Norwegian School of Economics

Bergen, Fall, 2019

The Cost of Extreme Weather: An Analysis of the Physical Climate Risk in Hordaland

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Master thesis, Master of Science in Economics and Business Administration, Major in Business Analytics and Energy, Natural Resources and the Environment

NORWEGIAN SCHOOL OF ECONOMICS

Abstract

Climate change is expected to have numerous societal impacts in the years to come through an increase in the intensity and frequency of extreme weather events. The climate impact is of socio-economic interest, as extreme weather events can impose high costs through their impact on physical capital. This thesis analyzes the costs of extreme weather events in Hordaland, as measured by insurance compensation related to building damage. We focus on daily aggregate insurance payouts related to natural damage incidents at a municipality level. We use a flexible regression model to estimate the relationship between insurance compensation and meteorological variables and apply the model to climate change scenarios for extreme weather. Our analysis is based on data from 1980 to 2019, provided by the Norwegian Natural Perils Pool and the Norwegian Meteorological Institute.

Our findings indicate that the physical climate risk facing Hordaland is mainly related to an increase in precipitation. We find that there is significant heterogeneity between municipalities and that the physical climate risk is higher for municipalities that are prone to floods and landslides. Our estimates indicate that the yearly natural-damage cost in Bergen alone can increase by close to NOK 16 million by the year 2100. The socio-economic consequences of this cost increase are limited. We also find that the relationship between cost and weather intensity is highly nonlinear. Whereas most weather causes little to no damage, extreme weather events can cause considerable damage. The highest 1% of precipitation incidents cause 74,5% of the costs related to floods and landslides in Hordaland. Nonlinearity also applies to wind-related costs. The average cost for wind-gust speeds exceeding 35 m/s in Bergen is NOK 171 million.

Preface

We wrote this thesis as a part of our master's degree in Economics and Business Administration. The topic of understanding the cost of extreme weather was one we found to be very interesting. Although extreme weather events receive much attention when they occur, limited literature exists on the cost related to these types of events. One of the perhaps most relevant questions of today is how the future climate will affect our society, and to work on a project that attempts to address this question was very appealing.

We would like to first and foremost thank our supervisor, Torfinn Harding. His eagerness to assist and offer guidance has been highly valuable for our work and is much appreciated. Furthermore, we would like to thank Kari Mørk, who kindly provided data from the Natural Perils Pool, as well as assisting us in interpreting and handling the data. We would also like to thank Gjensidige Forsikring for guidance and aid in the preliminary phases of this thesis, and the Norwegian Meteorological Institute and Statistics Norway for providing additional required data.

Bergen, December 2019

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1. Introduction

The report "Climate in Norway 2100" states that a continued increase in greenhouse gas emissions will lead to several climatic changes for Norway by the end of this century (Hanssen-Bauer et al., 2015). These changes include rising temperatures, more frequent and intense events of heavy rainfall, and consecutive floods, as well as increasing sea levels (Hanssen-Bauer et al., 2015). Only small changes are projected for wind speeds and wind intensity (Hanssen-Bauer et al., 2015), but varying climate model estimates indicate uncertainty as to this development. Furthermore, Hanssen-Bauer et al. (2015) point out that the frequency of landslides in steep terrain associated with heavy rainfall and erosion may increase. In other words, climate change will increase the extent of natural perils, defined as "damage caused directly from natural elements, such as landslide, storm, flood, storm surge, earthquake or volcanic eruption" (Norwegian Natural Perils Pool, 2019). Understanding how changes to the natural environment affect our society is of importance to both policymakers and the private sector, to mention a few (Khanduri & Morrow, 2003).

With an expected increase in the frequency and intensity of natural perils, the climate risk will also increase. We subdivide climate risk into two main categories: physical risk and transition risk. Physical risks relate to the implications of changes in the physical environment. Transition risks are associated with the consequences of climate policy and technological advances related to the transition to a low emission society (Norway's Climate Risk Commission, 2018). According to Norway's Climate Risk Commission (2018), there is limited knowledge about how climate change will increase the costs related to natural damages on physical capital in Norway.

The aim of this thesis is two-fold. First, we investigate the relationship between extreme weather and insurance payouts related to building damages. Second, we combine the estimated model with climate scenarios to calculate expected future costs and provide insights about the physical climate risk in Hordaland.

We focus on daily aggregate insurance payouts related to natural-damage incidents at a municipality level. We use a flexible regression model to estimate the relationship between insurance compensation and daily precipitation and daily maximum wind gusts. The model and climate scenario estimates are based on insurance data and meteorological data from the Norwegian Natural Perils Pool and the Norwegian Meteorological Institute, respectively. Our data cover the period from January 1980 to March 2019, and we focus on 11 municipalities in Hordaland, Western Norway. Hordaland is one of the counties in Norway with the highest costs related to natural perils, with only Møre and Romsdal presenting higher total costs for the period 1980-2018 (Finance Norway, 2018). The natural peril that is the most prevalent in Hordaland is by far storms, but landslides, floods and storm surges, also make up a significant share of the damage incidents (Finance Norway, 2018). We focus mainly on damages related to storms, floods, and landslides.

We find that the physical climate risk related to building damages in Hordaland will increase with climate change, namely through an increase in the frequency and intensity of heavy precipitation. Our estimates indicate that the total natural-damage cost in Bergen alone can increase by 72%, equaling close to NOK 16 million per year. This increase is found to have limited socio-economic consequences. The cost increase corresponds to less than 0,2% of the yearly tax income for Bergen Municipality. Furthermore, we find that there is significant heterogeneity between municipalities, which must be accounted for when modeling climate risk and the need for mitigative measures in the individual municipalities. As the climate risk relates mainly to increased precipitation, it is higher for flood- and landslide-prone municipalities. This indicates that climate-risk-mitigation efforts should be focused around such municipalities.

We find that the relationship between cost and weather intensity is highly nonlinear. Most weather causes no damage, whereas extreme – but unlikely – events can cause considerable damage. As much as 74,5% of the costs related to floods and landslides in Hordaland are caused by the 1% most intense precipitation incidents. Similarly, the highest 1% wind-gust speeds cause 63,6% of the costs for storms and storm surges. Whenever the wind-gust speed in Bergen exceeds 35 m/s, the cost is NOK 171 million, on average.

Existing literature on the costs of extreme weather in Norway is limited, and arguably somewhat outdated, considering the progress in the field of climate science of the last decade. According to Vennemo & Rasmussen (2010), the risk is not significant for Norway as a whole, although costs can be high at a local level or sector level. This coincides with our findings that the cost increase generally is more than manageable, but that some municipalities are more prone to damages from increased precipitation than others. Thiis et al. (2005) find that a 10% increase in the wind speed during windstorms will more than double the financial costs related to wind damages on residential buildings. Our findings indicate more than a three-fold increase in costs from the same increase in intensity. Orskaug and Haug (2009b) propose a 10-30% increase in costs from increased water-based damages to buildings for Norway. Our findings indicate an increase in costs of 570% from floods and landslides in Bergen, but should not be directly compared with Orskaug and Haug's (2009b) findings. They investigate a wider range of damages, with different climate models.

This thesis consists of eight sections. In Section 2, we present information on natural damages, existing literature on the relationship between costs and weather, and how climate change may affect these costs and damages. In Section 3, we introduce the data and the estimation strategy used in our analysis. Section 4 presents our results, divided into a graphical analysis and estimation results. In Section 5, we present climate scenarios and apply our estimates to them. In Section 6, we assess the physical climate risk in Hordaland with a basis in these scenarios. Section 7 introduces an analysis of the robustness and validity of our results. Section 8 offers a summary of the main findings of the thesis and the conclusion of our research.

2. Literature review

In this section, we present information on the costs of natural perils in Norway, existing literature on the relationship between costs and weather, and cost scenarios for climate change in Norway. Additionally, we discuss research on the distributional characteristics of meteorological variables which affect our analysis.

2.1 Damages from natural perils and weather in Norway

Compensation related to damages from natural perils in Norway totaled NOK 10,4 billion for the period from 2008-2018 (Finance Norway, 2019). Natural damage relates to damages caused by storms, floods, landslides, storm surges, earthquakes, and volcanic eruptions. Insurance compensation claims due to natural damage are, to a large degree, driven by storm damage, which accounts for 50,5% of the total cost from 2008-2018. Floods (34,8%), landslides (8,7%), and storm surges (5,9%) represent the remainder of the cost. As there is virtually no damage from earthquakes and volcanic eruptions in Norway, these will not be addressed further. Storms are defined by the intensity of the wind gusts, which must exceed 20,8 m/s. A flood occurs when rivers or watercourses exceed their normal limits. Landslides are defined as avalanches of rocks, earth, mud, snow, etc. Storm surges occur as a result of high tides, low-pressure weather systems, and strong winds.

The Norwegian Natural Perils pool distinguishes between natural damage and other weather-related damage. Other weather-related damages, such as water penetration from outside, frost, and sewer backup, are not covered by the definition of natural damage. However, the costs related to such damages are higher than those related to natural perils: For the period 2008 to 2018, natural damage accounted for 36,3% of the total costs related to building damages, whereas other weather-related damage accounted for 63,7%.

The degree to which the different municipalities and counties are financially equipped to handle the climate risk related to more extreme weather varies (Hauge et al., 2018). Municipalities are aided financially by governmental organizations to manage the damages related to natural damages like floods. However, this is not the case for other weather-related damages. For instance, the municipalities must cover damages from stormwater without financial aid (Hauge et al., 2018). Investing in mitigative options against such damages could, therefore, be a way to reduce damages and costs. As investing in preventive measures is expensive, knowledge about what areas are prone to flood damages is important when deciding which mitigation efforts to pursue (Hauge et al., 2018). Insurance companies possess more specific geographical information about natural damages than local governments. As almost 100% of private property is insured in Norway, geographical information on damages is valuable in assessing local risks, and, thereby, the optimal mitigative measures. Therefore, acquiring such information is of interest to both municipalities and other government risk managers, such as the Norwegian Directorate for Civil Protection (Hauge et al., 2018).

2.2 Natural perils and climate change in Norway

Norway's Climate Risk Commission (2018) states that there is no total estimate of the natural damages on physical capital in Norway. Furthermore, there is uncertainty related to both the costs and the physical climate risk facing Norway. According to Vennemo & Rasmussen (2010), the risk is not significant for Norway as a whole, although costs can be high at a local level or sector level. Although extreme weather causes significant damages, non-extreme weather is also of relevance to damages from natural perils (Aall et al., 2015). Long periods of non-extreme rain may not be defined as extreme weather, but may still have indirect consequences that affect costs, for instance, through an increase of building decay (Hauge et al., 2018). Furthermore, non-extreme weather can induce natural perils like saturated landslides (Aall et al., 2015).

Thiis et al. (2005) evaluated the costs of wind damages by constructing models for calculating damage costs induced by wind, both in the present and future climate scenarios. They found that a 50% increase in the frequency of storms with a 1-year return period leads to a 2.4% increase in total cost over 50 years. A 50% increase in the frequency of all storms was found to increase costs by 50%. It appears that an increase in the intensity of storms has a higher effect on costs than does the frequency of storms: Thiis et al. (2005) also find that a 10% increase in the wind speed during windstorms will more than double the financial costs related to wind damages on residential buildings.

Orskaug and Haug (2009b) use several climate models- and scenarios to provide predictions for future levels of damages and costs related to water damage on private buildings for Norway as a whole. They find that such damage costs will increase by anywhere between 10% and 30%, depending on the climate model used to create the predictions.

Apart from the above papers, which propose some estimates for how damages and costs may change, limited research appears to exist on the actual costs of natural perils in Norway and how they may change with climate change.

2.3 Nonlinearity and tail risk

Prior research on the topic of wind-induced insurance losses has found the relationship between wind speed and damage ratio to be nonlinear (Khanduri & Morrow, 2003). Furthermore, Haug & Orskaug (2009a) present a figure which indicates that the relationship between precipitation and insurance compensation is nonlinear. This nonlinear relationship between weather intensity and cost has the consequence that extreme weather events can be extremely costly.

In discussing unlikely climate catastrophes, van den Bremer (2018, p. 127) states that "For these low-probability, high-impact effects to be accounted for in integrated climate assessment, the tail of the probability must be carefully considered." In climate change literature, the concept of an unlimited expected loss caused by a severe incident with a low probability is referred to as the 'Dismal Theorem' (Nordhaus, 2009). Weitzman (2009) shows that the tail risk related to climate change is non-negligible due to the uncertainty related to the consequences of hitherto unobserved outcomes. Weitzman's finding can be connected to extreme weather events, which, due to nonlinearity, can have severe consequences if combined with potentially fatter tails induced by climate change. Weitzman highlights in one of his later publications that his research intends to challenge the assumptions of traditional cost-benefit analyses that are frequently used in climate policy today (Weitzman, 2011).

3. Empirical approach

3.1 Data

The data used in this thesis mainly stem from two sources: The Norwegian Natural Perils Pool and the Norwegian Meteorological Institute. The Norwegian Natural Perils Pool's database of damage incidents was provided by Finance Norway. This database contains information on compensation for natural damages to buildings. We retrieved the meteorological data from the Norwegian Meteorological Institute's online database for meteorological data. We present information about the data sets and operations performed on them in the following subsections.

3.1.1 Data from the Norwegian Natural Perils Pool

Finance Norway provided the insurance data from the Norwegian Natural Perils Pool. The data comprise all incidents where buildings have been damaged as a consequence of natural perils in Norway from 1980 until March 1st, 2019. This sums up to 332,195 observations of damages from storms, floods, landslides, storm surges, earthquakes, and incidents with unknown origin. It is worth to emphasize that other weather-related damages in Norway are not covered by the Natural Damage Compensation Act (2019). For instance, damages directly caused by precipitation and frost, such as leakage or burst pipes, are not covered by the definition of natural perils, and therefore not a part of this data set.

The following variables describe each damage incident: Compensation, Date, Payment, Municipality, County, Natural Damage Type, Incident Name, and Insurance Type. Information on the variables is presented in Table 1.

To be able to analyze data at a more aggregated level, we created a variable that holds aggregated insurance payments per municipality and date. Furthermore, as we cannot expect to be able to estimate a relationship between meteorological variables and earthquakes, there is no reason to keep such incidents in our dataset. Consequently, we removed incidents of earthquakes from the dataset. The same applies to an uncategorized incident.

Since our analysis only requires data from Hordaland, the data frame is filtered to include only observations from the county of Hordaland. The filtered data frame consists of 41 209 observations of damage incidents from 31 municipalities, with variables for compensation, aggregated compensation per municipality and date, date, municipality, season, natural damage type, insurance type, building mass for the corresponding municipality, and if applicable, the incident name.

Variable	Description
Date	The date in which the damage incident occurred
Compensation	The compensation paid in relation to the damage incident
Municipality	The municipality in which the damage incident occurred
County	The county in which the damage incident occurred
Natural Damage Type	The type of natural damage that caused the incident, for instance a storm or a flood.
Incident name	Provided for incidents that belong to a larger weather incident which caused a large amount of damage incidents.
Insurance type	Defines the type of insurance that covers the damages from the given damage incident.

Table 1: Description of variables in the data set from the Norwegian Natural Perils Pool.

3.1.2 Data from The Norwegian Meteorological Institute

The data retrieved from the Norwegian Meteorological Institute database comprise data from all weather stations in Hordaland for the years 1980 to 2019. Approximately 100 variations of meteorological variables are available for retrieval from the database. Most weather stations do, however, only measure a couple of the variables, so there will necessarily be a lot of missing data if one chooses to download all available variables. The variables precipitation and wind gusts were downloaded, providing us with the data set presented in Table 2. The choice of these specific meteorological variables and information about them are discussed below.

The downloaded data frame consisted of the variables *Date*, *Station Number*, *Maximum wind gust*, and *Precipitation*. *Station Number* allowed us to identify the municipality in which a station is located. Variables were retrieved if they could plausibly contribute to explain the compensation resulting from natural damage incidents. Precipitation causes both floods and landslides (Hanssen-Bauer et al., 2015), and as such, this variable was included. The precipitation data is only available as the sum of precipitation per day. It would, however, be preferable to have information about precipitation on an hourly scale, as the 24-hour resolution makes it impossible to distinguish between short, intense precipitation events, and evenly distributed rain over the whole 24-hour period. Naturally, the damage potential of the two varies significantly, and hourly precipitation data could have enabled us to explain more of the variation in costs.

Variable	Description
Date	The date in which the weather occurred
Station Number	ID number for a weather station. Used to identify in which municipality the station is located.
Maximum wind gust	Highest value of wind gust speed measured per date
Precipitation	Sum of precipitation per day

Table 2: Description of the variables in the data set downloaded from the Meteorological Institute

The Norwegian Meteorological Institute provides many measures of wind speeds, and both the maximal sustained wind speed and the maximum wind-gust speed are available variables. The maximum wind-gust speed, rather than the maximum sustained wind speed, is the best indicator of damage related to storms (Meteorologisk institutt, 2018). Therefore, the variable for maximum wind-gust speed is used in the analysis.

Among other variables that might help to explain the damages from natural perils, are temperature and wind direction. The temperature variable could possibly have been used to estimate floods caused by snowmelt. Similarly, the wind direction could possibly have been used to estimate the costs related to storm damages as well as storm surges. However, this was not reflected in the data when regression model tests were made.

As mentioned above, data from all available weather stations in Hordaland were downloaded. The reason for this is that even if there is more than one station per municipality, a lot of stations have incomplete data. For instance, some weather stations offered information solely on measurements of wind gusts, but not on precipitation. Similarly, sometimes the station will have been replaced by a new one, and, therefore, not possess data for the entire period in question. The data retrieved consisted of 848 222 observations from 122 weather measurement stations in 25 municipalities.

Downloading all available data allowed us to combine incomplete pieces of data through averaging wind-gust speed and precipitation across stations, and for a certain municipality and a certain date. We aggregate the data per municipality-date, as this is the most natural level of aggregation on which to perform our analysis. Once we average and aggregate the information per municipality-date, we are left with 288 496 observations. However, we do not have complete information on all variables for these 288 496 observations. This is illustrated in Figure 1, which shows the data frame's missing values in orange.

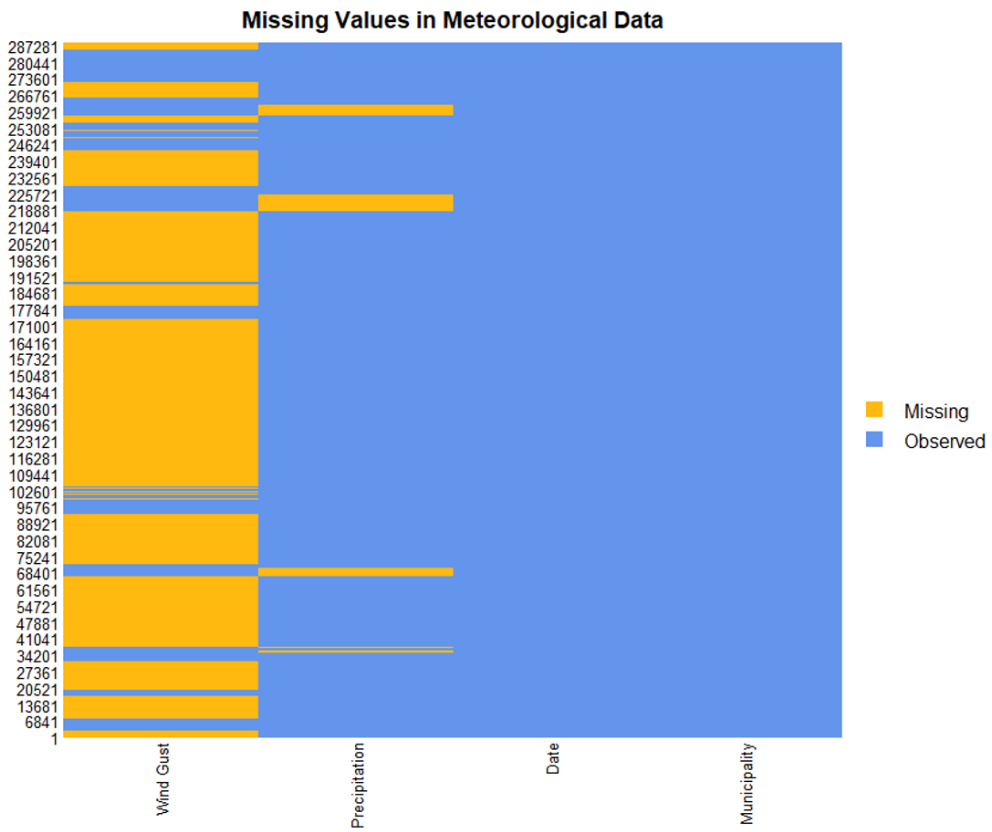

Figure 1: Overview of the meteorological data frame. Rows containing missing values are indicated by orange. Rows containing observed values are indicated by blue. Far more weather stations measure precipitation as compared to wind gusts, resulting in a lot of missing values for wind gusts.

Figure 1 presents an overview of our meteorological data frame. The y-axis displays the rows of the data frame, whereas the x-axis displays the variables. Each row consists of a unique combination of municipality and date, with corresponding observations of weather variables. Missing variable values are colored orange. As we can see from the plot, relatively few rows include information on wind gusts, whereas the majority of rows contain values for precipitation. The explanation for this is that only a minority of the weather stations measure wind gusts, and as such, few municipality-date-observations will have information on both wind gusts and precipitation. Consequently, once we remove the observations which do not contain complete information on all variables, the number of observations is reduced to 58999, and the number of municipalities is reduced from 25 to 11. Finally, we create categories for wind and precipitation, to more easily be able to classify different ranges of wind and precipitation.

3.1.3 Combining the data sets

For the analysis of insurance data and weather data, we first merge the two data frames into a combined data frame. This data frame has a total of 74 350 rows, each of which contains information about the weather in the municipality, and if applicable, information about the damage incident in the municipality.

For the data frame, we also create an identity key that allows us to aggregate damage incidents as the sum of compensation in a given municipality on a given date. Furthermore, we create a dummy that indicates whether a damage incident is related to the row or not, allowing us to separate rows into damage rows and non-damage rows. In our final data frame, each damage incident is aggregated to a municipality-date level. In other words, each row in the data frame contains information about both the weather and aggregate damage cost for a given municipality on a given date. For the bulk of the rows, no damage incident occurred, and the damage cost equals zero.

Matching the damage incidents from the insurance data with meteorological data has the simple consequence that if there is no meteorological data for a given date, the damage incident is excluded from the data frame. In Figure 2, the frequency of damage incidents per municipality is graphed for the untreated insurance data, and for the matched data. From Figure 2, we see that some municipalities are underrepresented in our sample. The deviation between total insurance claims and the insurance claims for which there is accompanying weather data is large for multiple municipalities, such as Bømlo. This could potentially reduce the representativeness of the data, and may, in turn, have implications for the validity of our models.

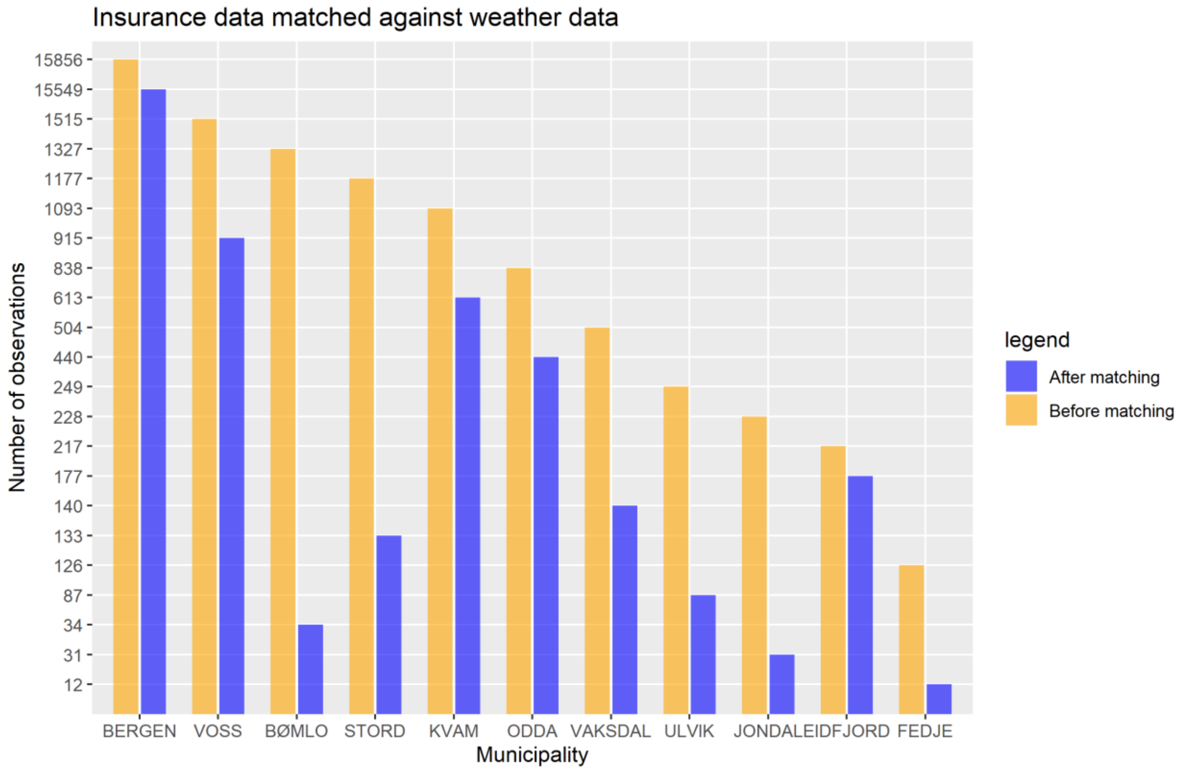

Figure 2: The number of damage observations in the untreated insurance dataset is represented by the orange bars. The number of observations that remain, after matching the insurance data against weather data, is represented by the blue bars. Due to limitations in the weather data, many insurance damage incidents are lost when matching. Note that the number of omitted observations varies by municipality.

3.1.4 Control variables

To more precisely be able to estimate the relationship between compensation and weather, additional variables were created, either with relation to the insurance data or to the meteorological data.

To correctly compare the insurance data across the dimensions of location and time, certain control variables were required. Namely, an index variable to correct for inflation and cost developments for rebuilding, and a building stock variable per municipality.

The insurance payments in the insurance dataset were provided in nominal terms. In order to correctly compare compensation payments from different years, the payments were indexed to correct for inflation and building cost developments. The compensation payments are defined by the costs related to repairs or rebuilding, and thus the indexing must account for the effects of both general inflation and any change in the cost of repairs or rebuilding. The Norwegian Natural Perils Pool provided an index that accommodates these effects, by averaging the trend for building price index and the consumer price index to create a general cost trend. The index is developed at a national level, but we assume that that the price development for building cost is the same all over Norway.

There are significant differences between the municipalities included in our sample. The municipalities are heterogeneous in terms of population, and therefore also the stock of buildings. The implication of this heterogeneity is that the payments related to a given weather incident will vary significantly due to the variation in the stock of buildings that can be damaged and associated reconstruction costs.

To accommodate the difference in building stock, we created a variable that indicated potential reconstruction costs for each municipality's building stock. Data on building types and quantities of each building type in each municipality per 2016 were provided by Statistics Norway. The Norwegian Natural Perils Pool provided estimates for the reconstruction cost for each building type. By combining the building data and the reconstruction cost index, the potential reconstruction cost for each municipality could be estimated, i.e., the cost of rebuilding the entire municipality's building stock. This estimate was then included as a variable in our data frame. The estimated building stock reconstruction cost for the municipalities in our sample is shown in Figure 3.

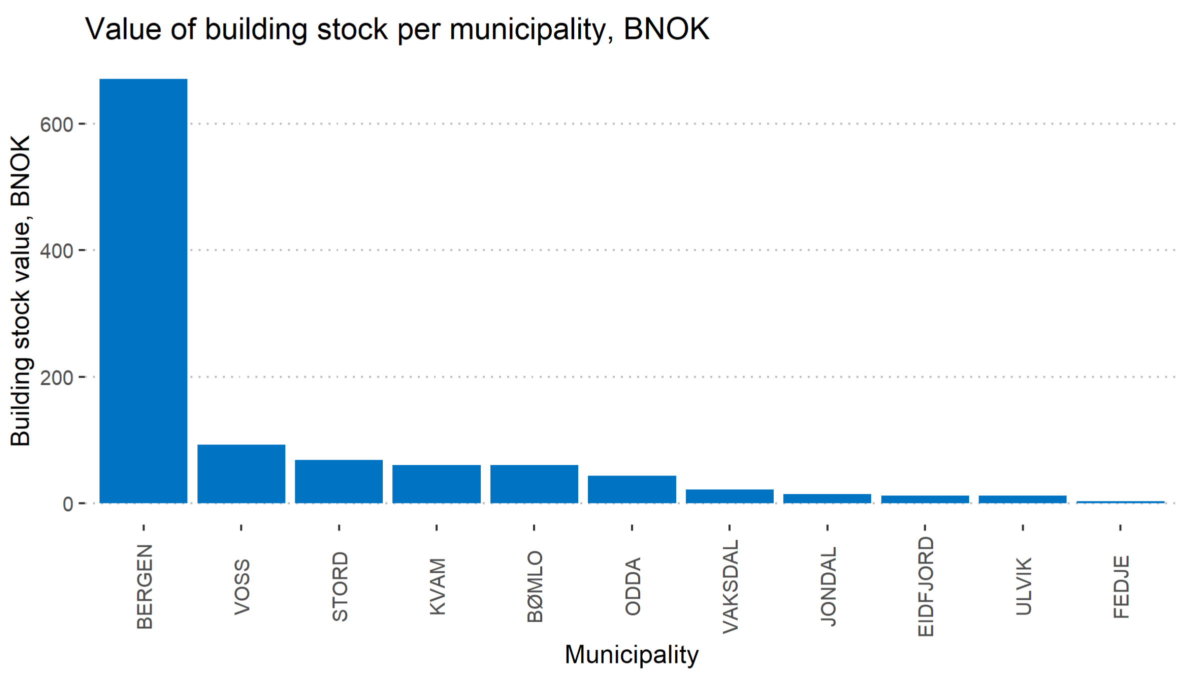

Figure 3: Estimated building stock reconstruction cost per municipality. The building stock variable is an indicator of the damage potential per municipality and may help to alleviate heterogeneity between municipalities.

By computing each municipality's building stock using data from 2016, we implicitly assume that the relative building stock reconstruction costs between municipalities do not change over time. Data for all years between 1980 and 2019 would be preferable, as it could allow for time variation in the building stock. Unfortunately, the data are not available in Statistics Norway's databases. In any case, the building stock is a slow-moving variable, and it is the cross-sectional variation that matters. The building stock values in our data frame are at a 1 MNOK level, as this was the level used in the index provided by the Norwegian Natural Perils pool. For instance, the building stock value for Bergen in our data frame is 670 476 (MNOK).

Aall et al. (2015) point out that long periods of evenly distributed, but non-extreme precipitation can cause extreme events such as saturated landslides. Representatives from the Norwegian Water Resources and Energy Directorate have also stated that a moderate level of precipitation on saturated grounds can have serious consequences as there is no absorptive capacity for the water (Kramviken, 2015). To investigate how this phenomenon affects damages, we create three saturation-variables, consisting, respectively, of the sum of precipitation for the 7, 3, and 2 days preceding an incident. After testing for the different saturation variables' contribution to explaining variation, the three-day saturation variable was found to be the most relevant. This resembles the findings of Pielke Jr. & Downton (2000), which indicate that two consecutive days of heavy rainfall is closely related to flood damage.

Furthermore, to check whether seasonal variations not explained by the mere meteorological variables might exist, a season variable was created. For instance, precipitation can often take the form of snow during the winter, especially in municipalities at higher altitudes. As previously discussed, the snow will melt at some point and can contribute to causing floods. Such seasonal variation cannot be explained by the saturation variable mentioned above, as a lag will exist between the time of precipitation and the actual flood. A season variable was created to accommodate such differences and other types of noise that may exist between seasons.

3.2 Estimation Strategy

To answer our research question, a model that estimates the effect of precipitation and wind gusts on costs related to natural damages is required. In the following section, the empirical strategy used to estimate such a model will be presented.

3.2.1 Choice of functional form

In estimating the relationship between insurance compensation and meteorological variables, the estimation strategy must be suited for the characteristics of the data. Precipitation and wind-gust speed follow a continuous scale, which indicates that we should measure the continuous effect of the meteorological variables on compensation. Applying a standard linear model is one way to achieve this. However, in doing so, we would be assuming that the relationship between compensation and meteorological variables is linear. In addition, the data would also have to be normally distributed.

The relationship between the meteorological variables and damages is nonlinear (Haug & Orskaug, 2009a; Khanduri & Morrow, 2003). Furthermore, the distribution of precipitation is highly skewed due to a high amount of non-zero values and considerable variance (Ye et al., 2018). The distribution of wind is generally right-skewed (Li & Zhi, 2016). These issues could be mediated by log-transforming the data or adding polynomial terms. However, in cases where the data is highly nonlinear, fitting a regression line to the data could be inexpedient, even when applying a higher degree of polynomials or by log-transforming the data (Grace-Martin, 2017). We must also consider the presence of fat tails (Weitzman, 2009). An important characteristic of the fat-tailed distribution is that measures describing its distribution, such as mean and variance, may not be determined. This is due to arbitrarily large insurance payouts occurring from time to time, causing significant movements in the mean value of the distribution (Wicklin, 2014).

Considering the elements mentioned above, an estimation strategy that provides a more flexible fit might be better suited to describe the relationship at hand. We attain a highly flexible model by creating ordinal dummy variables from the continuous meteorological variables. Each dummy relates to a different level of intensity for a given meteorological variable. This model enables us to estimate the relationship between insurance compensation and various combinations of the independent variables' levels. The estimated model is on the form presented in *Equation 1*. The model coefficients are presented in Table A. 1 in the Appendix.

Equation 1:

$$Y = \alpha + \sum_{i=1}^{8} X1_i\, W_i + \sum_{j=1}^{6} X2_j\, P_j + \sum_{k=1}^{24} X3_k\, PS_k + \sum_{l=1}^{8} X4_l\, WB_l * B + \sum_{m=1}^{6} X5_m\, PB_m * B + \epsilon_{ijklm}$$

Y is the aggregated compensation per municipality and date. W_i is the wind-gust speed category, P_j is the precipitation category and PS_k is the dummy for the interaction between precipitation category and saturation category. B is the building stock value, and is unique for each municipality. WB_l and is the dummy for the interaction between wind gust category and building stock, and PB_m is the dummy for the interaction between precipitation category and building stock. $X1_i$, $X2_j$, $X3_k$, $X4_k$ and $X5_m$ are the corresponding coefficients for the variable levels of the variables listed above. As is illustrated in *Equation 1*, we have eight categories for wind-gust speed and six categories for precipitation, in addition to the category in the intercept. The interactions with building stock have equally many categories for wind gust and precipitation, respectively. As there are four categories for saturation and six categories for precipitation, the interaction between precipitation category and saturation category has 24 combinations, in addition to the intercept category. The regression returns an estimate for the aggregated compensation, Y, for a specification of weather intensity and building stock.

3.2.2 Step-up strategy for variable selection

In developing the model presented above, we used a step-up strategy to determine which variables to include. In other words, we began with a simple model with a few independent variables and increased the number of variables and interactions in a stepwise manner. This approach allows us to investigate the importance of the individual variables in explaining compensation amounts (Grace-Martin, 2012). In building the regression model, we input the variables we considered the most likely to explain the compensation amount and tested for their significance and ability to explain variance. This allowed us to see the relative importance of each variable in explaining the variation in compensation and to test hypotheses about the predictors. If a variable proved to contribute to the model through raising the adjusted R^2 while also proving to be significant at a 5% level, it was included in the following models. If not, it was excluded. Through this process, we arrived at the model development presented in Table 3. This led us to model 7, which is the model presented in *Equation 1*.

Model Development

	Dependent variable: Compensation						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Wind gust	■	■	■	■	■	■	■
Precipitation	■	■	■	■	■	■	■
Municipality		■	■	■	■	■	
Season			■				
Saturation				■	■	■	■
Precipitation*Saturation				■	■	■	■
Wind gust*Municipality					■		
Precipitation*Municipality					■		
Building stock						■	■
Wind gust*Building stock						■	■
Precipitation*Building Stock						■	■
Constant	-5,359.889	59,096.510	72,287.110	57,010.730	170,682,621.000***	372,377.800	2597.659
Observations	58,999	58,999	58,999	58,999	58,999	58,999	58,999
R^2	0.02	0.020	0.020	0.050	0.761	0.716	0.715
Adjusted R^2	0.019	0.020	0.020	0.049	0.760	0.715	0.715
Residual Std. Error	1,174,162.000 (df = 58984)	1,173,838.000 (df = 58974)	1,173,846.000 (df = 58971)	1,156,220.000 (df = 58950)	581,021.400 (df = 58825)	632,463.900 (df = 58936)	632,755.400 (df = 58945)

Table 3: Overview of estimated regression models. Variables that were included in a model are marked in blue. A step-up strategy was used to determine the importance of each variable, starting at model 1, which includes only the two meteorological variables, wind-gust category, and precipitation category.

Model 1 includes only the simple meteorological variables, wind-gust category, and precipitation category. Alone, these variables appear to explain little of the variation in compensation per municipality. In models 2 and 3, we include the variables for municipality and season, respectively. The municipality variable is significant for all categories, but it does not raise the adjusted R^2 by much. The season variable is not significant for any values, which may indicate that there is little seasonal variation, except for the variation explained by the meteorological variables. We do, therefore, not include Season in the succeeding models. In model 4, we include the saturation variable, and we find that there is an interaction between precipitation and saturation that further explains the compensation amount. Thus, high levels of precipitation in the days preceding a damage incident caused by precipitation appears to increase the damages - and thereby also the compensation amount – caused by the precipitation. Intuitively, this makes sense, as it adds more water that can contribute to flood or landslide incidents caused by precipitation.

In models 5 to 7, we include variables to control for heterogeneity in the municipalities in our sample. In model 5, we investigate whether there is an interaction between wind-gust speed and municipality and precipitation and municipality - i.e., checking whether or not the damage inflicted by a wind gust or precipitation event depends on the municipality in which it occurs. The adjusted R^2 spikes to as much as 76%, which indicates that the heterogeneity between municipalities is critical to explaining the resulting compensation amount for a weather incident. In model 6, we attempt to explain the same municipality heterogeneity, but instead of using the municipality variable, we use the building stock variable. As described in Section 3.1.4, we presumed that the value of the buildings that can be damaged in a given municipality would serve as a good proxy for the damage a storm can inflict on the municipality. As it turns out, this variable explains municipality differences almost as well as the municipality dummy itself. When interactions between building stock and meteorological variables are included in model 6, the municipality variable gets a p-value higher than 5%. This can indicate that the building stock variable explains much of the same variance explained by the municipality variable. Since the municipality variable is no longer significant, we remove it from model 7 and find that this does not affect the model's adjusted R^2.

Model 7 indicates that there is an interaction effect between the sum of a municipality's building stock and the weather it is exposed to. Intuitively, this can be understood by considering the sum of building stock as the maximum destruction potential of a storm. For larger municipalities, more buildings can be destroyed for a given weather specification, and thus the compensation amount will be larger for a larger municipality, all else held equal. As shown in Table 3, the building stock variable explains much of the same variation as the municipality variable, with the variation in R^2 only being slightly lower in model 7 than in model 5. We proceed with model 7, as it provides more specific information about the variation between municipalities than do models 5 and 6, i.e., it tells us that the variation in compensation between municipalities is caused by heterogeneous building stock values, rather than just that there is a difference in compensation amounts between municipalities.

3.2.3 Categorization of variables

An aspect of our estimation strategy that must be addressed is that by categorizing continuous independent variables, some information about the relationship between the dependent variable and the independent variables is omitted. When using a continuous scale both the vertical variation in the dependent variable and the horizontal variation in the explanatory variable is used to determine the steepness of the regression curve, and, consequently, the coefficient estimates. Thus, by categorizing the continuous data, we leave out information about the incremental changes in cost that may exist within each category. However, in situations where the data is highly nonlinear, investigating the means within categories might provide more information about the relationship between the variables in the dataset than a complex nonlinear model (Grace-Martin, 2017). Thus, there is a trade-off between the level of detail in the information derived from the model and the flexibility of the fit. It appears that the more flexible ordinal fit is well-suited to answer our research question.

It can be said that the far end of categorization, namely doing a median split, creates arbitrary sets of observations that ignore important differences within the categories (Grace-Martin, 2017). By dividing the data into multiple categories, more information about the underlying distribution is preserved. This means that we can still assess relevant differences between the categories, which allows us to obtain information about how compensation changes for different weather intensities. However, in making multiple categories, it is important that each category contains a sufficient number of observations to ensure the representativeness of the estimated means.

In determining the category intervals for wind gust and precipitation, qualitative considerations were made. We sought to make the categories narrow enough that the relevant information about the relationship between cost and meteorological variables was preserved. Due to the high number of observations in our data set, this was only a problem for the highest categories for wind gust and precipitation, for which there are relatively few observations. The interval width for wind gust categories was made to resemble Beaufort’s scale for wind speed, which operates with approximately 5 m/s intervals. Although Beaufort’s scale was made for mean wind speeds, using similar interval sizes was considered a logical approach to separate the damage potential of each wind gust intensity. For precipitation, which ranges from 0 to 130 mm in our data set, somewhat wider categories of 15 mm intervals were created.

4. Empirical results

The results section consists of three subsections. In 4.1, the relationship between weather events and insurance claims is investigated through graphical analysis. Estimation results are presented in subsections 4.2 and 4.3.

4.1 Graphical analysis

In this section, the data will be analyzed to better understand the relationship between costs and weather. We make use of the data frame with both insurance data and meteorological data, as presented in Section 3.1. We will now explore in detail how individual damage incidents, the municipality-date aggregated damage incidents, and costs are related to precipitation and wind-gust speeds.

4.1.1 Wind-gust speed

Figure 4 shows the kernel-density distributions of maximal wind gusts for all dates and sum of costs per wind-gust speed, where each bar represents a 1 m/s interval. The bars are color-coded: Costs related to storms and storm surges are colored black, and the costs related to floods and landslides are colored orange. The figure shows that the mode value for wind gusts is approximately 8 m/s and that the frequency of wind gusts decreases for higher gust speeds. However, the costs related to wind gusts do not follow the same distribution, illustrating the concept of tail risk related to wind gusts. The highest sum of costs is found for the highest wind-gust speeds. This indicates that although extremely rare, the most intense wind gust events are also the costliest.

As we can see in Figure 4, there is a significant variation in costs per m/s. All cost peaks below gust speeds of 20 m/s are caused by floods and landslides, rather than storms, which become increasingly costly at wind-gust speeds above 20 m/s. This coincides with the general rule for storm incidents used by the Norwegian Natural Perils Pool, which states that only wind-gust speeds above 20.8 m/s qualify for compensation (Norwegian Natural Perils Pool, 2015). However, some discretion is applied, as the measured wind-gust speeds need not coincide with the wind-gust speed at the damage incident’s location (Norwegian Natural Perils Pool, 2019).

Figure 5 shows the aggregated cost for damage incidents per municipality and date, which helps to explain the variation in costs further: For many of the bars in Figure 4, a few unique incidents from the largest municipalities drive the costs up. The three costliest incidents all occurred in Bergen municipality, which is the largest municipality in Hordaland, by far, measured by building stock value. The fourth and fifth costliest incidents occurred in the second-largest municipality, Voss. In comparison, the costliest event in Fedje totaled only NOK 100 000, despite being the result of a 35 m/s wind gust. Thus, the variation in costs per weather incident can, in part, be explained by the heterogeneity of the municipalities.

In other topics of analysis, extreme incidents like those discussed above might be considered outliers that create a wrong impression of the relationship between the variables. However, this analysis seeks to investigate the effect of such extreme incidents on the costs, and their importance can, therefore, not be neglected. Comparing the total costs in Figure 4 to the costs per incident in Figure 5 reveals another important insight: Each incidence of an extreme weather event can have enormous costs. This is indicated by the fact that the costliest incidents in Figure 5 are close to equal to the total cost for their wind-gust speed in Figure 4.

Figure 6 shows the kernel-density distributions of maximal wind gusts for all dates and the damage incidents resulting from storm and storm surge. The distributions for all dates and damage incidents differ. The wind gusts for all dates are concentrated at lower wind gust intensities and with a definitive peak frequency of approximately 8 m/s. Damage incidents plotted per wind-gust speed shows that the number of damage incidents from storms and storm surges increases significantly with the gust speed, even though the distribution of wind gusts is concentrated around lower gust speeds. In fact, 99.3 % of wind gust observations are to the left of the median for damage incidents – which means that 0,7% of the wind gusts cause more than half of the storm and storm damage incidents in our sample. This indicates that the frequency of damage incidents increases nonlinearly with the wind-gust speed. Consequently, whenever extreme wind gust events occur, they can cause extremely many damage incidents, resulting in high costs. This nonlinearity in the data indicates that an increase in the intensity of the wind gusts would steeply increase the costs related to storms.

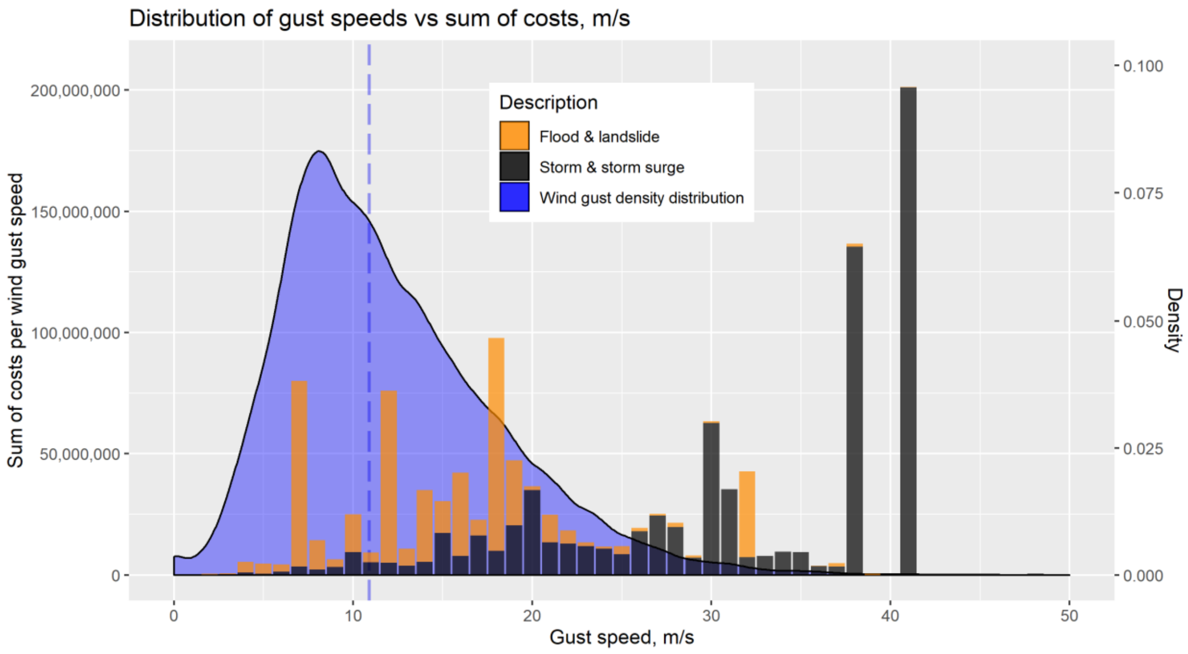

Figure 4: The kernel-density distribution of maximal wind gusts for all dates is shown in blue, with the median wind-gust speed indicated by the dashed blue line. The sum of costs per wind-gust speed is indicated by the stacked bars. Dark orange represents costs related to flood and landslide, whereas black represents storm and storm surge. Each bar represents a 1 m/s interval of wind-gust speeds.

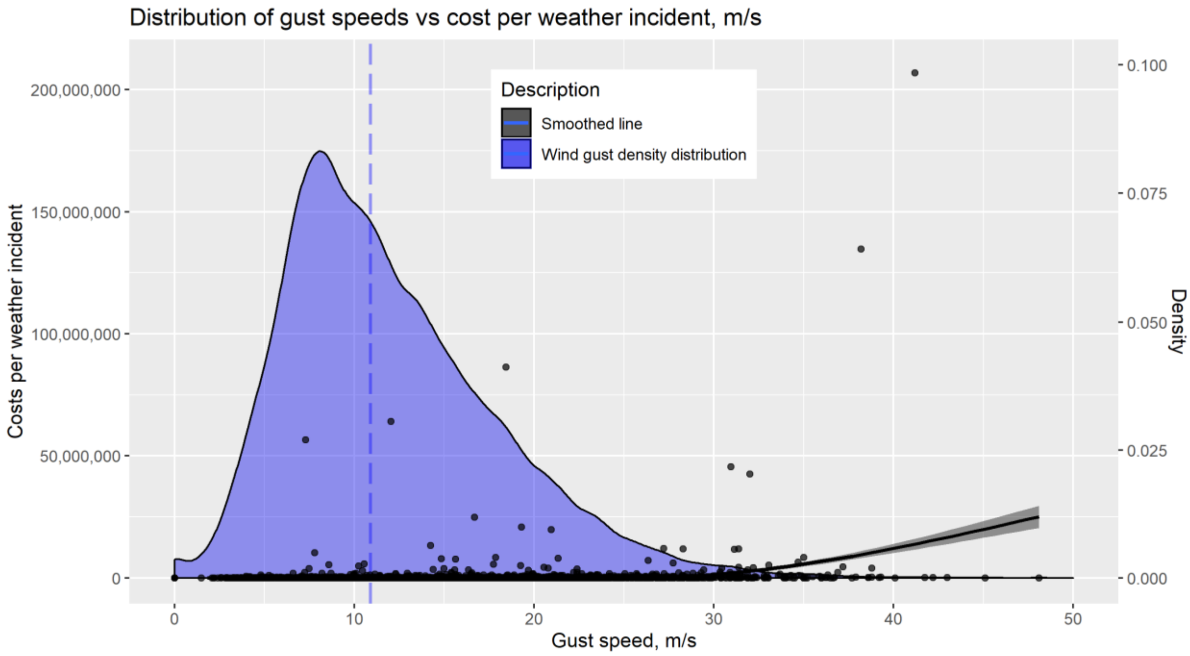

Figure 5: The kernel-density distribution of maximal wind gusts is shown in blue. Black dots indicate the cost and related wind-gust speed per municipality-date-aggregated damage incident. The costliest incidents represent a very large share of the total cost in the bars in Figure 4. The smoothed line indicates a nonlinear relationship where costs per incident start increasing rapidly after 30 m/s.

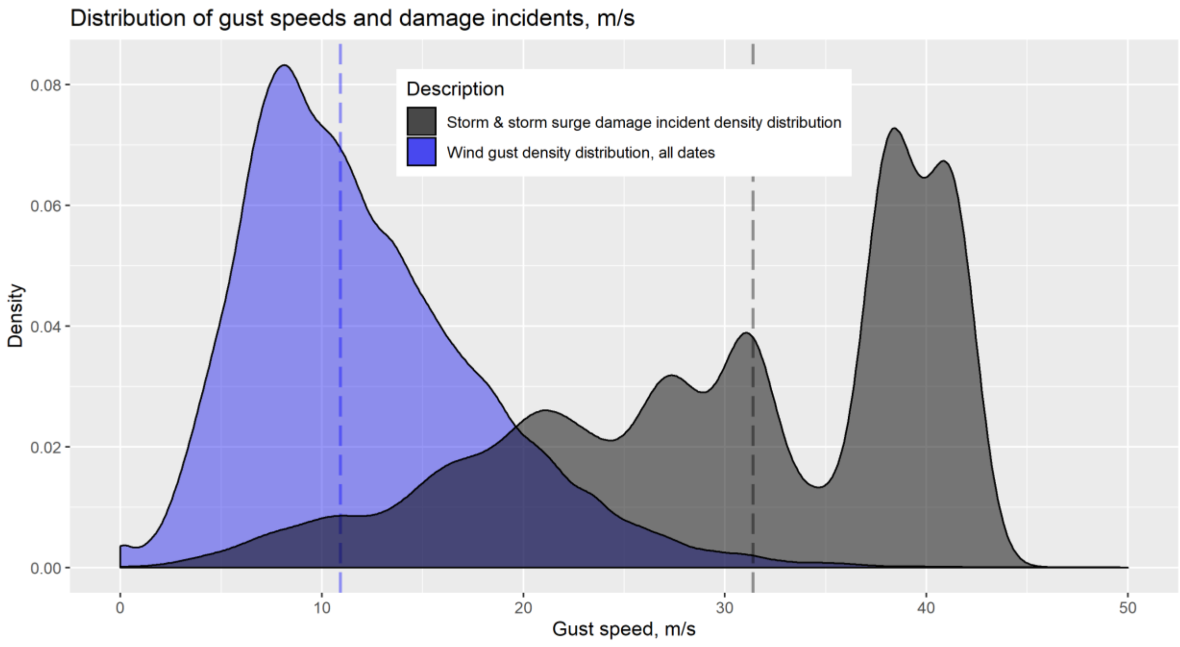

Figure 6: Kernel-density distributions of maximal wind gusts for all dates are shown in blue. Kernel-density distributions for storm and storm surge damage incidents per wind-gust speed are shown in black. The blue dashed line indicates the median wind-gust speed, whereas the black dashed line represents the median wind-gust speed for storm and storm surge damage incidents.

4.1.2 Precipitation

Figure 7 shows the kernel-density distributions of daily precipitation for all dates and the sum of costs per precipitation level, binned per millimeter. Looking at the distribution of precipitation for all dates, we see that the precipitation data are largely concentrated around low values, with a median value of 1,1 mm. The distribution of precipitation displays an exponential shape, with a sharp decrease in the frequency of incidents for increasing precipitation levels. The sum of costs per precipitation level, binned per 1 mm, does, however, show a different distribution. The costs related to floods and landslides increase rapidly once precipitation levels exceed 50 mm, although these weather incidents are extremely rare. Nevertheless, 72,9 % of the costs related to floods and landslides occur at precipitation levels exceeding 50 mm, which represent only 0,5% of the precipitation incidents. The costs that occur below 50 mm, are largely dominated by storms and storm surges, which are unrelated to precipitation. The fact that nearly all storm and storm surge incidents occur for precipitation levels below 40 mm further illustrates the rarity of heavy precipitation incidents.

Figure 8 shows that the costliest flood and landslide incidents represent a large share of the total cost for precipitation levels above 50 mm. More generally, the costliest weather incidents represent a large share of the costs in the bars in Figure 7. As was the case in Figure 5, the tail of the smoothed line is defined by a single extreme event. Although scarce, such incidents provide relevant information as to how costs change with weather intensity.

Figure 9 shows the kernel-density distributions of precipitation incidents and damage incidents for flood and landslide. From precipitation levels of approximately 50 mm, more damage incidents start occurring. This is followed by another decrease in damage incidents, and a spike at 129 mm, caused by a single precipitation event in Bergen. It does, however, appear clear that the relative frequency between damage incidents and precipitation incidents changes significantly with the precipitation intensity. Only 0,5% of the weather incidents exceed precipitation levels of 50 mm, yet 40,5 % of the flood and landslide damage incidents occur when precipitation levels exceed 50 mm. Furthermore, there are relatively few damage incidents for precipitation levels higher than 50 mm, even though Figure 7 shows that precipitation levels above 50 mm are associated with high costs. This indicates that such intense precipitation incidents cause fewer, but more severe damage incidents than do the more wide-reaching wind gust incidents, which cause many damages that need not be individually costly.

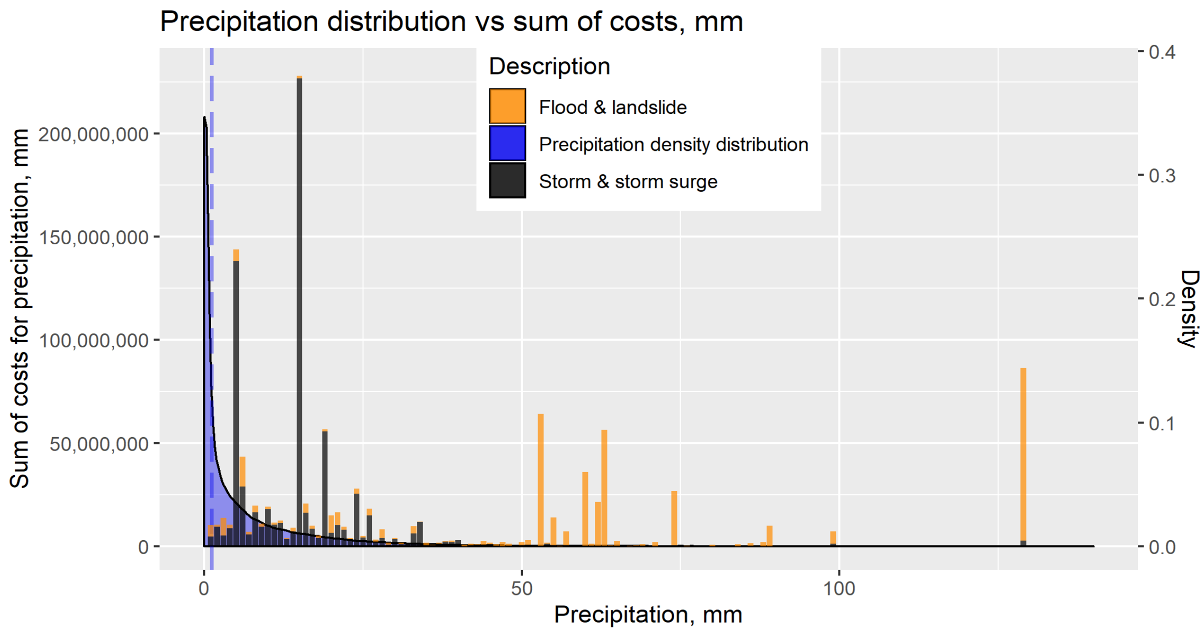

Figure 7: The kernel-density distribution for precipitation for all dates is shown in blue, with the median precipitation level indicated by the blue dashed line. The sum of costs per precipitation level is indicated by the stacked bars, where each bar represents one millimeter of precipitation. Dark orange indicates costs related to flood and landslide, whereas black represents storm and storm surge.

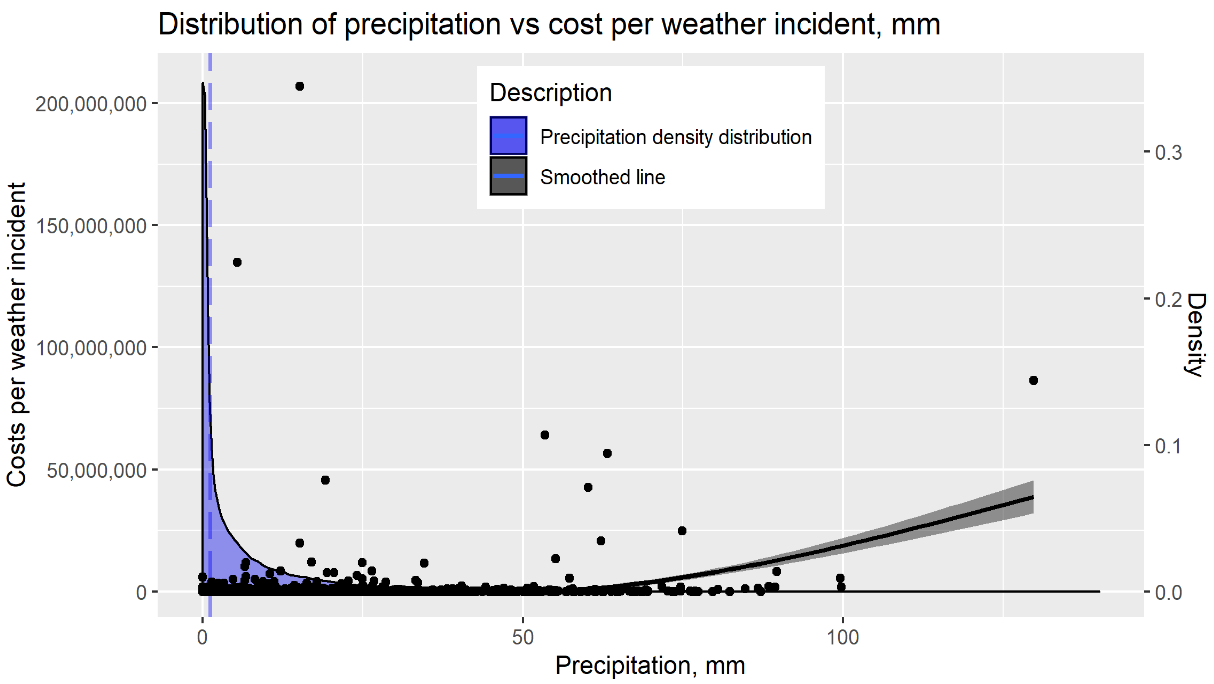

Figure 8: The kernel-density distribution of precipitation is shown in blue. Black dots indicate the cost and related precipitation level per municipality-date-aggregated damage incident. The costliest incidents all represent large shares of the total cost of the bars in Figure 7. The smoothed line indicates that the cost of flood and landslides start increasing nonlinearly above precipitation levels of 50 mm.

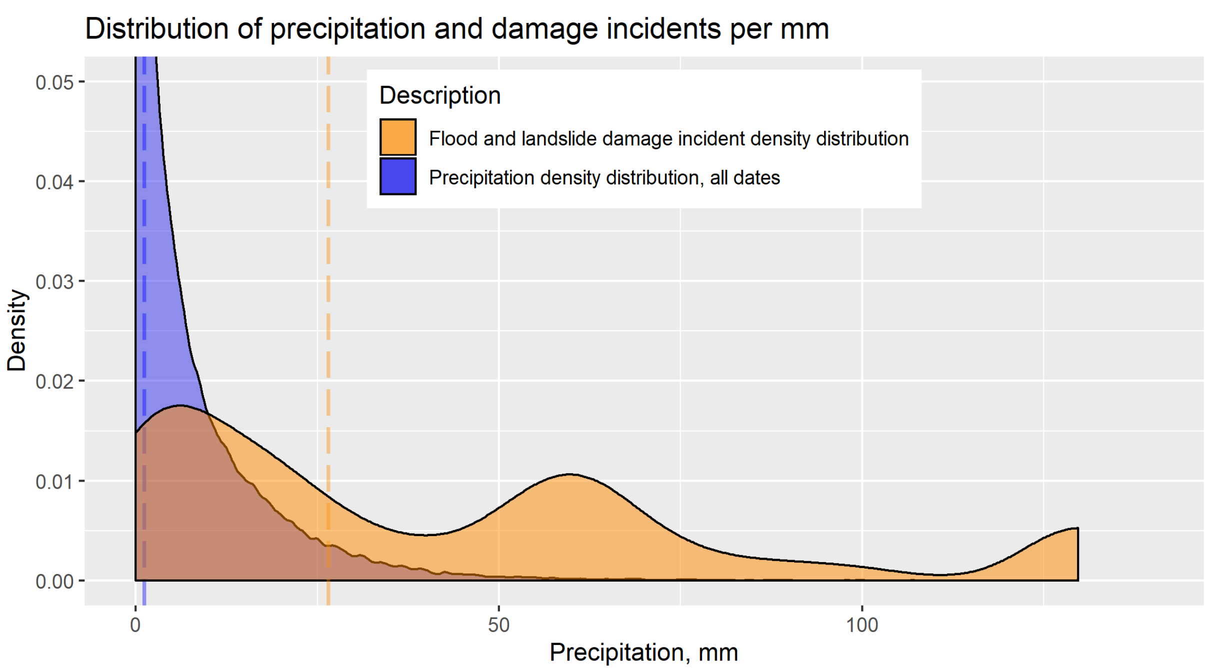

Figure 9: Kernel-density distributions of precipitation for all dates are shown in blue. Kernel-density distributions for flood and landslide damage incidents per mm of precipitation are shown in orange. The dashed blue and orange lines indicate the median precipitation level and the median precipitation level for flood and landslide damage incidents, respectively. This figure is a cropped version of Figure A 1.

4.1.3 Synthesis of graphical analysis of meteorological variables

The graphical analysis of the data indicated a nonlinear relationship for increasing intensities of the meteorological variables. Namely, these nonlinear relationships are displayed for wind-gust speeds exceeding 20 m/s and for precipitation levels exceeding 50 mm. In Figure 4 and Figure 7, we saw that the costs related to extreme wind and precipitation incidents are the highest. In Figure 5 and Figure 8, we saw that individual municipality-date aggregated incidents often represent a significant share of the total cost for a given gust or precipitation level. Additionally, there appears to exist heterogeneity in costs per weather incident between municipalities. Figure 6 and Figure 9 help to explain how a single incident can be so costly: For extreme wind gust incidents, the cost can, in part, be explained by the high number of damage incidents caused by a wind gust. For extreme precipitation events, on the other hand, the total cost relates to few, but expensive damage incidents. The common denominator is that as the intensity of the weather incident rises, so does the cost.

4.2 Estimation results, full sample

The regression model was presented in subsection 3.2. It appears to explain much of the variation in compensation, but the use of interactions makes the direct effect of the individual variables on the compensation amount hard to distinguish from mere regression coefficients. To allow for a simpler understanding of these relationships, we create two tables that illustrate how the model's estimates of compensation vary for different parameters for building stock and the meteorological variables. Table A. 2 and Table A. 3 are presented in the Appendix. The tables show that the estimates for compensation per municipality are found to be imprecise for several of the municipalities. This may be the result of insufficient damage data for all municipalities, or that the heterogeneity is not successfully addressed by the model. Therefore, it appears ill-advised to draw conclusions on the basis of these estimation results.

4.3 Estimation results, Bergen Municipality

Due to the unreliable estimates proposed by the regression model, when estimated for all municipalities in our sample, we estimate a model for a single municipality to alleviate the issue of heterogeneity between municipalities. As 65,5% of the municipality-aggregated damage incidents in our sample stem from Bergen, the data basis for estimating a simple municipality model is the best for Bergen. Since we are estimating the model solely on data from Bergen, we exclude the variables used to correct for municipality differences. Using the regression model to estimate costs solely for Bergen yields more reasonable results. The model variables and coefficients are shown in Table A. 4 in the Appendix. The adjusted R^2 is 82,9 %, indicating that the included meteorological variables for wind gusts, precipitation, and saturation explain a large share of the variation in compensation.

Table 4 shows the cost estimates for different wind gust and precipitation intensities resulting from the model for Bergen, with 95% confidence intervals:

	0-5 m/s	5-10 m/s	10-15 m/s	15-20 m/s	20-25 m/s	25-30 m/s	30-35 m/s	35-60 m/s
Upper 95%	69 969	26 823	23 681	84 464	134 915	916 373	6 003 863	172 009 679
Estimated	- 2 096	- 3 945	- 8 003	38 764	59 932	715 218	5 592 943	170 681 615
Lower 95%	- 74 161	- 34 714	- 39 686	- 6 937	- 15 051	514 063	5 182 023	169 353 551

	0-15 mm	15-30 mm	30-45 mm	45-60 mm	60-75 mm	75-130 mm
Upper 95%	69 969	143 870	120 726	255 750	504 103	12 404 432
Estimated	- 2 096	53 695	- 12 892	13 185	105 626	11 736 569
Lower 95%	- 74 161	- 36 479	- 146 511	- 229 380	- 292 851	11 068 705

Table 4: Estimated insurance claims for Bergen with varying levels for wind-gust speeds and precipitation. The model is estimated solely on data from Bergen, and generally yields estimates that reflect the nonlinear relationships discovered in the graphical analysis. The cost-estimates for wind-gust speeds are made by varying wind-gust speed, while specifying precipitation and saturation to 0-15 mm and 0-50 mm, respectively. For the precipitation estimates, wind-gust speed and saturation are specified to 0-5 m/s and 0-50 mm, respectively.

The values in Table 4 indicate the estimated cost of the damage that is incurred each time a given weather specification occurs. The estimates for wind-gusts reflect the nonlinear relationship discovered in the graphical analysis: For wind-gust speeds higher than 20 m/s, the cost estimates increase approximately tenfold for each category, and even more so for the highest category, where cost estimates are close to 30 times higher than for the preceding category. Thus, whenever the maximum wind-gust speed exceeds 35 m/s, the estimated cost is NOK 170 681 610. This translates to a per capita cost of NOK 602 every time wind-gust speeds exceed 35 m/s in Bergen.

Despite some estimates being negative, the general trend of the data is reflected in the estimates. The negative categories correspond well with categories where the costs per incident are close to 0, i.e., although a negative compensation value is nonsensical, the estimates are fairly precise in absolute terms. Low costs for wind-gust speeds under 20 m/s are also reflected in the coefficients' significance levels. For the wind-gust categories between 0 and 25 m/s, the coefficients are not found to be significantly different from the intercept value. As such, it is unsurprising that some of these estimates make little sense. The same applies to precipitation, for which only precipitation levels exceeding 60 mm are found to be significantly different from the intercept. For the significant categories, however, the nonlinear relationship is expressed clearly: An almost 100-fold increase in cost per incident was estimated from 60-75 mm to 75-130 mm.

There are few observations for the most intense gust and precipitation categories, which is why the categories for 75-130 mm and 35-60 m/s cover as wide an interval as they do. This could be part of the reason as to why the variation between the upper categories is as considerable as it is. Note, however, that for Bergen, the highest recorded wind-gust speed is 41.2 m/s. As such, the wide range used for the upper category could have been reduced in the model for Bergen, with no implication for the estimates. For normal weather intensities there are many incidences of weather where no damages are incurred. Every incidence of weather where no damages are incurred, reduces the estimated cost related to the associated weather intensity. On the other hand, whenever the most extreme weather intensities occur, they consistently cause considerable damages, which contributes to maintaining the estimated cost level.

5. Climate Scenario Estimates

In this section, we present scenarios for increased frequencies and intensities of precipitation and wind gusts, and calculate the impact of these scenarios on the natural damage cost to buildings. We use the model estimates presented in Section 4.3 in doing so.

Hanssen-Bauer et al. (2015) propose scenarios for how the climate in Norway may be in the year 2100. The scenarios are based on results from global climate models for different emissions scenarios. The Intergovernmental Panel on Climate Change's fifth report presents four emissions scenarios based on climate policy outcomes for the 21st century (Pachauri et al., 2014). A continued increase in emissions is in line with the Representative Concentration Pathway 8.5 (RCP 8.5) scenario, which is referred to as the business-as-usual scenario, i.e., what happens if we follow the current trajectory of emissions (Hanssen-Bauer et al., 2015).

With a basis in this emissions scenario, Hanssen-Bauer et al. (2015) indicate the following development for heavy precipitation in Norway: *«a doubling of days with heavy precipitation, and an increase in the precipitation on these days of 19%"* by the end of the century. Thus, the number of days with heavy precipitation will increase, and so will the intensity of the precipitation on these days.

Hanssen-Bauer et al. (2015) propose only small changes to the wind speed, but varying climate model estimates indicate uncertainty as to this development. For absolute maximum wind-gust speeds per year, some projections indicate a 20% increase (Hanssen-Bauer et al., 2015). Thiis et al. (2005) also point to uncertainty regarding the development of wind-gust speeds but nevertheless propose cost scenarios for cases where frequencies of storms and wind gust intensities increase. One scenario relates to frequency: *A 50% increase in the frequency of all storms*. Another relates to *a 10% increase in wind-gust speed for all storms*.

The effect on the physical climate risk in Hordaland will be discussed with a basis in the precipitation- and wind speed scenarios presented above. As discussed in Section 4.2, using the full sample of municipalities to generate cost estimates for the individual municipalities yielded estimates of varying credibility. Using unreliable estimates for extrapolation to a climate scenario would cause scenario estimates to deviate from realistic costs, thereby diminishing their value in providing insights about the future. The estimates for Bergen in Table 4, on the other hand, are generally in line with observed costs, especially for the high-intensity categories that are relevant for the climate-scenarios presented above. This indicates that applying the data for Bergen in a climate scenario will yield more relevant estimates as to how costs may develop in the climate scenarios presented above. Thus, the scenarios for wind gusts and precipitation will now be implemented for the single municipality model for Bergen.

The projected change in precipitation will now be implemented for the single municipality model for Bergen, with precipitation levels above 60 mm considered to be *heavy precipitation*. In the precipitation scenario presented above, there are two components to consider. First, a doubling in frequency will lead to a doubling of the cost. There are 40 recorded weather incidents in our sample for Bergen with precipitation exceeding 60 mm - 31 days of 60-75 mm and nine days of 75-130 mm. Our model estimates the costs of heavy precipitation, for today's climate, to be 108 900 000. If these numbers double by 2100, there will be twice as many days of heavy precipitation, for an equally long 39-year period. The estimated costs for the precipitation events in our sample are NOK 108 900 000, and the estimated increase in cost resulting from a doubled frequency would, therefore, also be NOK 108 900 000.

When we also factor in the increase in the intensity of the events, the cost rises further. A 19% increase in precipitation intensity will move several of the precipitation incidents to much costlier levels. Using the estimates from our model for Bergen, costs related to precipitation would total NOK 729 600 000. As such, the cost increase from the sample estimate of NOK 108 900 000 is 570%. The costs per category for both components of this scenario are shown in Figure 10. The calculations for these cost estimates can be found in Table A.5. Since costs increase nonlinearly with intensity, the intensity increase has a significantly larger effect on costs than the frequency increase.

Another point to make is that if the RCP 8.5-scenario were to become the case, the most extreme precipitation incidents may rise to levels well above our sample's maximum precipitation level, and to cost levels exceeding those that have been observed per today. The highest precipitation incident in our sample measured 129,5 mm at the cost of NOK 86 300 000. It appears reasonable that the nonlinear relationship found in the model estimates and in Figure 10 will hold for higher levels of precipitation as well, and as such, one could imagine situations where a single 150 mm precipitation event in Bergen could cost well above a hundred million NOK.

Although the projected change in wind intensities is uncertain, it is relevant to evaluate the effect of changes in high wind gust frequencies and intensities, should they occur. All wind gust events in our sample that were measured to be higher than 20 m/s are defined as storms in this scenario. The resulting cost estimates from a 50% increase in the frequency of all storms are shown in Figure 11 (a). Such an increase in the frequency of all storms leads to a 50% increase in costs. In Figure 11 (b), the effect of a 10 % increase in the intensity of storms is shown. The calculations for these costs can be found in Table A. 6 and Table A. 7.

The effect of an increase in wind-gust intensity is much larger than a frequency increase, as it leads 20-30 % of the storms in each category to move to higher wind-gust categories, for which the related costs are extremely much higher. The costs related to 20-25 m/s wind gusts decrease in the scenario, as wind gusts move to higher categories due to the intensity increase. The decrease in costs is, however, offset by an increase in the costs for the higher wind gust intensities. Since the cost increases approximately 10-fold for each category of wind gusts, an increase in the incidences of higher wind-gust speeds leads to a radical increase in the total costs. The total estimated cost for the sample is 563 800 000, whereas the cost for a 10 % increase in wind intensity is as high as 1 961 400 000. If the estimates represent reality in an accurate manner, this means that a 10 % increase in wind-gust speeds will more than triple the costs of high wind-gust incidents.

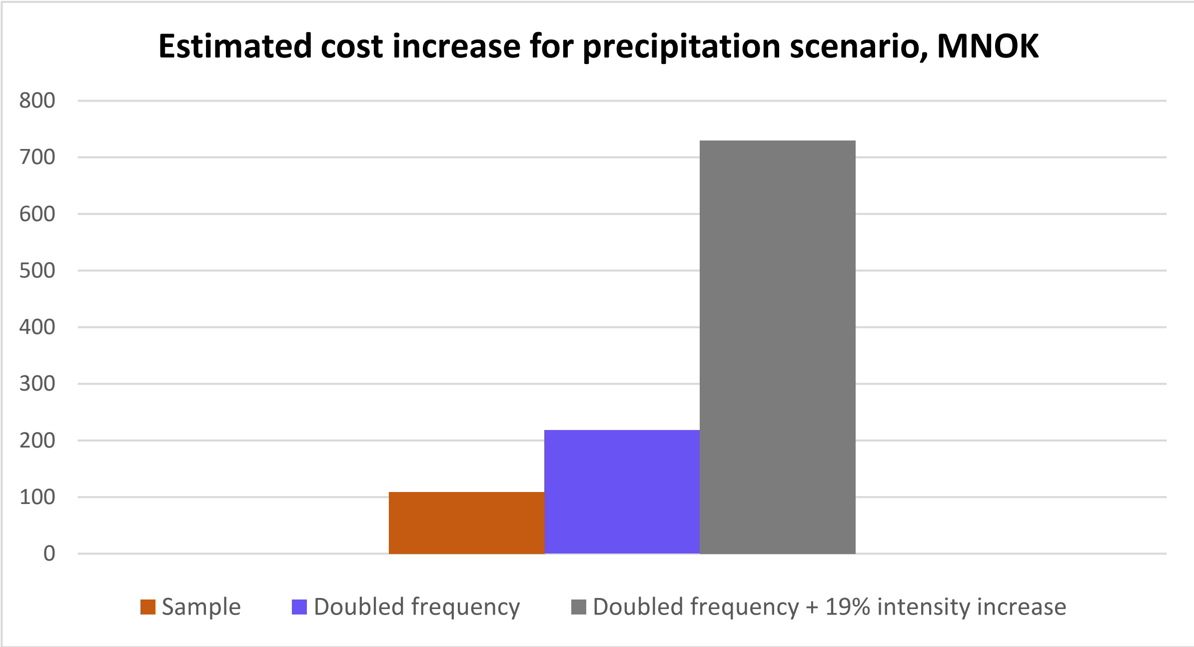

Figure 10: The effect on total costs of implementing the projected changes in precipitation, in millions of NOK. The estimated cost for our sample, with no climate scenario, is shown in the orange bar. The scenario can be decomposed into a frequency increase and an intensity increase. The estimated costs for a doubling in the frequency of days with heavy precipitation is shown in the purple bar. The estimated costs when also factoring a 19% increase in the intensity of precipitation on these days is shown in the grey bar.

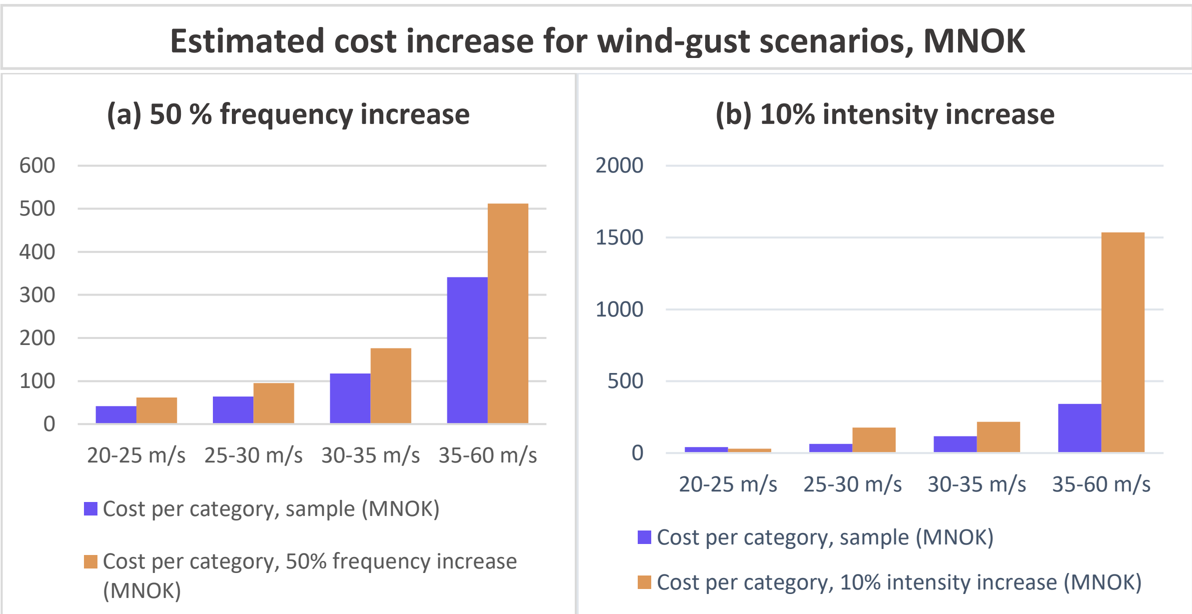

Figure 11: The cost-effects of a 50 % increase in the frequency of storms and a 10% increase in the intensity of storms, respectively. A 50 % increase in frequency leads to a 50 % increase in costs. A 10 % increase in intensity leads to a more than three-fold increase in total cost. This cost increase is caused by the movement of wind gust observations between categories, increasing the number of events in all categories except 20-25 m/s, for which the number of incidents is reduced. The effect of an intensity increase illustrates the nonlinearity of the data.

6. Climate Risk Assessment

The estimates for the single municipality model for Bergen were found to reflect the nonlinear relationships discovered in the graphical analysis better than the regression model for all municipalities in our sample, and thus the climate-scenario cost estimates were estimated with a basis in the single municipality model. In this section, the physical climate risk in Hordaland will be discussed with a basis in the estimated costs from the single municipality model for Bergen with corresponding climate-scenario extrapolation. Since we do not have reliable estimates for the other municipalities in Hordaland, the discussion of climate risk for other municipalities in our sample must rely on generalizable findings from the estimates for Bergen.

6.1 Cost estimates

The extrapolation of the single municipality model's estimates to climate scenarios provided estimates for the costs of increasing intensities and frequencies for wind gusts and precipitation, as presented in Section 5. The estimated increase in costs illustrates the importance of the nonlinear relationship between weather intensity and costs. An increase in intensity has major consequences for the costs related to extreme weather events – much more so than a frequency increase. The most interesting finding from the climate scenarios above is the estimated 570% increase in costs related to floods and landslides. This finding implies that the costs related to precipitation for the years from 2100 to 2139 could very well be as large as NOK 729 600 000, which is close to a six-fold increase as compared to today's level. The scenarios for wind gusts indicate even higher cost increases of almost NOK 1 400 000 000 for a 39-year period, but due to the uncertainty of future wind projections, the applicability of these estimates is debatable.

In evaluating the physical climate risk for Bergen, a conservative interpretation of the estimates would be to assume that cost increases related to wind-gust speeds would be marginal, due to the uncertainty related to these estimates. For the precipitation scenario, the total cost increase estimated from the precipitation scenario is as large as NOK 620 000 000 for a 39-year period. Compared to the total costs of extreme weather events in Bergen in our sample, the cost increases proposed must be said to be significant: The total costs for our sample of Bergen is NOK 858 000 000 for the entire period of 1980-2019. If the estimates represent the potential cost increase accurately, the cost increase constitutes a 72% increase in the total natural damage costs for Bergen for the years from 2100 to 2139. A 72% increase in costs must be said to be quite substantial, considering that the entirety of this increase is driven by precipitation-related incidents.

6.2 Climate risk for heterogeneous municipalities

In the graphical analysis, heterogeneity between municipalities was identified to be a major factor in explaining the variance in cost between weather incidents of the same intensity. In the full sample model, the building stock variable was used to mediate differences between municipalities, but it appears that the variable does not sufficiently explain these differences. The heterogeneity can also be related to factors such as differing topography and local climatic conditions. It can appear that the heterogeneity is richer for precipitation-related damages than it is for wind gust-damages, which can explain why flood damages are costlier in Voss than in Bergen, despite more high precipitation incidents occurring in Bergen. Furthermore, there could be several other factors not accounted for. Local adaptation to local climatic conditions, for instance, would result in differing consequences related to the costs of windstorms, floods or landslides per municipality.

The complex heterogeneity described above provides a relevant indication as to how policymakers should approach the physical climate risk in different municipalities: Both the climate risk and mitigating measures must be related to the municipality in question. Considering that the RCP 8.5 scenario indicates a significant increase in precipitation frequency and intensity, it seems plausible that the climate risk in Hordaland is higher for municipalities whose topography makes them prone to floods and landslides than it is for counties where storms are the main driver of costs.

The assertion that the climate risk is higher in municipalities prone to flood and landslides can be illustrated by a two-component analysis of the municipalities Voss and Eidfjord, which are heterogeneous with regard to the weight of precipitation-related damages. The first component relates to the relative weight of precipitation-related damages in the municipalities: In Voss, flood and landslide damages account for NOK 171 000 000, or 90% of the total natural damage cost for the sample period. In Eidfjord, on the other hand, they constitute NOK 3 400 000, or 26 % of the costs. Thus, we can establish that the relevance of precipitation events is much higher for municipalities that share topography characteristics with Voss than it is for municipalities like Eidfjord.

The second component relates to combining the effect of an increase in precipitation in line with the RCP 8.5 and the nonlinear relationship between cost and precipitation that was established in the analysis. Since the baseline share of costs is much higher in Voss, both in absolute numbers and percentages, the consequences of an increase in the frequency and intensity of precipitation would also be much larger for Voss. We found that for Bergen, the estimated cost growth from an increase in precipitation in line with RCP 8.5 would be 570%. If we make a simple assumption that this relationship will also hold for Voss and Eidfjord, precipitation costs in Voss will increase by as much as NOK 975 000 000, as opposed to only NOK 19 380 000 in Eidfjord. This indicates a five-fold increase in the total costs for Voss, as opposed to a 150 % increase in the already low costs for Eidfjord.

From the analysis of Voss and Eidfjord, it appears that, generally, the physical climate risk is higher for municipalities prone to floods and landslides. Furthermore, the heterogeneity of municipalities should have definitive implications for how the climate risk is modeled, and which municipalities are focused on with regard to mitigative measures. Hauge et al. (2018) point out that mitigative measures can be very costly. As such, it seems prudent to also evaluate the financial ability to initiate such measures when evaluating the climate risk in a municipality.

6.3 Assessing the impact from an overall perspective

Considering the cost estimates for the climate scenarios presented in Section 5, it may appear confounding that the climate risk related to precipitation and wind gusts can, in fact, be considered to be relatively insignificant. A 72% increase in total costs must be said to be quite considerable – in relative terms. Nevertheless, one can argue that the cost increase does not result in major consequences for society.

In discussing the magnitude of a cost increase like the one described above, it can be relevant to break down the numbers to define the impact on society as a whole, rather than just a percentage increase from a base number. For instance, if we divide the costs over a period of 39 years, a 620 000 000 increase in costs adds up to as little as NOK 15 900 000 per year, or approximately 1,83 ‰ of the tax income for Bergen Municipality for 2016 (Bergen Kommune, 2017). Moreover, if we evaluate the damage costs as a share of the estimated building mass in Bergen, the cost appears nearly insignificant. We can consider the increased cost of NOK 15 900 000 to be the increase in yearly depreciation of the building stock caused by extreme weather events. The total building stock of Bergen has been estimated to be NOK 670 474 000 000, so the yearly increase in depreciation caused by a cost increase of NOK 15 900 000 is as little as 0,02 ‰ of the building stock. This equates to the value of approximately three houses. In other words, the share of the building stock that is damaged each year is still going to be extremely low. Therefore, although the percentage-wise increase in costs is considerable, the physical climate risk posed by precipitation and wind-gusts to building damages is close to negligible when we consider the number of years and people to divide the costs over. This resembles the findings of Pielke Jr. (2018), who shows that, as a percentage of GDP, the costs related to extreme weather events are both low and declining.

The anticlimactic finding that the increase in costs for Bergen can be considered close to negligible is one that must be appreciated. However, this does not necessarily apply to all municipalities. From the above discussions, we can infer that the higher a municipality's precipitation-related costs are, the higher will the impact of the RCP 8.5 scenario be. Voss municipality, for instance, is only a tenth of the size of Bergen but has higher costs related to precipitation. A cost increase in line with the estimates from the single municipality model will, therefore, have a more forceful impact on Voss than Bergen. This coincides with Vennemo & Rasmussen (2010), who find that the costs may still be significant a local level or sector level. This serves as yet another reminder that the heterogeneity of municipalities has implications for the climate risk they are exposed to, and that local conditions must be accounted for when evaluating the climate risk in a municipality as well as the need for mitigative measures.

The extreme weather frequencies and intensities described in the RCP 8.5-scenario indicate the type of extreme weather we can expect to see in Norway in 2100, which is still 80 years from now. The cost estimates presented in the analysis above can provide indications as to the value of investing in mitigative measures to reduce the costs related to extreme weather. The value of mitigative measures will increase when also accounting for an increase in future costs, although future costs must necessarily be discounted at a relevant discount rate. Since mitigative measures can help to reduce the overall impact of more extreme weather, the costs may become lower than projected, if such measures are implemented. This will further reduce the physical climate risk related to more extreme weather.

From the analysis above, it seems clear that the socio-economic consequences of an increase in extreme weather are in no way devastating. On a final note, it is worth emphasizing that although the damages to buildings do not constitute significant consequences from a socio-economic perspective, not only buildings will be damaged by extreme weather. Extreme weather can also incur damages to other types of physical capital, such as infrastructure and vehicles, as well as people. Moreover, the majority of precipitation-inflicted damages to buildings is not related to floods or landslides but result from other water damages (Norway's Climate Risk Commission, 2018, p. 129), which are not accounted for in our estimations. As such, the analysis above does not account for all damages that can be inflicted by an increase in precipitation. This means that the socio-economic costs related to more intense precipitation events will inevitably be higher than those reflected in damages to buildings. It would, therefore, be desirable to conduct more comprehensive studies to arrive at a complete picture of the costs related to extreme weather events.

7. Discussion of robustness and validity

We will now discuss factors that may affect the robustness and validity of our findings, with respect to the estimated model in Section 4.3 and, thereby, the applicability of the estimated costs for the climate scenarios presented in Section 5.

It is worth considering whether insurance data are a good approximation for the costs of extreme weather. Natural damages represent 36,3% of the damages to insured buildings, whereas the remaining damages are caused by other weather-related damage (Finance Norway, 2019). This indicates that our data represent a significant share of the total damages incurred to buildings by the natural environment. Moreover, the data can be expected to be of high quality as they are measured by the Norwegian Natural Perils Pool. Considering that the property insurance rate is close to 100% in Norway (Hauge et al., 2018), data from insurance claims can provide valuable insights for this segment of costs from natural damage.

The meteorological data can also be assumed to be of high quality, as they are measured by the Norwegian Meteorological Institute. Matching the meteorological data and insurance data does, however, offer some challenges. The discrepancy between the location of weather stations and damage incidents may affect the robustness of our estimates, as the weather data do not necessarily coincide perfectly with the weather that caused a damage incident. If the station is atop a mountain, high wind gusts may be more prevalent, without corresponding damages. This location-dependency is a weakness in the data that may distort the estimated relationship between weather variables and damages: High wind-gust speeds may be matched with no damages and vice versa.

Even though the data are of high quality, data for extreme weather observations are scarce. By definition, there are fewer of the most extreme weather events, regardless of which municipality is studied. As we estimate the costs for high wind gust and precipitation-categories with a small pool of observations, the estimates will likely change significantly for new observations for these categories. The most intense categories are also very wide, which may reduce the robustness of the climate scenario estimates in these categories. Thus, the estimated costs for precipitation in the climate scenarios may be higher or lower than real future costs. A low number of observations for the most intense weather yields uncertainty related to the estimates. The results should be interpreted with this caveat in mind. One way to mediate this problem would be to create categories based on the quantiles of observations.

This would increase the robustness of the model estimates, but we would be forfeiting information about the costs of the most extreme weather events, as the quantile categories would cover a wider range. For instance, the highest 5% of our observations for wind gusts range from 23,2 m/s to 55,8 m/s, so the estimated cost would be equal within this quantile. Thus, there is a tradeoff between acquiring estimates for specific weather intensities and robustness. The estimated models generally indicate that higher intensities of weather lead to a nonlinear increase in costs. This coincides with the findings of Khanduri (2003) and Haug (2009a). As such, one might argue that our analysis does, in fact, reflect the relationships we have sought to investigate.

Our full sample model was estimated with a basis in 11 municipalities located within the same geographical area. Even so, there appears to be significant heterogeneity between the municipalities in our area of investigation. As such, it seems implausible that the model estimates can be validly generalized to other areas. However, the more general findings of this thesis can presumably be applied elsewhere. For instance, it seems likely that other municipalities in Norway where floods and landslides are prevalent will be more susceptible to an increase in damages following climate change.

Our estimates may be biased if we have omitted variables affecting both the weather and the costs. The dependent variable in our models is compensation, whereas the independent variables are meteorological variables and building stock. It seems a reasonable assumption that the time variation in weather is exogenous in our setting. This one-way dependency increases the robustness of our analysis. According to the Norwegian Meteorological Institute, the wind direction is relevant for determining where damages will occur (Meteorologisk institutt, 2018). It is possible that the cost-estimates for storm damages could have been further improved by accounting for wind direction in the analysis. The Norwegian Environment Agency (2016) indicates that a change in wind direction can have consequences for damages. Under new wind conditions, buildings and infrastructure could become more exposed to wind gusts. Furthermore, the wind gusts could hit buildings from angles they were not designed to withstand (Miljødirektoratet, 2016). As such, including wind direction as a variable in future studies may allow for more precise estimates of the costs related to different wind scenarios. Furthermore, both the wind direction and the earth's rotation are relevant factors that explain when a storm surge can occur.

Finally, as the climatic consequences of global warming for the costs of extreme weather in Hordaland cannot be known with absolute certainty, evaluating the physical climate is not straight-forward. The risk is, to a large degree, defined by an expected increase in the tail risk for precipitation, as illustrated in the proposed climate scenario estimates. There is, however, uncertainty related to how the intensity and frequency of both precipitation and wind-gusts will change with climate change. Hanssen-Bauer et al. (2015) state that the possibility of a higher increase in precipitation cannot be ruled out. The median change in intensity for precipitation on days with heavy precipitation is projected to be 19%, but the projections range from 12% to 25% (Hanssen-Bauer et al., 2015). Due to the great uncertainty that exists in climate predictions, the future cost estimates we present in our analysis must be said to be uncertain.

8. Conclusion

This master's thesis provides insights about the physical climate risk in Hordaland by analyzing the relationship between insurance payouts and meteorological variables. We estimate the relationship using a flexible regression model. The model estimates are used to calculate the potential change in costs related to a set of climate change scenarios for extreme weather and provide insights about the extent of the physical climate risk in Hordaland.

We find that the relationship between natural damage costs and extreme weather events is highly nonlinear. Whereas most weather causes little to no damage, rare and extreme weather events correspond with significant costs. 74,5% of the natural damage cost related to floods and landslides occurs for the highest 1% of precipitation incidents. Moreover, whenever the wind-gust speed in Bergen exceeds 35 m/s, the average cost is NOK 171 million. This equates to a per capita cost of NOK 602 in Bergen.

The perhaps most interesting finding from the climate scenarios relates to increased precipitation. Our estimates indicate close to a six-fold increase in estimated costs related to floods and landslides. This amounts to a yearly increase in costs of NOK 15,9 million. Our climate scenarios for wind-gusts indicate more than a three-fold increase in wind-related costs. However, with regard to Hanssen-Bauer et al. (2015), it appears unlikely that wind-gust speeds will increase significantly.

We also find that there is significant heterogeneity between the municipalities investigated, which has implications for the costs of extreme weather. For municipalities such as Voss, the share of natural damage costs related to floods and landslides is high, as compared to other municipalities. We find that municipalities that are susceptible to floods and landslides can expect to see higher cost increases from increased precipitation.

In conclusion, the physical climate risk related to building damages does not seem to be severe for Hordaland. For Bergen, our findings indicate an increase in yearly costs of close to NOK 16 million, which is approximately 0,2% of the yearly tax income in Bergen. However, the heterogeneity between municipalities indicates that the climate risk is higher for municipalities that are prone to damages induced by precipitation, through floods and landslides. This suggests that mitigative measures for extreme weather should be focused towards municipalities that are prone to floods and landslides.

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Appendix

Table A. 1

Model 7 (Full sample model)

	Dependent variable:
	Compensation
Wind_gust0-5 m/s	-486.373 t = -0.007
Wind_gust5-10 m/s	2,433.094 t = 0.036
Wind_gust10-15 m/s	6,795.646 t = 0.100
Wind_gust15-20 m/s	-1,051.697 t = -0.015
Wind_gust20-25 m/s	-8,097.795 t = -0.118
Wind_gust25-30 m/s	-40,374.140 t = -0.575
Wind_gust30-35 m/s	-69,393.580 t = -0.919
Wind_gust35-60 m/s	-7,015,458.000*** t = -77.547
Precipitation0-15 mm	-11,047.530 t = -0.584
Precipitation15-30 mm	-46,393.640 t = -0.641
Precipitation30-45 mm	-3,094.125 t = -0.012
Precipitation45-60 mm	105,370.700 t = 0.234
Precipitation60-75 mm	392,362.200 t = 0.506
Precipitation75-130 mm	3,122,616.000*** t = 6.567
Saturation0-50 mm	-303.543 t = -0.026
Saturation50-100 mm	-3,045.803 t = -0.062
Saturation100-150 mm	-6,241.966 t = -0.039
Saturation150-250 mm	-2,379.076 t = -0.004

Building_stock	-0.052 t = -0.015
Precipitation0-15 mm:Saturation0-50 mm	11,436.480 t = 0.581
Precipitation15-30 mm:Saturation0-50 mm	18,464.720 t = 0.253
Precipitation30-45 mm:Saturation0-50 mm	-25,836.870 t = -0.100
Precipitation45-60 mm:Saturation0-50 mm	40,286.910 t = 0.089
Precipitation60-75 mm:Saturation0-50 mm	-564,009.800 t = -0.722
Precipitation75-130 mm:Saturation0-50 mm	-2,659,650.000*** t = -5.165
Precipitation0-15 mm:Saturation50-100 mm	11,325.280 t = 0.214
Precipitation15-30 mm:Saturation50-100 mm	56,562.350 t = 0.637
Precipitation30-45 mm:Saturation50-100 mm	-67,705.650 t = -0.255
Precipitation45-60 mm:Saturation50-100 mm	839,438.200* t = 1.843
Precipitation60-75 mm:Saturation50-100 mm	1,996,977.000** t = 2.535
Precipitation75-130 mm:Saturation50-100 mm	-4,522,805.000*** t = -8.892
Precipitation0-15 mm:Saturation100-150 mm	18,925.620 t = 0.114
Precipitation15-30 mm:Saturation100-150 mm	-20,912.850 t = -0.113
Precipitation30-45 mm:Saturation100-150 mm	-105,600.000 t = -0.328
Precipitation45-60 mm:Saturation100-150 mm	14,507.020 t = 0.028
Precipitation60-75 mm:Saturation100-150 mm	26,703,725.000*** t = 30.646
Precipitation75-130 mm:Saturation100-150 mm	
Precipitation0-15 mm:Saturation150-250 mm	752,505.100 t = 1.148
Precipitation15-30 mm:Saturation150-250 mm	52,699.930 t = 0.072
Precipitation30-45 mm:Saturation150-250 mm	
Precipitation45-60 mm:Saturation150-250 mm	494,336.200 t = 0.494

Precipitation60-75 mm:Saturation150-250 mm	
Precipitation75-130 mm:Saturation150-250 mm	
Wind_gust0-5 m/s:Building_stock	0.054 t = 0.015
Wind_gust5-10 m/s:Building_stock	0.047 t = 0.013
Wind_gust10-15 m/s:Building_stock	0.033 t = 0.009
Wind_gust15-20 m/s:Building_stock	0.110 t = 0.031
Wind_gust20-25 m/s:Building_stock	0.158 t = 0.044
Wind_gust25-30 m/s:Building_stock	1.156 t = 0.323
Wind_gust30-35 m/s:Building_stock	8.447** t = 2.357
Wind_gust35-60 m/s:Building_stock	250.533*** t = 68.785
Precipitation0-15 mm:Building_stock	-0.005 t = -0.215
Precipitation15-30 mm:Building_stock	0.156*** t = 4.099
Precipitation30-45 mm:Building_stock	0.041 t = 0.605
Precipitation45-60 mm:Building_stock	-0.422*** t = -3.243
Precipitation60-75 mm:Building_stock	0.492** t = 2.135
Precipitation75-130 mm:Building_stock	15.475*** t = 34.330
Constant	2,597.659 t = 0.038
Observations	58,999
R^2	0.715
Adjusted R^2	0.715
Residual Std. Error	632,755.400 (df = 58945)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table A. 1: Regression coefficients for Model 7

Figure A. 1

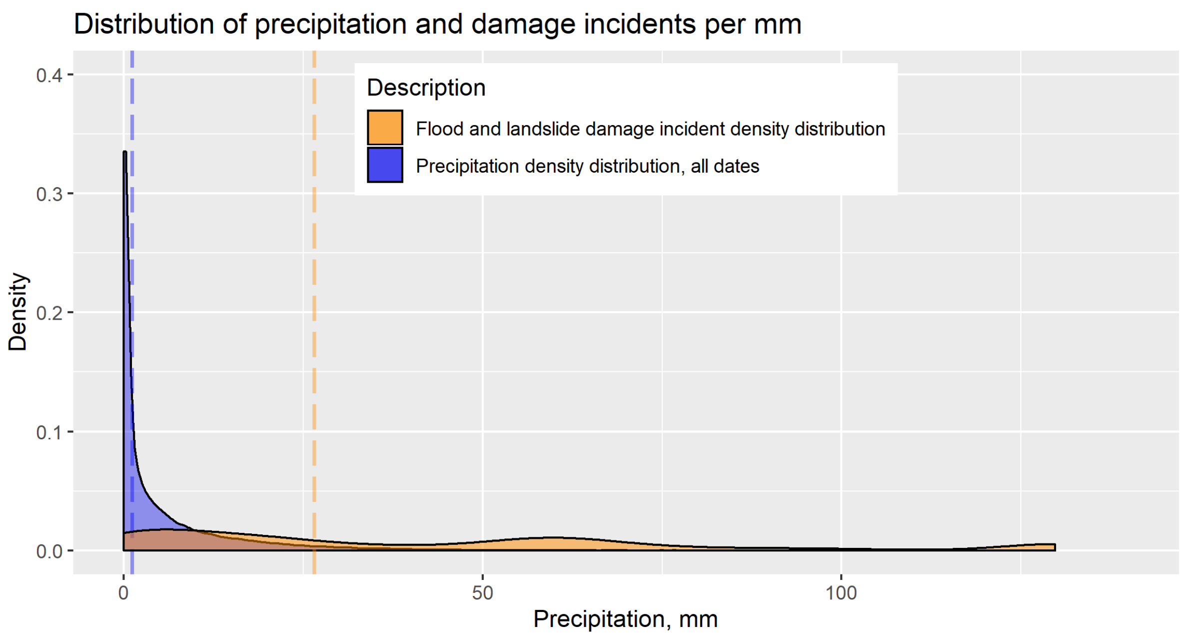

Figure A 1: Kernel-density distributions of precipitation for all dates are shown in blue. Kernel-density distributions for flood and landslide damage incidents per mm of precipitation are shown in orange. The dashed blue and orange lines indicate the median precipitation level and the median precipitation level for flood and landslide damage incidents, respectively.

Table A. 2

Table A. 2 shows how the estimated compensation per municipality varies per wind category and building mass - which is a proxy for the municipalities - holding saturation and precipitation constant. In Table A. 2, we have set the precipitation category to 0-15 mm, and the saturation category to 0-50 mm. The municipalities are sorted by municipality building stock, from largest to smallest. Table A. 2 illustrates that municipalities with low values for building stock achieve the least precise estimates. The nonlinear trend discovered for wind-gust speeds above 20 m/s in the graphical analysis is not reflected in the estimates for smaller municipalities, as the model proposes negative estimates for several of the higher the wind gust categories. The p-values are far from significant for the wind-gust categories that fall below 30 m/s gust speeds, which reflects the fact related to wind gusts do not start increasing significantly until a certain threshold-value is exceeded, coinciding with the findings from the graphical analysis in Section 4.1.1.

Municipality	0-5 m/s	5-10 m/s	10-15 m/s	15-20 m/s	20-25 m/s	25-30 m/s	30-35 m/s	35-60 m/s
Bergen	1 837	63	-4 961	38 818	63 955	700 814	5 560 235	160 927 023
Voss	4 148	6 418	9 482	8 777	6 183	66 483	713 784	16 223 859
Stord	4 246	6 687	10 094	7 504	3 734	39 593	508 337	10 089 726
Kvam	4 277	6 772	10 288	7 101	2 960	31 085	443 339	8 149 046
Bømlo	4 277	6 773	10 288	7 100	2 959	31 081	443 305	8 148 044
Odda	4 343	6 956	10 705	6 233	1 292	12 772	303 419	3 971 373
Vaksdal	4 430	7 194	11 246	5 107	-874	-11 013	121 696	-1 454 416
Jondal	4 461	7 279	11 440	4 704	-1 649	-19 523	56 682	-3 395 598
Eidfjord	4 470	7 305	11 497	4 585	-1 878	-22 029	37 530	-3 967 432
Ulvik	4 471	7 308	11 505	4 569	-1 909	-22 371	34 921	-4 045 330
Fedje	4 504	7 399	11 711	4 140	-2 733	-31 422	-34 230	-6 109 995

Table A. 2: Estimated insurance claims per municipality for all wind gust categories. The values indicate the cost in NOK per incident of each weather specification. Precipitation and saturation are held constant at 0-15 mm and 0-50 mm, respectively. Municipalities are sorted by building stock, from largest to smallest. Estimates for small municipalities do not reflect the nonlinear trend found in the graphical analysis, where costs increase rapidly for wind gusts speeds above 20 m/s.

Table A.3

Table A. 2 shows how the estimated compensation per municipality varies per precipitation category and building mass, which is a proxy for the municipalities. The variables for saturation and wind-gust speed are held constant at 0-50 mm and 5-10 m/s, respectively. The p-values for precipitation are only significant for the 75-130 mm-category.

Kommune	0-15 mm	15 - 30 mm	30 - 45 mm	45 - 60 mm	60 - 75 mm	75 - 130 mm
Bergen	-1 589	78 040	-67	-135 908	159 601	10 839 957
Voss	4 189	-9 195	-20 864	110 776	-121 746	1 902 706
Stord	4 433	-12 893	-21 746	121 233	-133 672	1 523 846
Kvam	4 511	-14 063	-22 025	124 541	-137 446	1 403 984
Bømlo	4 511	-14 063	-22 025	124 543	-137 448	1 403 922
Odda	4 678	-16 581	-22 625	131 663	-145 568	1 145 960
Vaksdal	4 894	-19 852	-23 405	140 913	-156 118	810 849
Jondal	4 972	-21 022	-23 684	144 222	-159 892	690 956
Eidfjord	4 995	-21 367	-23 766	145 197	-161 004	655 638
Ulvik	4 998	-21 414	-23 778	145 330	-161 155	650 827
Fedje	5 080	-22 659	-24 074	148 850	-165 170	523 308

Table A. 3: Estimated insurance claims per municipality for all precipitation categories. The values indicate the cost in NOK per incident of each weather specification. Wind gust category is held constant at 5-10 m/s, and saturation is held constant at 0-50mm. Municipalities are sorted by building stock, from largest to smallest. The nonlinear trend identified for precipitation events above 50 mm is, to a limited degree, reflected in these estimates.

Several estimates deviate significantly from the nonlinear relationship identified in the graphical analysis. This is especially true for the categories 15-30 mm, 30-45 mm, and 60-75 mm, which are negative for all municipalities except Bergen. The category for 15-30 mm in Bergen is presumably high due to many wind-gust damages occurring at this precipitation level. For the category 75-130 mm, the nonlinearity is reflected. Furthermore, we see that heterogeneity relating to other factors than the building stock is not reflected in the cost estimates. For instance, the sum of precipitation-related damage costs in Voss is higher than in Bergen, but the model does not reflect this.

Table A. 4

Single municipality model, Bergen

	Dependent variable:
	Compensation
Wind_gust5-10 m/s	-1,849.378
	t = -0.049
Wind_gust10-15 m/s	-5,906.648
	t = -0.153
Wind_gust15-20 m/s	40,859.820
	t = 0.966
Wind_gust20-25 m/s	62,027.660
	t = 1.191
Wind_gust25-30 m/s	717,313.900***
	t = 6.614
Wind_gust30-35 m/s	5,595,039.000***
	t = 26.325
Wind_gust35-60 m/s	170,683,711.000***
	t = 251.566
Precipitation0-15 mm	-3,313.733
	t = -0.058
Precipitation15-30 mm	-2,791.883
	t = -0.014
Precipitation30-45 mm	4,590.624
	t = 0.005
Precipitation45-60 mm	-61,052.940
	t = -0.064
Precipitation60-75 mm	2,667,079.000***
	t = 7.311
Precipitation75-130 mm	1,901,597.000**
	t = 1.966
Saturation0-50 mm	2,596.386
	t = 0.070
Saturation50-100 mm	2,925.028
	t = 0.021
Saturation100-150 mm	-7,197.032
	t = -0.017
Saturation150-250 mm	-15,035.800
	t = -0.035
Precipitation0-15 mm:Saturation0-50 mm	-2,694.567
	t = -0.044
Precipitation15-30 mm:Saturation0-50 mm	52,574.860
	t = 0.267
Precipitation30-45 mm:Saturation0-50 mm	-21,395.480

	t = -0.022
Precipitation45-60 mm:Saturation0-50 mm	70,325.840
	t = 0.073
Precipitation60-75 mm:Saturation0-50 mm	-2,565,366.000***
	t = -6.164
Precipitation75-130 mm:Saturation0-50 mm	9,831,059.000***
	t = 9.595
Precipitation0-15 mm:Saturation50-100 mm	6,910.752
	t = 0.046
Precipitation15-30 mm:Saturation50-100 mm	191,032.100
	t = 0.786
Precipitation30-45 mm:Saturation50-100 mm	-11,168.530
	t = -0.011
Precipitation45-60 mm:Saturation50-100 mm	89,424.020
	t = 0.091
Precipitation60-75 mm:Saturation50-100 mm	
Precipitation75-130 mm:Saturation50-100 mm	
Precipitation0-15 mm:Saturation100-150 mm	17,434.830
	t = 0.039
Precipitation15-30 mm:Saturation100-150 mm	47,798.020
	t = 0.094
Precipitation30-45 mm:Saturation100-150 mm	34,581.640
	t = 0.032
Precipitation45-60 mm:Saturation100-150 mm	255,474.600
	t = 0.205
Precipitation60-75 mm:Saturation100-150 mm	
Precipitation75-130 mm:Saturation100-150 mm	
Precipitation0-15 mm:Saturation150-250 mm	
Precipitation15-30 mm:Saturation150-250 mm	
Precipitation30-45 mm:Saturation150-250 mm	
Precipitation45-60 mm:Saturation150-250 mm	
Precipitation60-75 mm:Saturation150-250 mm	
Precipitation75-130 mm:Saturation150-250 mm	
Constant	1,316.025
	t = 0.029
Observations	13,564
R^2	0.829
Adjusted R^2	0.829
Residual Std. Error	957,318.800 (df = 13532)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table A. 4: Regression summary, Model Bergen

Table A. 5

	60-75 mm	75-130 mm	Total
Sample			
Number of incidents	31	9	40
Cost per incident (MNOK)	0,1	11,7	
Total cost (MNOK)	3,3	105,6	108,9
Doubled frequency			
Number of incidents	62	18	80
Cost per incident (MNOK)	0,1	11,7	
Total cost (MNOK)	6,5	211,3	217,8
Doubled frequency + 19% intensity increase			
Number of incidents	18	62	80
Cost per incident (MNOK)	0,1	11,7	
Total cost (MNOK)	1,9	727,7	729,6

Table A. 5: Climate scenarios for Bergen and corresponding cost increases. Sample values indicate estimated values for the sample. Doubled frequency indicates the cost of twice as many days of heavy rain. Doubled frequency + 19 % intensity increase indicates the estimated cost for twice as many days of rain, and a 19 % higher precipitation level for the these days. Increasing intensity more than triples the cost of precipitation, and thus has the biggest effect on costs.

Table A. 6

	20-25 m/s	25-30 m/s	30-35 m/s	35-60 m/s	Total
Sample					
Number of incidents	690	89	21	2	
Cost per incident (MNOK)	0,1	0,7	5,6	170,7	
Total cost (MNOK)	41,4	63,7	117,5	341,4	563,8
10% intensity increase					
Number of incidents	508	247	39	9	
Cost per incident (MNOK)	0,1	0,7	5,6	170,7	
Total cost (MNOK)	30,4	176,7	218,1	1536,1	1961,4

Table A. 6: Climate scenario estimates for sample and a 50% increase in frequency of wind-gust speeds exceeding 20 m/s.

Table A. 7

	20-25 m/s	25-30 m/s	30-35 m/s	35-60 m/s	Total
Sample					
Number of incidents	690	89	21	2	802
Cost per incident (MNOK)	0,1	0,7	5,6	170,7	
Total cost (MNOK)	41,4	63,7	117,5	341,4	563,8
50% frequency increase					
Number of incidents	1035	134	32	3	1203
Cost per incident (MNOK)	0,1	0,7	5,6	170,7	
Total cost (MNOK)	62,0	95,5	176,2	512,0	845,7

Table A. 7: Climate scenario estimates for sample and a 10% increase in the intensity of wind-gust speeds exceeding 20 m/s. An increase in intensity is much more costly than an increase in the frequency.