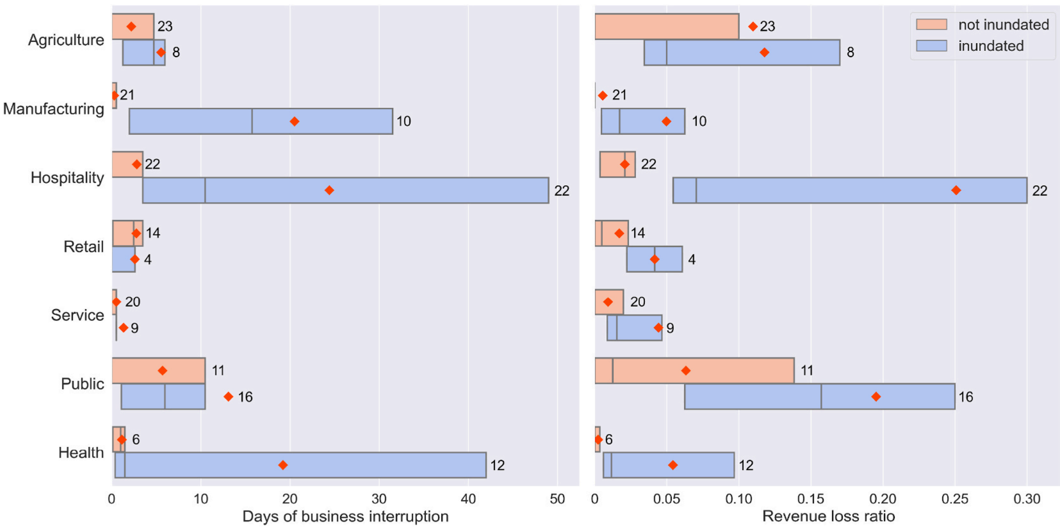

Fig. 2. Business interruption (left) and revenue losses (right) for different economic sectors for flooded (blue) and non-flooded (red) firms. The 25th percentile, median, and 75th percentile are shown by the boxplot and the mean by the red marker. Number of observations at the end of the boxes. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

2.3. Variables and operationalization

Table 1 gives an overview of the variables included in this study, differentiated between flooded and non-flooded firms. The two main dependent variables of interest are business interruption in days and revenue losses after the flood event in July 2021. Both revenue losses and business interruption duration are reported by the firm. However, since not all firms knew their revenue or business interruption, some observations are missing in the regression. There is a large heterogeneity between firm sizes when using absolute values for revenue losses [13]. To allow for comparison between different firm sizes, we normalized revenue losses by relating these to

Table 1
Overview of the included variables in this study, based on the business survey (N = 223).

Variable	Description	Mean	
		Non-flooded	Flooded
Firm impacts			
Business interruption	The number of days the firm was unable to operate due to flooding.	15.05 (21.61)	2.01 (3.72)
Revenue loss ratio	The ratio between the firm's reported revenue losses due to flooding and the 2019 annual revenue.	0.14 (0.21)	0.04 (0.10)
Received compensation (%)	The reported percentage of compensation the firm received at the time of the survey (6–8 months after flooding) related to total expected compensation.	84.98 (31.44)	97.19 (15.89)
Hazard			
Inundation depth	Self-reported inundation depth at the ground floor of the firm's main property in centimeters.	61.12 (60.93)	0 (0)
Flow velocity	Ordinal variable describing flow velocity near the building (1 = average man could easily stand up, 2 = average man could barely stand, 3 = average man would have been swept away).	2.02 (0.86)	1.67 (0.92)
Contamination	Dummy variable with the value 1 if the flood water near the firm's location has been contaminated by either oil, chemicals, sewage materials, or other waste, and the value 0 otherwise.	0.55 (0.50)	0.10 (0.30)
Access difficulty	Days of the firm being difficult to access for either customers, suppliers, or employees.	4.16 (4.00)	1.96 (2.70)
Exposure			
Employees	The absolute number of employees prior to the flood event of July 2021.	15.85 (42.39)	20.96 (43.9)
Geul River	Dummy variable with the value 1 if the firm is located near the Geul River and value 0 otherwise.	0.33 (0.47)	0.10 (0.30)
Sector	Dummy variable with the value 1 if the firm is operating within the respective economic sector from Fig. 1 and value 0 otherwise.	See Fig. 2	See Fig. 2
Vulnerability			
Building age	Years since the firm's main building has been built.	102.20 (100.85)	73.00 (79.65)
Supply dependency	Days the firm can operate without stock inflow.	35.53 (29.47)	33.69 (29.43)
Region connection	Dummy variable with the value 1 if at least 50 % of the firm's customers or suppliers are located within a 10 km radius around the firm and value 0 otherwise.	0.23 (0.42)	0.24 (0.43)
FDM			
Dry-proofing	Dummy variable takes the value of 1 if the firm has implemented dry-proofing measures before the flood event, with the aim of preventing water from entering the building. Otherwise, it takes the value of 0.	0.36 (0.48)	0.33 (0.47)
Wet-proofing	Dummy variable takes the value of 1 if the firm has implemented wet-proofing measures before the flood event, with the aim of reducing flood damage once the water enters the building. Otherwise, it takes the value of 0.	0.59 (0.50)	0.48 (0.50)
Structural FDM	Dummy variable takes the value of 1 if the firm has implemented structural FDM measures as precautionary measures before a future flood event. Otherwise, it takes the value of 0.	0.41 (0.50)	0.33 (0.47)
Emergency FDM	Dummy variable takes the value of 1 if the firm has implemented emergency FDM measures shortly before the flood event. Otherwise, it takes the value of 0.	0.57 (0.50)	0.50 (0.50)

Note: Standard deviations in parentheses. Mean values and standard deviations are determined based on the survey responses.

the reported annual revenue of2019[5] and defined this as the revenue loss ratio. We decided to relate revenue losses to the 2019 annual revenue rather than the 2020 annual revenue, as the COVID-19 pandemic resulted in strong revenue shocks within most economic sectors [36]. As the July 2021 flood occurred in a period with less strict COVID-19 regulations in the Netherlands, we believe that relating revenue losses to 2019 annual revenue from before the pandemic will give a more realistic representation of firm sizes compared to 2020 revenues, during a period with the most strict lockdowns.

The mean business interruption for flooded firms in our sample is fifteen days and two days for non-flooded firms (Table 1). Fig. 2 differentiates both business interruption and revenue losses for economic sectors between flooded and non-flooded firms. It becomes apparent that both outcome variables follow a right-tailed distribution with also large differences within economic sectors. Looking at the median business interruption for flooded firms, the hospitality, health, and manufacturing sectors were the longest out of business. A potential explanation for this is the destruction of physical capital required to produce. When considering non-flooded firms, it stands out that the agricultural, public, retail, and hospitality sectors also show higher median business interruption compared to the other sectors. A potential explanation for this is that these sectors are labor-intensive and/or location-bound. In the first few weeks after a flood event, firms may temporarily face employment shortages, as employees may be occupied elsewhere in the recovery after a flood event [13]. These employees may need to clean up and repair their own homes or help in their social network after the flood event. Additionally, cleaning up the firm's assets takes longer as well, as these firms only open when the entire property is fully cleaned and equipment is replaced. Mean business interruption for the health, hospitality, and manufacturing sectors shows strong deviations from the median. From the right section of Fig. 2, it can be observed that sectors with larger median business interruption also face

[5] The Dutch economy grew by 1.8 % in 2019. Almost all economic sectors experienced similar growth rates between 0.8 % and 4.8 %. The financial services sector is an exception with a growth rate of −1.4 % [68]. Only one respondent of this sector is included in the survey (within the broader service sector).

larger median revenue losses. The service sector faces the lowest business interruption, as operations are often not bound to a physical location.

We describe flood impacts at the firm level using the risk framework defined by Kron [37], who defines risk as a function of hazard, exposure, and vulnerability. All variables used to explain both business interruption duration and revenue losses can be related to one of these categories: where hazard includes the severity of the flood event, exposure represents the economic value at risk, and vulnerability describes the firm's susceptibility to flooding [37]. Besides the two dependent variables in this study, Table 1 also describes all explanatory variables related to the risk framework. The hazard components included are self-reported inundation depth at the ground floor of the firm's main property, self-assessed flow velocity, floodwater contamination, and access difficulty. The variable inundation depth is often used through depth-damage curves in physical flood risk models that form the basis for indirect flood loss assessments [10].

The variable *access difficulty* has been included as a proxy for supply chain disruptions. Revenues may be harmed when a firm is difficult to access for customers, suppliers, or employees, even though the firm is operational already [38]. Fig. 3 gives an overview of the days the firm was difficult to reach. More than half of the firms who answered the question and were not inundated remained accessible at all times after the flood event. Only for a small fraction, this difficulty to access lasted longer than a week. The difficulty in accessing the firm is more evenly distributed for the flooded group. A bit over 20 % of the inundated firms who answered the question were difficult to access for more than a week after the flood event.

With respect to exposure, we control for firm size in the analysis by including the reported number of employees prior to the flood event. Next, firm impacts greatly differ between economic sectors, also driven by how capital-intensive these sectors are [20]. For this reason, we include sector-fixed effects in the analysis. The final exposure indicator included is whether the firm is located along the Geul River or not. Fig. 8 in Appendix I gives a geographical distribution of business interruption of the sample. Although the sample per postal code area is relatively small, the figure indicates that average business interruption is the largest along the Geul River. For this reason, we control for the firm's presence along the Geul River, as a proxy for larger disruptions in infrastructure and supply chains in this area. Moreover, Endendijk et al. [26] show that household losses are also concentrated along this river.

To capture firm preparedness and vulnerability, we include FDM measures taken before flooding and building age as indicators that affect vulnerability through physical damage. In line with Endendijk et al. [15], we distinguish between two different FDM category[6] distinctions. First, wet-proofing and dry-proofing refer to the goal of the FDM measure. Wet-proofing is aimed at reducing the impact of the water once it has already intruded the building (e.g., building with waterproof materials, elevating electrical appliances). Dry-proofing refers to measures targeted at keeping the water out of the building (e.g., placing barriers, or elevating the building). De Ruig et al. [70] indicate that dry-proofing is generally effective with shallow inundation depths. Another distinction is made between emergency FDM and structural FDM. Emergency FDM is taken in advance of a flood event, often after an early warning is given (e.g., placing sandbags, moving household contents to higher floors), while structural FDM is applied in advance of a potential flood event (e.g., building with waterproof materials, elevating the building). Note that the distinctions between wet- and dry-proofing on the one side and emergency FDM and structural FDM are not mutually exclusive (e.g., sandbags are both a dry-proofing and an emergency FDM measure). The distinctions are included this way to allow for more generalization to both modeling and policy contexts [15].

The variable supply dependency has been added as a vulnerability indicator because firms are more resilient to supply chain disruptions if they can operate longer without receiving additional stocks [10]. The variable region connection describes the firm's connection to the region, which may alter the impacts of business interruption on revenue losses.

The restoration of direct flood damage prolongs business interruption [39] and insurance compensation supports post-disaster recovery [40]. For firm impacts, the self-reported percentage of received compensation related to total expected compensation has been included, which reflects a received compensation fraction at the time of the survey. Fig. 4 gives an overview of the progress of compensation six to eight months after flooding. The amount of still expected compensation corresponds to the firms that are waiting for insurance or government payments. However, it may be possible that respondents were overestimating their compensation, where in reality these firms are not eligible for this compensation. As a relatively large part of the firms were not insured against flood damage, CCA is the largest form of compensation in our sample.

In Fig. 4, it stands out that the major share of compensation from the inventory insurance has already been paid out six to eight months after the flood. The building and consequential loss insurance are slower in their compensation, possibly because these claims are more difficult to assess. The two public compensation schemes (the CCA and Disaster Fund[7]) have both paid out more than half of the total expected compensation by firms. According to the survey, firms expect that 61.2 % of their total losses (i.e., physical damage and revenue losses) after the flood event will be compensated by either insurance or public compensation schemes, which would be substantially lower if not for the public compensation schemes that compensate damage for uninsured firms. This indicates that around 40 % of all economic losses experienced by companies were not compensated after the flood event; a number that is similar to the findings for household loss compensation [26]. However, households received a larger share of their compensation from their home or contents insurance, whereas firms relied more on the government's leniency for compensation of damages after the flood [26].

[6] For a full overview of all included individual FDM measures within each category, see Endendijk et al. [15].

[7] The Disaster Fund is a non-profit foundation that aims to support victims of disasters that hit the Kingdom of the Netherlands. The Disaster Fund accepts private donations to partly compensate residents and firms who experienced severe flood impacts. Severely impacted households received €2000 per household. €3.6 million in total has been reserved for businesses operating in civil society, and €3 million in total for "distressing cases" for households. The foundation has the discretion to decide who to compensate after a disaster.

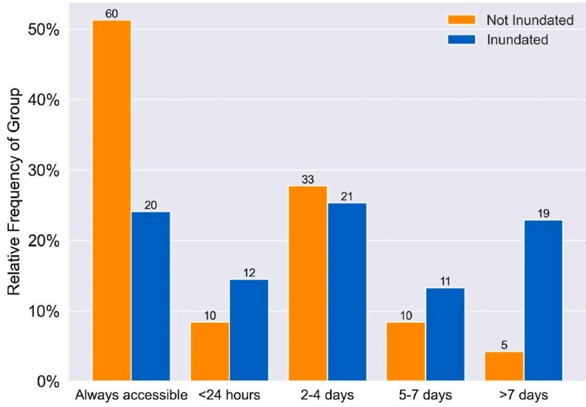

Fig. 3. Relative frequency of the number of days of the firm being difficult to access for customers, suppliers, or employees after the flood event, separated by the firm being inundated (blue) or not (orange). The number of observations is given on top of the bars. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

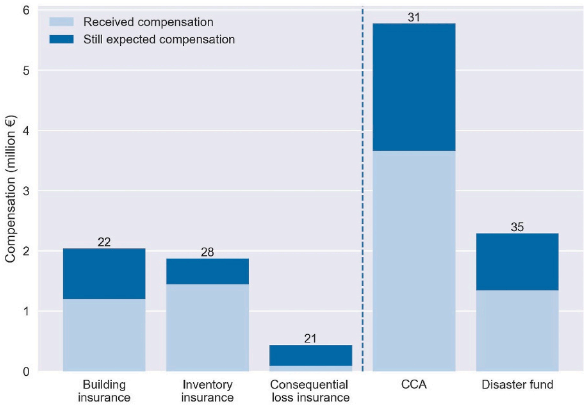

Fig. 4. Total received and still expected compensation from insurance policies (left) and public compensation schemes (right) six to eight months after the flood. Number of firms that received or expect compensation are given on top.

3. Methodology

3.1. Estimation strategy

To estimate the impact of flooding on business interruption duration and revenue losses, two separate regressions have been applied using ordinary least squares (OLS). The regression equation for *business interruption* duration is as follows[8]:

$$Business\ interruption_i = \beta_0 + \beta_1 inundation\ depth_i + \beta_2 still\ expected\ compensation_i + \beta_k X_i^{'} + a_i + \varepsilon_i \quad (1)$$

where business interruption in days for firm ***i*** is the function of the self-reported inundation depth at the ground floor of the property, the percentage of total direct damage compensation that is still expected, and additional control variables.[9] As flood impacts strongly differ between economic sectors [35], sector-fixed effects have been applied (a_i). The error term is given by ε_i.[10] Previous studies that estimate empirical depth-damage functions for physical damage to properties have found non-linear relationships between inundation depth and physical flood damage (e.g. Ref. [15,41]). To identify the potential functional form for the regression, a flexible nonparametric model that does not impose a functional form has been applied [42]. For this, inundation depths have been divided into bins as dummy variables and are included in a regression on business interruption in Table 4 in Appendix II. The outcomes of this

[8] Controlling for the different waves of the distribution of the questionnaire did not influence results, and is thus excluded from the regression.

[9] The hazard, exposure, and vulnerability indicators from Table 1 are included in the regression, except access difficulty, connection to the region, and FDM. The first two variables are excluded because they describe demand-driven shocks, rather than shocks in capital and labor that affect the extent to which a business can operate. FDM is excluded as it is likely to bias the outcomes [15,16].

[10] A Breusch-Pagan test identified heteroskedasticity in the data, for which robust standard errors have been applied [69].

flexible nonparametric regression model are visualized in Fig. 9 in Appendix II. It stands out that inundation depth follows a linear relationship with business interruption, thus indicating that we can include inundation depth as a linear function in equation (1).

The regression equation for *revenue losses* is as follows:

$$\begin{aligned} Revenue\ loss\ ratio_i = \beta_0 + \beta_1 business\ interruption_i + \beta_2 still\ expected\ compensation_i + \beta_3 access\ to\ firm_i + \beta_4 region\ dependency_i \\ + \beta_5 business\ interruption_i \times region\ dependency_i + \beta_k X_i^{'} + a_i + \varepsilon_i \end{aligned} \tag{2}$$

where the revenue loss ratio for firm ***i*** is a function of business interruption duration, the firm's connection to the region, the number of days of the firm being difficult to reach after the flood, still expected insurance compensation, and other covariates.[11] Flood events are very local events, but indirect impacts may reach far beyond the flood zone, where a disruption in local infrastructure and supply chains can occur [3]. This implies that the impact of business interruption changes for firms with different connections to their region. To test for this difference, an interaction between business interruption and the region connection dummy has been introduced to the regression equation.

3.2. Propensity score matching (PSM)

A second goal of this study is to assess the impact of FDM measures taken at the firm level on business interruption duration. Endendijk et al. [15] show that estimating the effect of FDM measures using an OLS-regression biases outcomes, as individuals who perceive higher flood risk are more likely to implement FDM measures. A comparison between the group that has applied FDM measures (i.e., treatment group) and the group that has not (i.e., control group) will lead to an underestimation of the true effect, as these groups are different in their background characteristics prior to flooding.[12] The same endogeneity problem is likely to occur with businesses. Using household survey data, Endendijk et al. [15] overcome this selection bias by applying prior flood experience as an instrumental variable, a variable that is not available in our dataset. Hudson et al. [16] and Sairam et al. [17] overcome this selection bias through propensity score matching (PSM).

To identify the impact of FDM measures on business interruption duration, PSM has also been applied in this study. Each observation in the treatment group is matched with a control observation that is most similar based on their background characteristics that influence both flood damage and FDM uptake, such as hazard indicators, economic sector, and ownership of the firm's building. This matching process results in treatment and control groups that are similar in terms of expected flood risk, overcoming the problem of endogeneity [43]. First, a logistic regression is applied to assign all observations a propensity score, which gives the predicted probability of an observation being in the control group based on all included confounding variables [44]. Each treatment observation is matched with one or more control observations based on similar propensity scores, which allows for unbiased comparison between both groups.

The matching process uses firm characteristics that drive FDM uptake. The treatment and control groups are matched on all the included variables in Table 2. Hazard indicators are included because individuals who perceive higher flood severity are more likely to adapt [45]. The included exposure indicators are the firm's number of employees, the economic sector, and the location near the Geul River. Larger firms may have more financial capacity to adapt before a flood event and these intentions and capabilities to adapt may also differ between economic sectors [14,46]. The vulnerability indicators are building age, supply dependency, and received compensation. Newer buildings may be more adapted in contrast to older buildings [47]. FDM measures can help firms that rely on their suppliers to be accessible after flooding, which is why supply dependency is also included in the matching process. Finally, there is mixed evidence about the extent of moral hazard occurring with respect to adaptation and flood risk [48–54]. Hence, we also include received compensation as a driver of FDM uptake.

There are three main assumptions when applying PSM. The first assumption is *unconfoundedness*, which means that all variables that could influence both the uptake of FDM measures and business interruption are included in the matching process [55]. The next assumption is *balancing*, which means that the treated and control groups should be balanced after matching so that both groups are comparable. Table 5 in Appendix III shows the outcomes of the balancing of covariates for each type of FDM. It stands out that the balancing for the inundation depth variable is somewhat uneven for both groups. This means that the selection bias is still partially present, where businesses with higher flood hazard were more likely to take adaptation actions. The outcomes of PSM should, therefore, be interpreted with caution. The final assumption is *overlap*, which means that there should be sufficient overlap between the propensity score distributions of treatment and control. To make sure this assumption is satisfied, matching is supplied with common support, where control observations are only matched if they lie within the upper and lower bound of the propensity scores of the treatment group [55]. Limitations of PSM are that the separate effect of all confounding variables cannot be estimated. For this reason, we apply PSM in addition to a regression in OLS. A second downside is that PSM may lead to a loss of sample size and statistical power, due to larger uncertainty when estimating propensity scores [56].[13]

Finally, the outcomes of PSM can be sensitive to the choice of the matching algorithm [55]. To generate more robust results, we apply multiple matching methods: stratification matching, kernel matching, radius matching, and nearest-neighbor matching [55].

[11] The included covariates from Table 1 are the Geul River dummy, supply dependency, employees, and economic sectors. The other covariates are included as they influence business interruption losses through their physical impact on business interruption duration.

[12] For further explanation of this selection bias, see Endendijk et al. [15].

[13] Matching has been applied using common support and with a maximum of five replacements. Standard errors are bootstrapped.

Table 2
Fixed effects regression with business interruption in days as the dependent variable.

Variables	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6
Inundation depth	0.168[a]	0.166[a]	0.138[a]	0.148[a]	0.178[a]	0.148[a]
	(0.026)	(0.026)	(0.029)	(0.032)	(0.029)	(0.032)
Received compensation (%)	−0.118[b]	−0.129[b]	−0.110[b]	−0.100	−0.133[b]	−0.102[c]
	(0.054)	(0.054)	(0.050)	(0.061)	(0.063)	(0.061)
Flow velocity			1.247	1.062		1.345
			(1.051)	(0.999)		(1.112)
Contamination			4.613[c]	6.183[c]		5.497[c]
			(2.673)	(3.264)		(3.185)
Employees					−0.009	−0.010
					(0.012)	(0.014)
Building age					−0.014	−0.012
					(0.013)	(0.014)
Supply dependency					−0.015	−0.011
					(0.041)	(0.043)
Geul River	7.359[a]	5.471[c]	5.113[c]	4.034	4.400	3.983
	(2.799)	(3.018)	(2.998)	(3.070)	(3.162)	(3.136)
Sector						
Service		−0.612	0.002	1.020	0.060	1.169
		(2.233)	(2.746)	(2.758)	(2.228)	(2.763)
Manufacturing		4.427	7.022[b]	6.720[b]	3.698	6.784[b]
		(2.681)	(2.906)	(3.101)	(3.018)	(3.234)
Hospitality		7.128[b]	8.501[a]	8.400[b]	7.368[b]	9.105[b]
		(2.929)	(3.198)	(3.839)	(3.646)	(3.992)
Retail		1.950	3.367	5.012[c]	2.610	4.478
		(2.411)	(2.773)	(2.864)	(2.454)	(2.925)
Public		0.692	2.056	1.769	0.637	2.277
		(3.271)	(3.331)	(3.707)	(3.700)	(3.802)
Health		8.638[c]	10.036[c]	11.329[c]	9.669[c]	11.311[c]
		(5.028)	(5.358)	(5.813)	(5.533)	(5.876)
Constant	12.518[b]	10.740[b]	4.816	4.348	13.488[b]	5.667
	(5.348)	(5.024)	(5.325)	(6.909)	(6.478)	(6.792)
Observations	177	177	170	147	153	147
Adjusted R-squared	0.419	0.459	0.473	0.510	0.498	0.514

Robust standard errors in parentheses.
Note: Model 1 gives equation (1) excluding covariates and sector-fixed effects. Model 2 adds sector-fixed effects. Model 3 adds hazard-related covariates. Model 4 uses only the same selection of observations as Model 6. Model 5 uses all available observations again and adds vulnerability-related covariates to Model 2. Model 6 is the full model with all relevant control variables.
[a] $p < 0.01$.
[b] $p < 0.05$.
[c] $p < 0.1$.

Nearest-neighbor matches control and treatment based on the most similar propensity score. Radius matching matches the treatment observation with all control observations within a specified bandwidth.[14] Kernel matching matches a treatment observation with all observations in the control group, but gives a larger weight to the more similar propensity scores. Finally, stratification matching divides both groups into blocks. Each treatment observation within a block is compared with all control observations in the same block. A main disadvantage of stratification matching is that each block requires a sufficient number of observations, which makes estimates more uncertain compared to other matching methods when using small sample sizes [57]. For a more detailed description of the different matching methods, see Caliendo & Kopeinig [55].

4. Results

4.1. Business interruption

The models in Table 2 explain the variation in business interruption duration between firms. Model 1 includes two variables that have similar significant effects throughout all other Models: self-reported inundation depth and received compensation. It stands out that the coefficient for inundation depth is similar and significant throughout all models in Table 2, where one additional centimeter of inundation depth in the building is associated with 0.14–0.18 additional days (i.e., 4 h) of business interruption. This effect can be

[14] A bandwidth of 0.05 is used in this study. Using smaller and larger bandwidths gives similar outcomes (details not shown here).

explained due to the period it takes for the firm's property to dry and be cleaned [58]. Another variable that has a similar and significant coefficient throughout most models is the received compensation after the flood event. One additional percentage point of received damage compensation (compared to total expected compensation) six to eight months after the flood event is associated with 0.10–0.13 days fewer business interruption (3 h). Firms that experienced physical flood damage need time to repair these damages to start business again. The longer damage compensation has not been received, the more difficult it is for the firm to start reconstruction and resume business. Additionally, if it is clear that the firm will not receive any additional compensation, the firm will take other actions to resume business again, instead of waiting for potential future compensation. The final included variable in Model 1 is the location dummy for a firm located near the Geul River, where the most economic damage has been observed [28]. The Geul flows through a relatively small V-shaped valley with rapid response to upstream precipitation. For this reason, residents along the Geul River often had short warning times before the flood occurred, if they were warned at all [26]. The area along the Geul River faced the most disruption in local networks and destruction of infrastructure, which led to longer business interruption, even if the firm itself did not face any water intrusion. This becomes apparent in Models 1–3, where firms located along the Geul River on average have five to seven days of additional business interruption compared to firms located in other areas. The Geul River dummy loses its significance and becomes smaller the more control variables are added to the model, which indicates that these newly added covariates explain some of the variation in business interruption duration previously captured by the dummy for the Geul River, which represents the area with the largest disruptions [28].

In Model 2, sector-fixed effects are added to control for different interruption durations between economic sectors. The agricultural sector functions as the reference category for these sector dummies. The coefficients and significance of the variables are mostly similar compared to Model 1 and the fit of the model improves by adding sector-fixed effects. It stands out that the coefficients for the hospitality and health sectors are positive and significant. This implies that these sectors face longer business interruption compared to firms in the agricultural sector, which is also shown in Fig. 2. Model 3 includes additional hazard indicators. It is found that self-assessed flow velocity does not significantly impact business interruption, while water contamination does. It appears that several observations are lost after adding additional covariates in Models 5 and 6. The reason for this is that not all respondents answered questions about these added variables. To check if this missingness is random, we run Model 4 using the same specification as Model 3 with only the observations where all outcome variables are available. It can be concluded that missing values for some variables are random, as the signs of the variables in Models 3 and 4 are of similar size, although the received compensation variable is no longer significant in the model with the lower number of observations. Compared to Model 2, Model 5 includes the firm's number of employees, the age of the building, and the period the firm can operate without stocks. None of these firm characteristics significantly impact business interruption after a flood event. Model 6 includes all covariates, which leads to similar results as found in the previous models, except the Geul River variable and a few of the sector variables. Overall, the models in Table 2 perform relatively well. Between 41.9 % and 51.4 % of the variation of business interruption duration has been explained.

It is also possible to distinguish an effect between firms that have been directly hit by the flood and firms that experience spillovers after the flood event due to the disruption of supply chains and infrastructure. The hazard indicators (inundation depth, flow velocity, and water contamination) as well as insurance compensation capture the effect of firms directly hit by the flood. Spillover effects are captured by the constant, the sector dummies, and the Geul River dummy, which corresponds to the firms in the most disrupted area. A robustness test in Table 6 in Appendix IV [15] confirms that the results on the hazard indicators (i.e., inundation depth, flow velocity, and contamination) are not affected by the fact that also non-flooded firms are included in the model. However, the sector variables have higher coefficients in Table 5 compared to the findings in Table 2. A potential explanation for this is that the agricultural sector functions as the reference category in both models. As observed in Fig. 2, there is little difference in business interruption between the flooded and non-flooded firms in the agricultural sector. This difference is larger for other economic sectors, such as manufacturing, hospitality, and health. Hence, the differences between sectors become larger when only considering flooded firms.

4.2. Effect of adaptation measures on business interruption

PSM is applied in Fig. 5 to estimate the impact of FDM measures taken before the flood event on business interruption. The coefficients of several FDM categories have been reported along with the 95%-confidence intervals. We cannot identify any significant effects of FDM measures. A potential explanation is that the matching process did not fully overcome the selection bias (Appendix III). The group that applied FDM measures still experienced higher water levels, even though some adaptation actions are aimed at reducing water levels. The coefficients and confidence intervals for structural adaptation actions are the smallest, but still cannot be distinguished from zero.

A consequence of PSM is that the matching algorithm increases standard errors and that the number of observations in the treatment group is reduced [59]. Hence, we cannot distinguish significant effects between FDM measures on business interruption. Positive coefficients are most frequently observed for emergency measures, primarily due to the large share of elevating valuable possessions in this category. However, placing sandbags has often proved to be ineffective during this flood event, as sandbags were either too low or not strong enough to protect the building from floodwater [26]. Consequently, these measures often failed to reduce

[15] A robustness test has been performed by running the same models as in Table 2 with only the directly flooded firms. It stands out that the coefficients of the hazard indicators do not differ compared to the same models in Table 2, as flood hazard indicators are uncorrelated with the other background variables included in the model. The significant relationship between inundation depth and business interruption remains, despite the small number of flooded firms included in the regression.

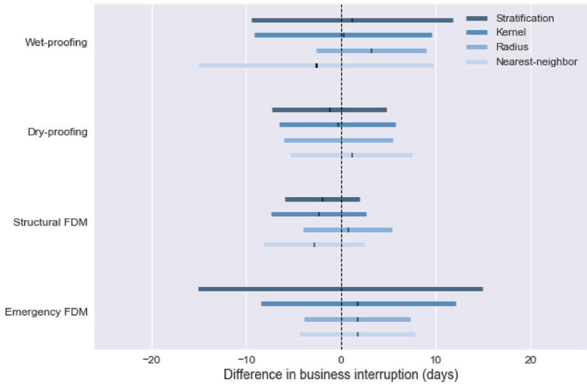

Fig. 5. Coefficients and 95%-confidence intervals using Propensity Score Matching (PSM) to identify the difference in business interruption (days) between the group that had FDM measures taken before the flood and the group that had not.

flood damage. Moreover, emergency FDM may be less suitable for PSM based on the matching variables described in Section 3.2, as emergency FDM is mostly driven by early warnings, in contrast to the other FDM categories [60]. All in all, significant effects of adaptation cannot be identified. To our knowledge, these are the only estimates in the literature that examine the relationship between

Table 3
Regression revenue loss ratio (compared to revenue of 2019).

Variables	(1)	(2)	(3)	(4)	(5)
	Model 1	Model 2	Model 3	Model 4	Model 5
Business interruption	0.006[a]	0.005[a]	0.005[a]	0.007[a]	0.007[a]
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Received compensation (%)		−0.000	−0.000	0.000	0.000
		(0.001)	(0.001)	(0.001)	(0.001)
Access difficulty		0.006	0.004	0.008	0.007
		(0.005)	(0.005)	(0.005)	(0.005)
Geul River		−0.008	0.036	0.015	0.023
		(0.028)	(0.030)	(0.023)	(0.024)
Region connection				0.006	0.017
				(0.020)	(0.023)
Business interruption × Region connection				−0.005[a]	−0.005[b]
				(0.002)	(0.002)
Supply dependency					0.001
					(0.000)
Employees					0.000
					(0.000)
Sector					
Service			−0.073[b]	−0.070[b]	−0.090[b]
			(0.033)	(0.032)	(0.038)
Manufacturing			−0.106[a]	−0.093[a]	−0.105[a]
			(0.035)	(0.034)	(0.038)
Hospitality			−0.047	−0.053	−0.073[c]
			(0.042)	(0.040)	(0.040)
Retail			−0.097[b]	−0.096[a]	−0.113[a]
			(0.038)	(0.036)	(0.039)
Public			−0.044	−0.032	−0.061
			(0.044)	(0.040)	(0.043)
Health			−0.187[a]	−0.181[a]	−0.202[a]
			(0.056)	(0.053)	(0.056)
Constant	0.029[a]	0.016	0.078[b]	0.070[b]	0.062[b]
	(0.009)	(0.010)	(0.030)	(0.030)	(0.030)
Observations	148	148	148	148	133
Adjusted R-squared	0.349	0.367	0.448	0.524	0.494

Robust standard errors in parentheses.
Note: Model 1 gives the relationship between the revenue loss ratio and business interruption. Model 2 adds the relevant impact and hazard-related covariates. Model 3 adds region connection and its interaction with business interruption and model 5 is the full model with all relevant covariates.
[a] $p < 0.01$.
[b] $p < 0.05$.
[c] $p < 0.1$.

FDM and business interruption, emphasizing the need for additional observational data.

4.3. Revenue losses

Table 3 shows an OLS regression with the firm's revenue loss ratio as the dependent variable. This loss ratio relates self-reported revenue losses after the flood event to the firm's annual revenue of 2019. Model 1 only captures the relationship between business interruption and revenue losses. Model 2 adds received damage compensation, the number of days the firm was difficult to reach for customers, employees, or suppliers, and the Geul River dummy. One additional day of business interruption is associated with a 0.5 percentage point annual revenue loss, ceteris paribus. This significant effect slightly increases to 0.7 percentage points in Models 4 and 5.[16] The difficulty to access firms represents potential supply chain disruptions but does not significantly impact revenue losses. There is also no direct effect found of the effect of quick compensation on revenue losses, which means that there only is an indirect effect where quick insurance compensation reduces revenue losses through shorter business interruption duration (see Section 4.1),[17] [18]. The Geul River dummy is not significant, which implies that revenue losses do not differ between the different flooded regions in Limburg when controlling for business interruptions, insurance compensation, and infrastructure disruption.

Model 3 adds the sector dummies, again with the agricultural sector as the reference category. It stands out that the service, manufacturing, retail, and health sectors all have significantly lower revenue losses compared to the agricultural sector, a pattern also described in Fig. 2. This implies that the agricultural sector suffered one of the highest revenue losses, which can be explained due to the destruction of croplands. Low inundation depths can already cause harvests to fail, especially during summer [61]. Most farms had their almost fully grown crops still on the field at the time of the flood. These farms lose the entire harvest of the flooded cropland, resulting in the loss of all potential sales from that property. These findings are supported by Fig. 2, where the agricultural sector faced relatively short business interruption, but large revenue losses. We cannot distinguish a significant difference between the agricultural sector and the hospitality and public sectors, which implies that these sectors also faced large revenue losses. A reason for higher revenue losses in the hospitality sector may be that this sector is very location-bound. Restaurants and hotels do not open before their entire property is fully cleaned and repaired and their equipment is replaced. In contrast, more footloose sectors, such as services and health, may start temporarily operating from non-affected properties, mitigating interruption and revenue losses. Tourism may have reduced as well, due to infrastructure disruption and potential safety issues [62]. This way, the firms in the hospitality sector may have opened again, but fewer potential customers were in the area. Higher revenue losses in the public sector may be explained by the large fraction of sports associations included in this group. Sports accommodations may have been temporarily closed, which may have led to missed sponsorships income because of canceled games.

Model 4 adds a new variable that describes the firm's connection to the region and Model 5 also includes firm characteristics. The firm's connection to the region is expressed with a variable with the value 1 if more than 50 % of the firm's customers or suppliers are located within a radius of 10 km around the firm. This variable is interacted with business interruption, to show how the impact of business interruption on revenue differs between firms based on the connection to their region. This effect has been visualized in Fig. 6.

The negative and significant coefficient implies that the impact of business interruption is larger for firms with less connection to the region compared to firms with a closer connection to the region. All firms experience higher revenue losses the longer business interruption lasts. However, firms that have less than 50 % of their customers or suppliers within a 10 km radius face higher revenue losses compared to firms with a stronger connection to the region. This difference becomes larger the longer business interruption lasts. A potential explanation for this is that customers of firms with weak connection to their region are more likely to seek alternatives during the firm being closed. These customers may prefer their new alternative or sign new contracts and will not return after the business has opened again, leading to structurally lower revenues. The longer business interruption lasts, the more customers will look for alternatives. This may not be true for firms with a strong connection to the region. There may be no alternatives for customers close by. Alternatively, stronger local relationships with the firm make customers return after the business has opened again.

Fig. 7 explores how this role of firm connection to the region differs per economic sector. Within economic sectors, firms with a weak connection to the region generally face higher revenue losses compared to firms with a stronger connection to the region. This is not the case for the manufacturing and retail sectors, where there are also few observations. The differences within the hospitality sector stand out, firms with a weak connection to the region on average face three times higher revenue losses compared to the group with a stronger connection. This supports the hypothesis of tourists temporarily staying away from the flooded area, resulting in lower demand. Firms in the hospitality sector that are less dependent on tourists may, therefore, experience lower revenue losses. Similar differences can be observed within the agricultural and health sectors. Firms with a strong connection to the region in the health sector may experience lower revenue losses during business interruption as patients are often connected to one dentist, pharmacy, or doctor in the region. Patients are, therefore, less likely to seek alternatives, as they are used to a health care provider. In contrast, firms with weaker connections may face higher revenue losses as patients may opt for alternative healthcare providers in the absence of their usual facility. An alternative hypothesis for the agricultural, health, and hospitality sectors is that residents in the region support these

[16] Including the squared term of business interruption in the model to accommodate nonlinear effects did not yield a noteworthy correlation, suggesting that a linear model is satisfactory.

[17] These direct and indirect effects have also been examined using a mediation regression, where the same results have been found (not reported in detail here).

[18] Due to the privacy regulations in the Netherlands, the location of some firms is unknown, as respondents were given the option to withhold their addresses.

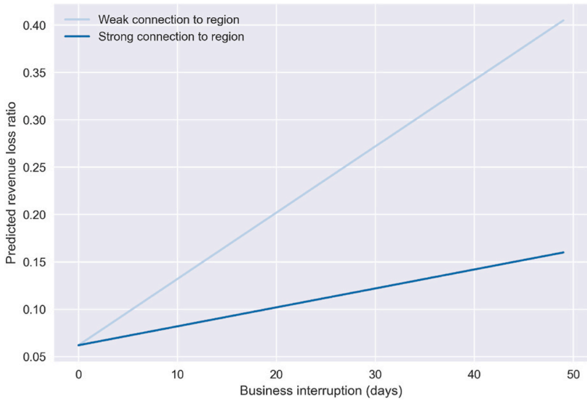

Fig. 6. Visualization of the marginal effect of business interruption on revenue losses for firms with low (light blue) and high (dark blue) connection to the region. Note: Based on coefficients from Table 3. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

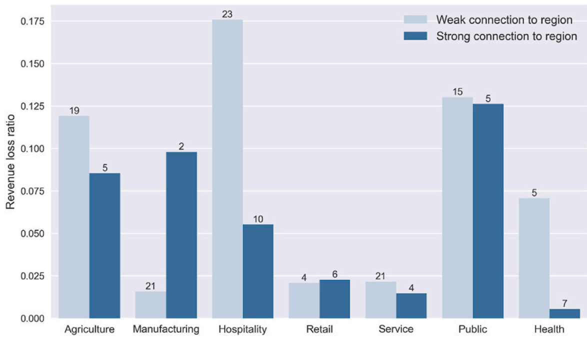

Fig. 7. Mean revenue loss ratio for firms with weak (light blue) and strong (dark blue) connection to their region, separated per economic sector. The number of observations is given on top of the boxes. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

businesses in the recovery process through additional demand or in-kind support.

5. Discussion

5.1. Comparison with previous literature

This study adds knowledge on business interruption duration, losses, and the potential impact of FDM measures following a flood event. To our knowledge, only three studies investigated business interruption duration caused by flooding. Yang et al. [12] assess the impact of pluvial flooding on business interruption and use a probabilistic approach to determine business interruption. The other studies that look into riverine flooding both use the same dataset from the 2013 summer flood event in Germany. Thieken et al. [11] described their dataset and found a median business interruption of two weeks, which is similar to our findings for flooded firms in Table 1. Sultana et al. [13] seek a relationship between inundation depth and business interruption duration. Using machine learning, they identify business interruption to be mainly driven by hazard characteristics, such as inundation depth, duration, and water contamination. Similarly, in Table 2 it is observed that both self-reported inundation depth and water contamination are associated with longer business interruption. Sultana et al. [13] used a bivariate linear regression to quantify the relationship between inundation depth and business interruption. Their model explains only 5 % of the variation in business interruption duration, while our models, which include sector-fixed effects and other covariates, explain 42%–51 % of the variation.

We also examine the role of FDM at the building level in reducing business interruption duration for firms; a relationship which has, to our knowledge, not been studied before. Moreover, empirical evidence on the effectiveness of FDM measures for reducing flood damage on the asset level is scarce, especially for commercial properties. Including FDM in a regression leads to a positive selection bias, as firms who expect higher flood risk are more likely to take FDM measures [15]. Studies on household FDM measures have applied an instrumental variable (IV)-regression [15] or PSM [16,17] to overcome this selection bias. Sairam et al. [17] and Hudson et al. [16] both report the impact of FDM measures in absolute values, which makes their findings more difficult to compare with ours in terms of days. Endendijk et al. [15] find that FDM measures have the potential to reduce economic damage to buildings by 20–29 %.

Kuhlicke et al. [63] cannot disentangle a relationship between adaptation measures and flood damage for firms. Using PSM, we cannot identify any significant impacts of FDM on business interruption. A potential explanation for the lack of significance in our study is that we estimate an indirect effect of FDM on business interruption through potentially lower damage to physical capital. Moreover, we operate with a relatively small sample size, which results in lower explanatory power, especially when applying PSM.

Studies that estimate the impact of flooding on firms use several impact indicators, such as changes in capital, labor, productivity, profits, or value added. However, these studies often use a time scale longer than one year and cannot identify whether a single firm was flooded or not (e.g. Ref. [19–21]). Moreover, these studies are quite coarse in the determination of the flood extent, where a firm is classified as flooded when its city or region has been flooded. As a consequence, the average impact of flooding in existing studies includes both impacts on flooded firms as well as spillovers to other firms in the same region. We reduce the heterogeneity between different firm sizes by relating revenue losses to previous annual revenues, which indicates a stronger relationship between interruption and losses and improves the fit of the revenue loss model compared to Sultana et al. [13]. Our study is one of the first firm-level studies that can estimate the impact of flooding in a region, where the indirect impacts on flooded firms and spillover effects on non-flooded firms can be distinguished from each other. We identify direct effects through the hazard and insurance indicators included in our models, where indirect effects also occur for nearly flooded firms through their presence in an area where disruption of infrastructure occurred. The relatively short timeframe of our study also explains the found negative effect of flooding on revenues, similar to what is found in other studies (e.g., Ref. [11–13,25]). In the longer run, firm growth may be positive due to increased demand for goods and services for reconstruction in the area, technological advancement because of the replacement of depreciated capital, or just macroeconomic growth in general [19].

5.2. Research implications

When interpreting our results, it should be noted that we report on the consequences of a relatively small flood event. For instance, the same flood event in the Ahr Valley in Germany or Hurricane Katrina in New Orleans caused much larger economic losses and disruptions [30,64]. As a consequence, infrastructure disruption and massive demand for reconstruction prolonged business interruption duration in these areas. We show an effect of self-reported inundation depth on business interruption duration, but one should be cautious when extrapolating this relationship to flood events of a much larger magnitude, where disruptions are larger. In this case, besides inundation depth, the total magnitude of economic losses caused by flooding should be considered.

Another limitation of our study is that it relies on self-reported revenue losses provided by the firms. While this approach is commonly used and offers valuable insights, it is important to acknowledge that self-reporting introduces the possibility of bias or inaccuracies in our data. Self-reported revenue losses are related to 'business as usual', so are an estimation of revenue losses rather than an accurate representation of impacts related to a counterfactual. However, this method helps map firm-level flood impacts, which gives more detailed flood characteristics and vulnerability indicators than modeled flood extents. Another limitation is that our study, which utilizes survey-based regression models, cannot fully examine interactions between economic sectors. Unlike approaches such as IO or CGE models, our models cannot capture complex interdependencies and feedback effects that can occur between economic sectors in the recovery process. We, therefore, stress that our findings are complementary to the findings from these macroeconomic models (e.g., Ref. [8,10,65]), where especially our findings on business interruption duration may guide the use of recovery periods in IO and CGE models.

Current literature on IO and CGE models often makes strong assumptions about business interruption duration [10]. In most cases, these models assume the recovery period after a flood event to last exactly one year, without any empirical calibration [66]. The constant and significant coefficient of inundation depth in Table 2 calls for the inclusion of depth-duration functions in IO and CGE models. This allows for differentiation in recovery periods between different firms within a flooded region and provides more accuracy to these models, which is in contrast to the current approach in these macroeconomic models where different scenarios of business interruption duration are assumed for all firms within a flooded region. Moreover, our results show that a majority of flooded firms recover within a month (Fig. 1), where there are large outliers to longer business interruption durations.

As the outcomes of the impact on FDM measures taken at the firm level are quite uncertain, future studies can look more into this topic by collecting more observational data after flood events. Additionally, future studies that look into the impact of flooding on firm performance would benefit from the inclusion of connections between economic sectors. Some economic sectors are more closely connected to each other [10]. This may indicate that disruptions in a closely connected economic sector will lead to larger revenue losses.

6. Conclusion

As the frequency and intensity of flood events are expected to increase due to climate change, it is useful to understand how flooding impacts businesses through interruption of business processes and revenue losses. Previous empirical studies on the impact of flooding on firms generally cannot distinguish separate direct effects on flooded firms and spillover effects on non-flooded firms. Moreover, flood magnitude and firm adaptation to flooding are often not considered in these existing studies. Therefore, after the flood event in the Netherlands in the summer of 2021, we distributed a survey among firms in the flooded area. Using a multivariate regression approach, flood characteristics have been found to explain business interruption duration, which resulted in depth-duration functions. These functions serve the purpose of reducing reliance on assumptions regarding business interruption duration and enabling a more nuanced distinction in the level of business interruption experienced across varying degrees of flood impacts in models that capture indirect impacts on firms. Using propensity score matching (PSM), no significant impact of flood damage mitigation

(FDM) measures taken at the building level on business interruption has been identified. PSM addresses the problem of endogeneity, which is caused by firms that expect higher flood damage being more likely to adopt these measures.

It is found that one additional centimeter of inundation depth reported by the firms is associated with 4 h of additional business interruption, where one day of business interruption costs a firm on average 0.5 % of its annual revenue. A way to support firm resilience is by strengthening local networks and customer loyalty. Firms that are more closely connected to their region, face less adverse effects from business interruption compared to firms less connected to the region. This difference is likely to be caused by customers returning to firms with a stronger connection to the region, where customers of other firms are more likely to seek substitutes. Next, commercial flood insurance uptake is relatively low in the Netherlands. However, it is found that quick loss compensation indirectly reduces revenue losses by shortening the duration of business interruption, calling for higher insurance uptake and efficient and streamlined insurance and government damage compensation. A way to accomplish this is by stimulating insurance uptake and establishing a central point for households and firms to claim their flood damage compensation, which can be distributed among different insurers at a later stage to help build more resilience to flooding.

CRediT authorship contribution statement

Thijs Endendijk: Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **W.J. Wouter Botzen:** Writing – review & editing, Supervision, Resources, Data curation, Conceptualization. **Hans de Moel:** Writing – review & editing, Supervision. **Kymo Slager:** Writing – review & editing, Supervision, Resources. **Matthijs Kok:** Writing – review & editing, Supervision. **Jeroen C.J.H. Aerts:** Writing – review & editing, Supervision, Conceptualization.

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

The authors do not have permission to share data.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.wre.2024.100244.

Appendix I. Geographical distribution of business interruption

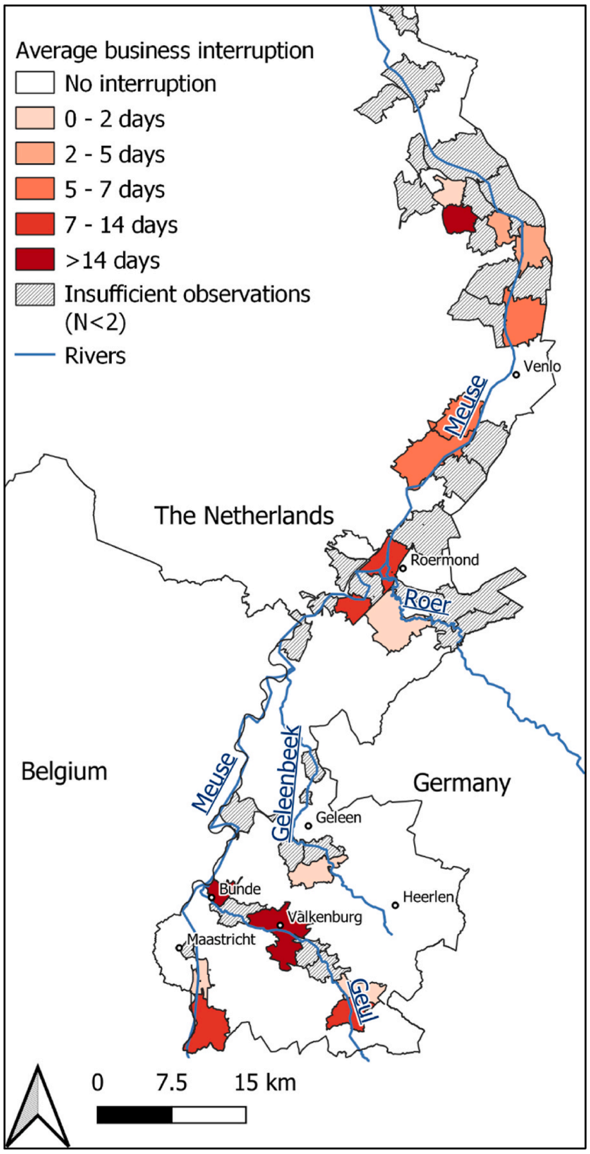

Fig. 8. Average business interruption per postal code area (N = 129) .

Appendix II. Flexible nonparametric model of inundation depth on business interruption

Table 4
Flexible nonparametric regression model for business interruption and inundation depth divided into bins using the same covariates as Model 6 in Table 2.

Variables	(6)
	Model 6
Inundation depth (1–20 cm)	2.024
	(4.880)
Inundation depth (21–50 cm)	3.041
	(3.952)
Inundation depth (51–100 cm)	11.105**
	(5.161)

(*continued on next page*)

Table 4 (*continued*)

Variables	(6)
	Model 6
Inundation depth (101–200 cm)	23.926***
	(6.452)
Inundation depth (201–400 cm)	35.470***
	(5.302)
Received compensation (%)	−0.108*
	(0.060)
Flow velocity	1.251
	(1.113)
Contamination	5.496*
	(3.258)
Employees	−0.011
	(0.014)
Building age	−0.013
	(0.013)
Supply dependency	−0.012
	(0.042)
Geul River	3.657
	(3.199)
Sector	
Service	1.275
	(3.020)
Manufacturing	7.076**
	(3.346)
Hospitality	9.149**
	(4.057)
Retail	4.534
	(3.036)
Public	1.710
	(4.255)
Health	11.883**
	(5.611)
Constant	6.624
	(7.071)
Observations	147
R-squared	0.518

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

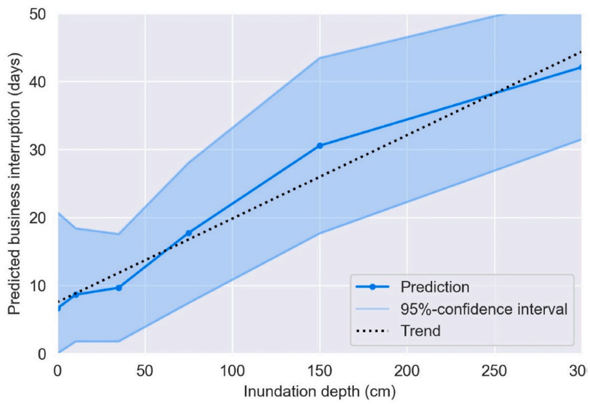

Fig. 9. Visualization of the nonparametric regression model. Note: based on the coefficients for inundation depth in Table 4, keeping all other variables constant.

Appendix III. PSM – Balancing of covariates

Table 5
Control and treatment groups for each category of FDM after balancing of covariates.

Variable	Wet-proofing		Dry-proofing		Structural		Emergency	
	Control (N = 113)	Treatment (N = 110)	Control (N = 152)	Treatment (N = 71)	Control (N = 148)	Treatment (N = 75)	Control (N = 138)	Treatment (N = 85)
Inundation depth	16.631 (34.007)	38.943 (60.816)	30.009 (53.603)	26.877 (48.236)	25.284 (49.832)	34.588 (54.147)	25.22 (44.046)	33.584 (59.950)
Received compensation (%)	95.602 (18.810)	90.144 (26.750)	94.092 (21.331)	90.378 (26.702)	94.593 (20.619)	89.588 (27.396)	94.11 (21.747)	90.961 (25.348)
Flow velocity	1.68 (0.857)	1.968 (0.928)	1.759 (0.906)	1.984 (0.896)	1.709 (0.812)	2.045 (1.007)	1.802 (0.980)	1.892 (0.804)
Contamination	0.212 (0.411)	0.318 (0.468)	0.23 (0.422)	0.338 (0.476)	0.236 (0.426)	0.32 (0.470)	0.232 (0.424)	0.318 (0.468)
Employees	15.379 (33.290)	22.019 (49.621)	16.89 (39.075)	23.079 (49.546)	16.094 (38.871)	23.817 (48.603)	14.758 (31.738)	25.063 (54.895)
Building age	70.291 (70.612)	91.791 (99.285)	76.08 (79.136)	93.408 (102.151)	77.339 (82.218)	90.453 (97.360)	75.73 (81.324)	91.012 (96.477)
Supply dependency	1.407 (2.935)	2.869 (3.295)	1.79 (3.172)	2.851 (3.146)	1.701 (3.121)	2.972 (3.192)	1.54 (2.916)	3.083 (3.409)
Sector								
Service	0.159 (0.368)	0.136 (0.345)	0.158 (0.366)	0.127 (0.335)	0.169 (0.376)	0.107 (0.311)	0.138 (0.346)	0.165 (0.373)
Manufacturing	0.124 (0.331)	0.173 (0.380)	0.178 (0.383)	0.085 (0.280)	0.142 (0.350)	0.16 (0.369)	0.174 (0.380)	0.106 (0.310)
Hospitality	0.142 (0.350)	0.264 (0.443)	0.171 (0.378)	0.268 (0.446)	0.149 (0.357)	0.307 (0.464)	0.159 (0.367)	0.271 (0.447)
Retail	0.097 (0.298)	0.091 (0.289)	0.092 (0.290)	0.099 (0.300)	0.095 (0.294)	0.093 (0.293)	0.101 (0.303)	0.082 (0.277)
Public	0.133 (0.341)	0.127 (0.335)	0.112 (0.316)	0.169 (0.377)	0.128 (0.336)	0.133 (0.342)	0.13 (0.338)	0.129 (0.338)
Health	0.133 (0.341)	0.055 (0.228)	0.105 (0.308)	0.07 (0.258)	0.115 (0.320)	0.053 (0.226)	0.109 (0.312)	0.071 (0.258)
Primary	0.142 (0.350)	0.155 (0.363)	0.132 (0.339)	0.183 (0.390)	0.149 (0.357)	0.147 (0.356)	0.13 (0.338)	0.176 (0.383)

Appendix IV. Robustness test with only flooded firms

Table 6
Fixed effects regression with business interruption in days as the dependent variable with only flooded firms

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Inundation depth	0.169*** (0.031)	0.169*** (0.031)	0.136*** (0.037)	0.156*** (0.042)	0.178*** (0.037)	0.151*** (0.043)
Received compensation (%)	−0.136* (0.070)	−0.145** (0.067)	−0.129** (0.063)	−0.106 (0.073)	−0.137* (0.074)	−0.111 (0.073)
Flow velocity			1.777 (2.710)	0.652 (2.895)		1.435 (3.761)
Contamination			6.044 (3.777)	7.967 (4.878)		6.520 (5.048)
Employees					−0.019 (0.028)	−0.022 (0.041)
Building age					−0.028 (0.025)	−0.020 (0.028)
Supply dependency					−0.010 (0.094)	−0.000 (0.096)
Geul River	11.217** (4.467)	9.647* (5.006)	9.098* (4.941)	6.873 (5.242)	7.470 (5.496)	6.969 (5.530)
Sector						
		−1.980	0.392	5.200	2.978	5.388

(continued on next page)

Table 6 (*continued*)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Service		(5.625)	(6.535)	(6.883)	(6.518)	(7.569)
		11.577	15.405**	17.506**	13.719	18.040*
Manufacturing		(7.202)	(7.443)	(7.989)	(8.572)	(9.265)
		14.941***	17.008***	19.344***	18.897***	20.675***
Hospitality		(5.230)	(5.536)	(6.871)	(6.866)	(7.179)
		−0.974	−0.068	6.037	5.714	6.147
Retail		(6.120)	(6.779)	(8.467)	(6.314)	(7.700)
		2.848	5.357	5.525	2.907	5.647
Public		(4.719)	(5.222)	(6.665)	(6.154)	(6.844)
		17.336**	18.772**	23.667**	21.338**	22.713**
Health		(7.843)	(7.974)	(9.452)	(9.762)	(9.774)
Constant	12.612*	5.768	−2.399	−5.088	6.701	−3.198
	(6.948)	(5.870)	(7.440)	(9.745)	(7.704)	(9.592)
Observations	83	83	83	66	66	66
Adjusted R-squared	0.348	0.464	0.484	0.496	0.486	0.502

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

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