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Natural disasters, insurance claims and regional housing markets

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Abstract

In this paper, I combine data on insurance claims related to natural disasters and water damages, with housing market data at the municipality level in Norway. This makes it possible to measure the severity and extent of such damages, and to investigate their effects on regional housing markets. This is especially relevant in Norway due to an extensive and relatively inexpensive insurance coverage against natural disasters, and a high homeownership share. I control for other regional economic activity and parameters in order to isolate the effect of damages on the housing market in the short and long run using local projections, cluster analysis and cointegration analysis. In general, there does not seem to be large effects on the housing market, but I find some signs of negative short run effects from storms and storm surges, and negative long run effects from avalanches. This is especially relevant for risk assessment, since we expect an increase in the frequency and severity of such events in the future.

Keywords: *Natural disasters, Extreme weather, Housing market, House prices*

JEL classification: *R21, R23, Q54, C23*

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1 Introduction

Houses can be prone to natural disasters and weather related events such as floods, land slides, avalanches, extreme rainfall and storms. This constitutes a substantial financial risk for capital tied up in the housing market. This risk is mostly present for individuals and households, but it may also in the aggregate influence regional housing markets. Risk may thereby in turn affect financial stability and the real economy through e.g. the financial accelerators (Bernanke et al., 1999). Even if insurance will provide a long term financial security against such losses from disasters for individual households, disasters may affect the housing market. The physical damage and subjective risk assessment it could inflict on people and households may affect the housing market both in the short and long run. Households may change their preferences regarding dwelling type and location based on this, thus affecting housing demand preferences in a local housing market.

The risk of natural disasters and extreme weather to a house may be priced into the local housing market, but events may cause a distortion in this risk and thereby affect the housing market through how households view the risk of being exposed to such events. This effect may be in the short run, the long run, or both. Local housing markets experiencing such events will then have negative economic impacts in the short run, but rebuild and renew the housing stock and thereby increase the total housing wealth and average house prices in the region in the long run. The effect may also be limited on regional house prices, especially if only a small portion of the area is affected by a disaster. Jahn (2013) argues that there may be negative economic effects of floods and storms on the housing market in the short run but positive in the long run. Thus, the dynamic effects of the impact may be important to analyze.

In the long run, it is also possible that the risk premium is changed, for instance that severe and/or repeated natural disasters leads to households opting to relocate or not move to the area. This may have large impacts for the price level in the local housing market, and thereby household wealth, through the value of the housing stock. The real economy in the region may also be affected by this. Climate change increasing the frequency and magnitude of natural disasters and extreme weather may thus affect the housing market, especially in areas which are at a high risk of experiencing such events. As climate change will lead to more severe and more frequent natural disasters, this may thus magnify the effects Ifind in our data when seeking to extrapolate our results to the future.

Risk should be fully capitalized into house prices since information about the frequency and severity of flooding associated with each location is accurate and widely known (MacDonald et al., 1987). Thus, with the exception of transitory post-flooding effects on the housing market while homes are being repaired, a hedonic approach would predict no temporal variation in home prices as a result of flood occurrences in an efficient market.

Several studies focus on flood risk and house pirces, but only a few investigate homes that have suffered actual damage (inundated properties) (Beltrán et al., 2019). Atreya and Ferreira (2015) looks at the Flint river in Albany, US, Daniel et al. (2009) use data from The Netherlands, Beltrán et al. (2019) focus on flooding in England 1995-2014 and Roth Tran and Wilson (2020) on natural disasters in the US 1980-2017.

Studies focusing on other areas than the housing market have also been carried out, for instance Guimaraes et al. (1993) investigating Hurricane Hugo in South Carolina in 1989 and Berlemann and Vogt (2007) investigating a flood in 2002 Elbe, Saxony, Germany. Further, Hsiang et al. (2017) estimates economic damage in the US due to climate change over the 21st century focusing on agriculture, crime, coastal storms, energy, human mortality and labor. They find an uneven distribution of risk across locations. Kim et al. (2017) investigates the effect of a landslide on property values, and find that the event had a negative impact on percieved risk and house prices.

Assessing real estate damages caused by extreme meteorological events is particularly important for private households that are not able to diversity their housing market investment portfolio such as larger investors that can eliminate some of their risk (Hirsch et al., 2015). Furthermore, Higgins (2015) emphasizes the challenge of "black swans", such as unforeseen, rare and extreme disasters, for assessing risk in the housing market. Hence, by looking at actual historical events and affected properties rather than potential risk in the local housing markets, it is possible to include "black swans" since all historical events then will be taken into consideration. By utilizing data on insurance claims, it is possible to see whether a property has been affected by damage, and to measure the magnitude of the natural disaster through the monetary value of each damage.

Every household that has fire insurance in Norway are also automatically insured against natural disasters, where the premium is a small share of the fire insurance premium. The vast majority of households has fire insurance, and are thereby also are insured against natural disasters. They pay a low premium which is not affected by the risk of natural disasters.

Insurance payouts should thereby reflect the total damage and not be affected by individual insurance contracts that depends on risk.

As highlighted in Pryce et al. (2011), natural disasters affecting homes are particularly important for household wealth when housing is a large part of households' total assets, and in countries where the home ownership share is high. Norway may therefore be an important area to analyze in this manner. Insurance for natural disasters is also quite inexpensive in Norway and the vast majority of private homes are fully covered. The insurance premium is uniform across households (currently at 0.07‰ of the fire insurance premium), but payouts are in line with rebuilding costs and as such unaffected by the premium paid by the households. Given perfect information and efficient markets, and that almost all Norwegian properties are insured against natural disasters through their fire insurance, we should expect natural disasters not to have an effect on house prices, at least in the long run. However, the risk perception of households may be affected, especially in the case of severe or frequent damages.

The housing market may be affected directly through damages from natural disasters and extreme weather, and indirectly by the effects of damages to the real economy. In this paper I look at historical data on insurance claims due to natural disasters and water damages caused by extreme weather, together with data on the housing market and other control variables. I utilize data on insurance claims at the municipality level in Norway since 1980 (since 1990 for water damages), as an indication on the size of the damage. This is combined with monthly housing market data where I also control for other regional effects in order to analyze the effect of extreme weather and natural disasters on the housing market. Hence, I seek to measure whether natural disasters and water damages affect regional housing markets, both in the short and long run.

In the next section I present a theoretical motivation linking environmental effects to the housing market, while I present the data and the econometric methods in Sections 3 and 4. The results are presented and discussed in Section 5, and the final section concludes.

2 Environmental effects, risk, and the housing market

2.1 Risk in a hedonic housing market model

Traditional hedonic house price theory suggest that house prices will reflect future risk. Buyer's valuation of housing can thus be affected by risk and thereby affect regional house prices through the demand side. This may be shown by the theoretical framework in Beltrán et al. (2019), who use the hedonic price model in Rosen (1974) extended to the flood risk literature. The hedonic price function is thus

$$P = P(Z, r, p(i, r))$$

where Z includes structural, neighbourhood and environmental characteristics, r risk for natural damage and $p(i, r)$ is subjective probability of damage where i is household information. Hence, without taking risk into account, the hedonic price function would be $P = P(Z)$.

Households will maximize their expected utility

$$EU = p(i, r) \cdot U^F[Z, r, Q] + (1 - p(i, r)) \cdot U^{NF}[Z, r, Q]$$

where U^F (U^{NF}) is utility with the possibility of a natural disaster (or not), and Q is level of consumption. Subject to the budget constraint

$$M = P(Z, r, p(i, r)) + Q + L(r) + I(\pi(r), C) - C$$

where $L(r) = 0$ if there is no disaster, or $L(r) = \bar{S}$ is the loss function where $\bar{S}$ is the cost of structural replacement in the case of a disaster. $I(\pi(r), C)$ insurance premium where $\pi(r)$ is the objective probability of disaster and C is insurance cover.

Maximizing utility yields

$$\frac{\partial P}{\partial p} < 0$$
$$\frac{\partial P}{\partial i} < 0$$
$$\frac{\partial P}{\partial r} < 0$$

Hence, both objective and subjective probability of risk will have a negative impact on house prices.

This should in turn affect regional average house prices if the aggregate effect is large enough when considering the sum of all houses in a region. Both the size of the effect and the number of affected houses in a region will then determine whether the average regional house price is influenced. A large disaster affecting a small number of houses or a small disaster affecting a large amount houses (or a combination of both) may thus affect the average regional house price. Further, damages caused by natural disasters or extreme weather may influence both objective or subjective risk, and thus affect the valuation of a property. The total risk, influenced by potential risk or historical events, may thereby affect house prices in a region and be reflected by the average house price.

If the local housing market is efficient, the risk should be reflected in the house prices and the occurence of events should not affect prices. If the insurance market also is providing financial coverage for the homes that are inundated, events should also not affect house prices. However, events may change how the risk is viewed by households. This may affect house prices in the short run, but also in the long run.

2.2 Dynamic effects on the housing market

There are several potential effects on house prices from natural diasters, and the current literature does not provide any consensus on this. As illustrated e.g. in Hsiang and Jina (2014), the dynamic impact on economic growth after a disaster may be both positive and negative, and there may be differences between the short run and long run effects. Hsiang and Jina (2014) separate between four different dynamic impacts on the economy; creative destruction, build back better, recovery to trend, and no recovery. These four hypotheses can also be relevant for the housing market. Creative destruction would be a result of inflowing insurance money promoting growth in house prices due to new capital replacing lost capital, thereby increasing the average house prices in a region. However, growth may suffer initially with destroyed capital, causing a short run decrease in prices. This is consistent with the build back better hypothesis if the destroyed capital is old and outdated leading to renewed housing with a higher standard. If house prices to converge back to the pre-disaster trend e.g. because housing becomes relatively scarce in the medium run, this is in line with the recovery to trend hypothesis. Finally, we may have no recovery, where the damaged capital is not replaced even if the growth may converge to pre-disaster growth. Furthermore, the effects on the housing market may be opposite of those to GDP since funds are used to restore damaged homes rather than used for productive investments (Field et al., 2012). Supply and demand factors may also both be relevant for the effects on a housing market after being exposed to damages. The first differences of these time series will thereby be transitory, which for house prices will approximate house price growth if we use log of house prices.

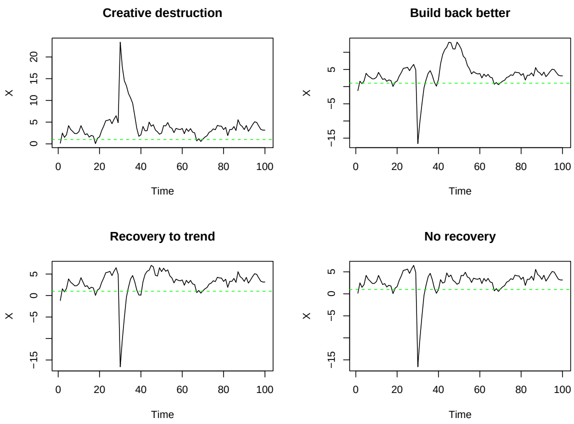
By simulating autoregressive data generating processes, it is possible to replicate the four scenarios outlined by Hsiang and Jina (2014). This enables us to also assess how the graphical representation of the dynamics of the growth rate will evolve. By using an autoregressive process of order one, i.e. an AR(1) process

$$X_t = \rho X_{t-1} + u_t \tag{1}$$

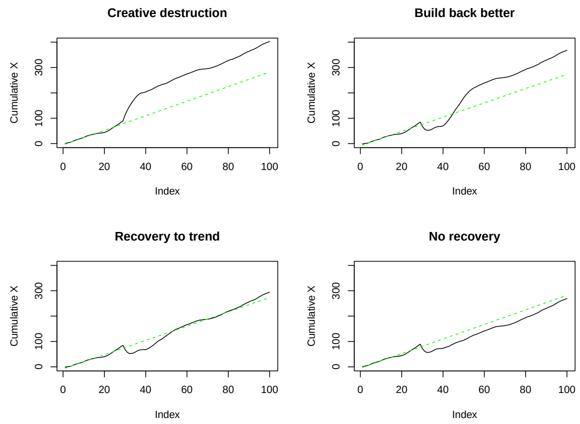
where X_t is a simulated variable for period t, ρ is the autoregressive parameter showing how period t depends on period $t-1$ and thereby the duration of shocks. I use a time frame of $T = 100$ periods with $\rho = 0.7$. X_t is generated as a random variable with a normal distribution using a mean of 1 and a standard deviation of one$X \sim N(1,1)$ and u_t is an i.i.d. error term. This can then be thought of as house price growth. In addition, I include a shock in period $t = 30$ to simulate a natural disaster or an extreme weather event affecting the housing market. For the scenario "creative destruction", this is set as a positive innovation, ($X_{30} = 20$) while is it set as a negative innovation for the remaining three scenarios ($X_{30} = -20$). In addition, periods 40 to 50 has a higher growth of a mean of $X_t = 4$ in the "build back better" and $X_t = 2$ in the "recovery to trend" scenario, assuming a temporary period with excessive growth. In the "no recovery" scenario, there is only the negative effect at period 30 such that the growth rate returns to the initial level.

By cumulating these autoregressive processes, we obtain the corresponding levels which can represent simulated house prices. The simulated growth rates X_t and accumulated growth rates are shown in Figure 1.

In particular, we see what the growth rates of house prices should look like under the four scenarios: For creative destruction, we would have a transitory positive movement, while the remaining scenarios have a transitory negative movement. Build back better and recovery would have a positive temporary effect after the initial negative effect – larger in the case



(a) Growth rates



(b) Cumulated growth rates

Figure 1: Simulated time series of growth rates and cumulated growth rates (solid lines) and constant growth of unity (dashed green line)

of build back better than in the case of recovery to trend. Finally, the no recovery scenario would have a tansitory negative shock followed by a growth rate as before the disaster. The simulated house price series in Figure 1b show how house prices would evolve following a natural disaster or extreme weather event under the four scenarios.

3 Data and summary statistics

3.1 Insurance claims data

I utilize insurance claims data from Finance Norway in order to measure the damage caused by natural disasters and water damages in Norway. The insurance claims data on natural damages separates between storms, floods, storm surges, avalanches/landslides, earthquakes, and volcano eruptions (the two latter not represented or negligible in our data set, thus not included in our analysis). For the water damage data, I use claims where the source of the damage is rainfall, meltwater and groundwater, thereby focusing on water damages caused by (extreme) weather. Hence, data covers all insurance claims at the household level, dated at the day the damage occurred. At the geographical scope however, due to anonymity, we only have information about in which municipality the claim is registered.

I aggregate claims for each month, which yields a panel of monthly data at the municipality level. The natural damages data set contains a total of 343 097 claims, from January 1 1980 to March 31 2020, while the water damages data set contains 509 607 claims, from Jan 1 2008 to September 30 2020. In our final data set however, I only include observations for detached homes. The main reason for this is that detached homes seem to be the type of dwelling most sensitive to natural disasters, see e.g. Kousky et al. (2020). Additionally, we do not have information on which floor the apartments are on, so it is not possible to distinguish between apartments that may have been affected by damages and those who have not. Semi detached homes constitutes a smaller part of the number of sales, so I do not perform a separate analysis on these. I also only regard water damages caused by (extreme) weather and not other causes of water damages such as plumbing or bathroom issues etc. This leads to a total of 144 665 claims related to natural damages and 91 744 related to water damages. The municipality structure follows the division after the 2020 reform[1], such that there is a total of 356 municipalities in our panel data set.

Insurance against natural damages is mandatory in Norway, and every household that has fire insurance on their property and their household goods thereby also have insurance against natural damages. This has a fixed cost of 0.07 per thousand of the fire insurance premium. In addition, the insurance premium is fixed for all households independent of type, size and location of dwelling (e.g. a large detached house or a small apartment in either high or low risk areas). The insurance claims in our data set is final determined claims, thus including both payments already being processed, and future liabilities from the insurance company to the affected household. NOK 8 000 is deducted. Expected processing time of claims are three months (which could be longer if there are a lot of homes that are damaged simultaneously), and repairs then need to be carried out within three years.[2] [3]

Even though natural disasters such as floods and storm surges are in essence water which damages the house, the classification of “water damages” in the insurance market is when water damages the house when not caused by a flood, storm surge or other natural disaster. The natural damages insurance does not cover other types of water damages, and households

[1] A lot of municipalities merged in 2020, reducing the number municipalities from 422 in 2019 to 356 in 2020. Even if the data set here ends in 2019, data follow the new geographical municipality borders also for historical data.

[2] See https://www.naturskade.no/siteassets/forside/felles-brosjyre-nnp-og-ldir.pdf

[3] See https://www.finansnorge.no/statistikk/skadeforsikring/statistikkgrunnlag/ for more information the statistics for insurance claims related to natural disasters (NASK) and water damages (VASK).

needs a separate insurance for this. Most water damages are caused by plumbing issues but a large part is also caused by extreme weather. Since the latter may be affected by climate change, I only concern the effect of water damages caused by extreme weather effects such as abnormall amounts rainfall. House insurance and household goods insurance will cover these damages, but insurance premiums and deductables vary more than for the natural diaster insurance. Hence, the interaction between risk, insurance claims and the housing market may be different than for natural disasters.

3.2 Housing market data

Our housing market data includes monthly data at the municipality level, including average sale price, average ask price (if available) per square meter and number of purchases. The data set spans all 356 Norwegian municipalities (related to the 2020 municipality division), and is provided by Eiendomsverdi AS[4].

I have data on monthly average square meter price and number of sales for detached homes, semi-detached homes and apartments. However, since the square meter price varies a lot between the three types of homes, I do not summarize all of the total sales in order to create an average square meter prices for all sold homes. Instead, I choose to focus on detached homes when looking at house prices in this analysis (see motivation in the previous section). This implies that we investigate how natural damages and water damages may impact prices of detached houses, and not how it will impact apartments and semi-detached houses.

3.3 Other data

In order to control for other regional effects, I also include municipality level data on the unemployment rate, changes in population and the number of newly built homes.

I include unemployment rate data to control for regional business cycles. The unemployment rate is gathered from the Norwegian Labour and Welfare Administration (NAV) and covers monthly data at the municipality level from 1995 to 2019. Municipalities are merged together using the 2020 municipality structure using total number of the workforce and total number of registered unemployed persons. For municipalities that have been divided into

[4] See eiendomsverdi.no

new municipalities, I have separated the number of unemployed and the workforce numbers based on the relative population size of the municipalities.

In order to control for population changes, I include data on net migration for each municipality. These data are gathered from Statistics Norway and are quarterly data at the municipality level from 1997Q1-2020Q3, which I interpolate to monthly data by averages.

Finally, I include number of newly built homes in order to control for supply side effects. These data are also quarterly (2000Q1-2020Q3) from Statistics Norway, such that I interpolate it to monthly data using averages. Data on the housing stock from Statistics Norway is only available on an annual level such that I rather use the number of newly built homes in order to control for the supply side of the housing market.

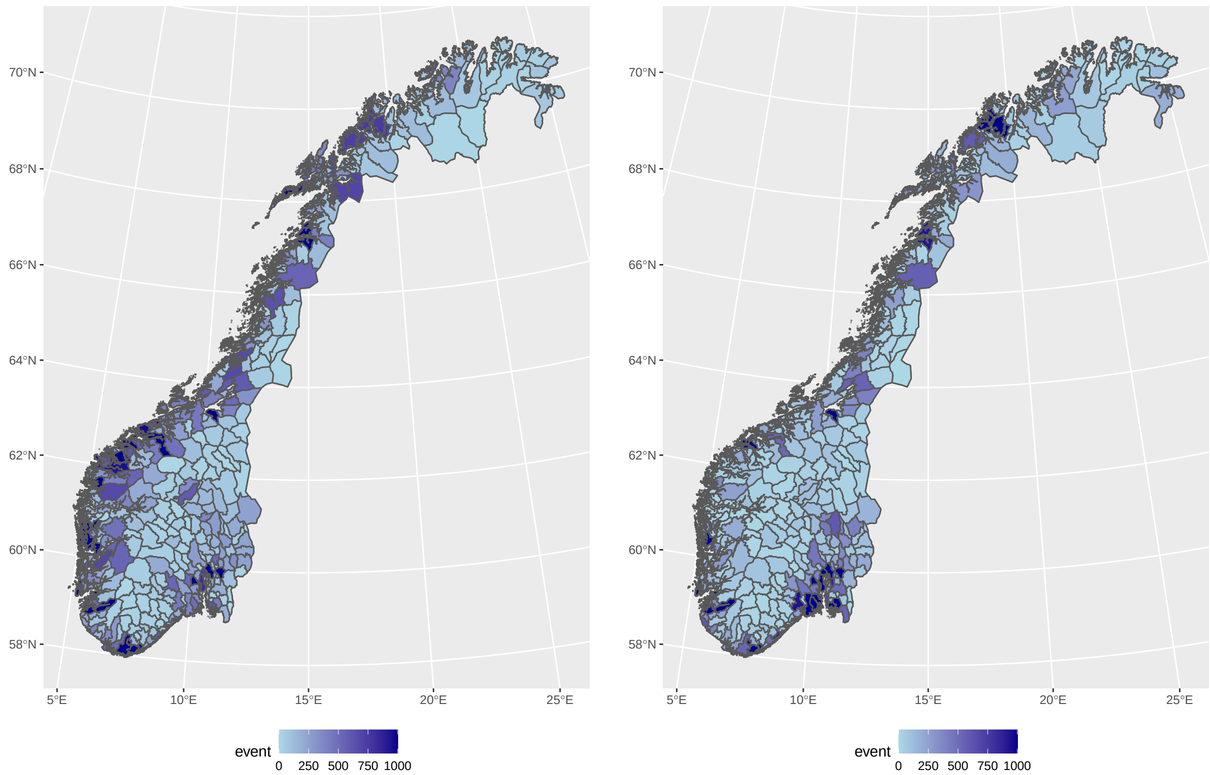
All nominal variables are deflated by CPI (using the national monthly CPI from Statistics Norway). Data from Statistics Norway are grouped together pertaining to the 2020 structure. By the limitations from the sample sizes of the control variables, I thus have a final panel data set from January 2000 until the end of 2019, spanning a total of 20 years or 240 months, such that $T = 240$ and $N = 356$, where some municipalities have certain months without any sales thus providing an unbalanced data set. The potential biased estimated from local projections when using a balanced panel is significantly reduced when including control variables and when having a sample that covers a long time frame, especially when estimating effects for shorter horizons (Herbst and Johannsen, 2021). Hence, our local projection estimates should not be strongly affected by having an unbalanced panel.

3.4 Summary statistics

The maps[5] in Figure 2 show that there is a significant geographical heterogeneity in how municipalities are affected by natural disasters and water damages. In particular, the municipalities with the largest cumulative natural damages are in more rural areas with relatively small populations, while the municipalities with the largest total amount of water damages seem to be in more urban areas.

Additionally, the distribution of number of claims each year is shown in Figure 3. These show that there is a substantial variation between years regarding the number of claims. Some years have more natural disaster and water damages, and the confidence bands illus-

[5] Source for the map shapefiles used in this paper: Kartverket (Norwegian Mapping Authority), Creative Commons 0.

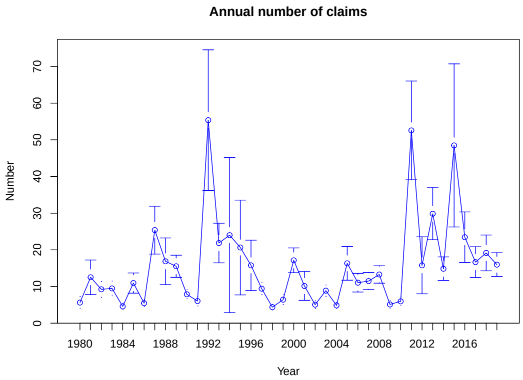


(a) Number of claims, natural disasters

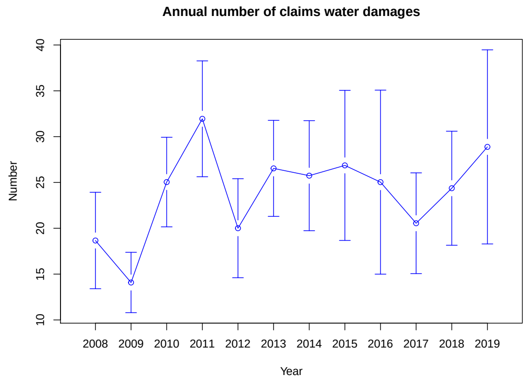
(b) Number of claims, water damages

Figure 2: Number of claims in each municipality over the sample related to natural disasters and water damages

trate that municipalities are affected differently. Hence, there is a also large heterogeneity across years related to how municipalities are affected.



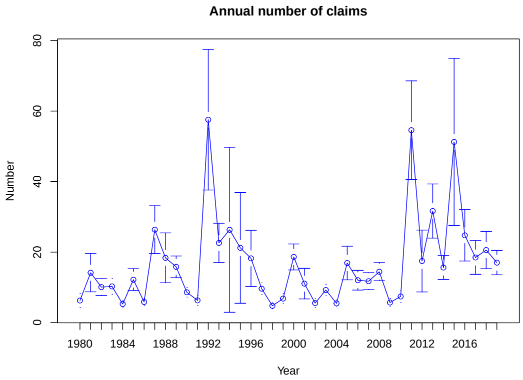
(a) Natural disasters. Means and 95% confidence bands.



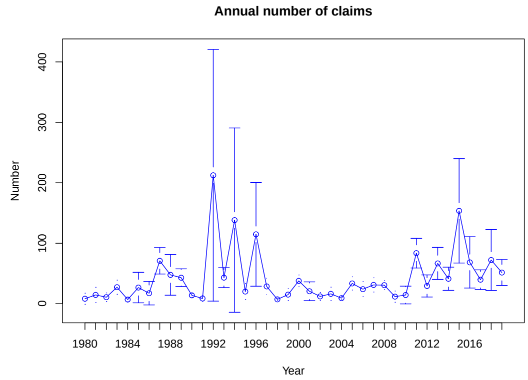
(b) Water damages. Means and 95% confidence bands.

Figure 3: Annual number of claims

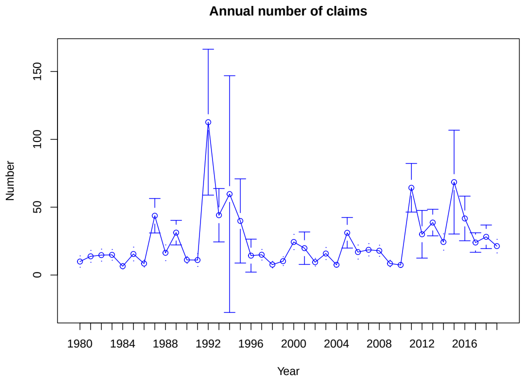
I also differentiate between the four types of natural disasters in our data (Storms, storm surges, floods and avalanches). These are presented in Figure 4 and Table 1.



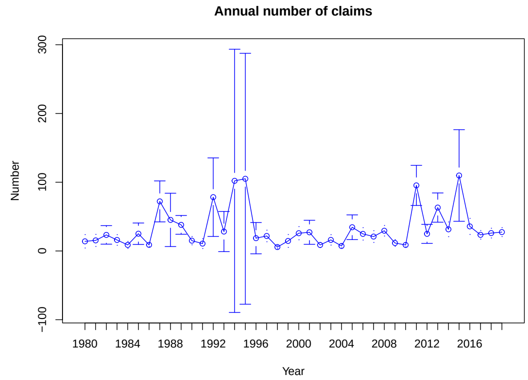
(a) Storms



(b) Storm surges



(c) Floods



(d) Avalanches

Figure 4: Annual number of claims, by type of natural disaster. Means and 95% confidence bands.

Storms seems to follow the pattern of total natural damages in total since these constitute almost 75% of the total number of claims (see Table 1). Storm surges also follows this pattern, which may be due to the connection between the meteorological events that cause storms and storm surges. Floods and avalances show a different pattern, but there are very large variations within certain years for these damages. [6] The average claim size is much smaller for storms and storm surges than for floods and avalanches. This indicates that avalanches and floods are more damaging and involves a greater risk for households. Even if most claims are related to storms, these damages are on average smaller. The severity of flood damages

[6] Note that the number of total claims in the table is smaller than in the full data set, since I disregard damages related to earth quakes which are very rare.

and avalances are much higher on average.

Table 1: Claim size measured as minimum, first quartile, median, mean, third quartile and maximum, and number of claims. For all natural disasters, by damage type and for water damages.

	Total nat. dis.	Storms	Storm surges	Floods	Avalanches	Water dam.
Min.	1	1	10	1	1	1
1st Qu.	4 940	4 536	8 000	6 800	6 119	6 040
Median	13 100	11 440	21 453	24 100	20 004	21 888
Mean	48 589	31 645	54 443	102 230	138 089	62 181
3rd Qu	35 944	29 164	51 068	81 554	73 696	58 024
Max.	43 917 904	25 000 000	4 826 238	9 347 868	43 917 904	48 746 043
Claims	142 799	105 983	6 098	25 523	4 620	91 744

4 Econometric framework

A lot of the previously mentioned empirical papers on the effect of floods and natural disasters on the economy and housing markets investigates the effect of a specific event or of being in a floodplain or an area with a risk of natural disasters. However, I look at regional time series of natural disasters and water damages across the sample and not only certain events. Each year and month have some amount of damages and insurance claims, so I am therefore interested in measuring the effect of how an increase in damages affects the housing market. The damage may be considered a shock, and I am interested in investigating whether the housing market reacts to such a shock. Hence, rather than using a difference-in-difference approach or a type of event study, I use a local projection approach. This allows me to treat natural disasters and water damages as shocks, as when investigating impulse response functions in an estimated system of variables.

4.1 Local projections

I use a panel version of the local projection procedure (Jordà, 2005) and the local projection instrumental variable approach in order to estimate dynamic effects. See Jordà et al. (2015), Ramey (2016) and Stock and Watson (2018). This will provide impulse responses of house prices to natural disasters and water damages on homes. I thus estimate

$$
\begin{aligned}
HP_{i,t+h} - HP_{i,t-1} = \alpha_{i,h} + \beta_h disaster_{i,t} + \sum_{l=0}^{L} \gamma_h X_{i,t-l} \\
+ \sum_{l=1}^{L} \phi_h HP_{i,t-l} + \sum_{l=1}^{L} \varphi_h disaster_{i,t-l} \\
+ \theta_n numsales_{i,t} + \theta_m \sum_{j=2}^{12} month_j + \theta_y \sum_{k=2000}^{2019} year_k, + \varepsilon_{i,t+h}
\end{aligned} \tag{2}
$$

where $HP_{i,t+h}$ is (log) house prices in municipality i for month t, and h denotes the horizon measured in number of months. Insurance claims per capita (deflated) are measured by $disaster_{i,t}$, which then shows the size of damage relative to the population in each municipality. The timing of the disaster is at the month t when the damage occurred. $X_{i,t}$ contains the control variables (log) unemployment rate, (log) newly built homes and (log) net migration. Log of number of sales is also included at time t in order to control for the housing market activity. I also include six lags of both the dependent and independent variables in the model. Dummy variables for each month, year and municipality fixed effects are also added, and I implement the Driscoll and Kraay (1998) Robust Covariance Matrix Estimator in order control for cross-sectional and serial correlation.

This enables us to estimate the dynamic effects that natural disasters and water damages may have on house prices, such that we can investigate the effect both in the short run and in a longer perspective. We include control variables for the supply and demand side factors in order to isolate the effect of disasters on house prices. Further, the panel structure of the data set controls for time and municipality fixed effects. This can be proxies the interest rate or other nation-wide factors relevant for the housing market nationally over time, and factors that are constant over time for individual municipalities such as supply side restrictions or demographic structures. All of the included control variables are also mentioned in the results section.

Utilizing fixed effects also controls for municipality specific risks to natural disasters and water damages that are constant over time. The long term risk associated with an area that are prone to avalanches or floods because of the local topography is thereby controlled for here. Municipality fixed effects such as the average price level over time, as well as demand and supply side fixed effects characterizing each municipality are also then taken into account. Since some municipalities are characterized by higher average house prices over time than others and thereby can be considered more “expensive areas”, this may affect the insurance premium for fire insurance. Hence, fixed effects will control for these average price differences and can thereby to a large degree take the endogeneity issue between insurance claims and house prices into account. I also take seasonal effects into consideration by using monthly dummy variables as control variables.

4.2 Clusters

The heterogeneity among municipalities regarding how they are affected by natural damages and water damages suggest that their housing markets may be affected differently. Instead of separating municipalities according to the distributions of average damages across the sample such as quartiles or percentiles, I utilize cluster analysis (see Romesburg (2004)) to group municipalities together based on how they have been affected by disasters over the sample.

For each year and each municipality, I calculate the number of claims relative to the number of (detached) houses and the average claim size. The former then measures the amount of houses in a municipality being affected by disasters, and the latter measures the average size of the damage. This is in line with collective risk models, see e.g. Hogg and Klugman (1984), where the aggregate loss distribution is a compound probability distribution of the intensity and size of claims. This enables us to investigate whether housing markets in municipalities that are affected more widely or more severely differentiate from those that have been less impacted by damages.

Since climate change is expected to lead to more frequent and more severe natural disasters and water damages, the municipalities that have experienced the largest amount of damages (both regarding the average number of properties being affected and the average claim size which measure the average severity of each damage) may be representative for future housing markets.

4.3 Cointegration

Since local projection methods may be inaccurate for long horizons, I investigate long run effects using an autoregressive distributed lag (ARDL) model in order to test for cointegration. I use data on house prices and accumulated claim sizes. Accumulated claims can be used for modeling operational risk, see e.g. Schmidli (2010). This yields two potentially non-stationary variables that may be cointegrated. Since some municipalities do not have sales of houses every month of year, I annualze the data in order to have observations for each time period in the sample, and estimate an ARDL model for each of the 356 municipalities.

The ARDL model is suitable to use here since we may have both stationary variables and variables that are non-stationary. Hence, there is no requirement that all variables included in the estimated model needs to be I(1) in order to be included in the ARDL model. This is useful since some of our observations may have this combination.

I first utilize the bounds test in order to test for cointegration between house prices and accumulated claims. If cointegration is found, I estimate the long run effect of insurance claims on house prices by using the R package by Natsiopoulos and Tzeremes (2021). I also include unemployment and housing starts as control variables (migration and number of sales are not included due to collinearity and identification issues). However, these are only included in the short run since we do not have enough degrees of freedom to estimate annual ARDL models with these as control variables in the long run. The estimated ARDL model will thereby control for short run effects related to the regional control variables.

The ARDL model in an error correction form can then be expressed as

$$\begin{aligned}\Delta \ln HP_t = &\sum_{j=1}^{m} \gamma_0 \Delta \ln HP_{t-j} + \sum_{j=0}^{m} \gamma_1 \Delta \ln accdisaster_{t-j} \\ &+ \phi_1 \Delta \ln u_t + \phi_2 \Delta \ln starts_t \\ &+ \lambda_1 \ln HP_{t-1} + \lambda_2 \ln accdisaster_{t-1} + \lambda_3 trend + const + \varepsilon_t \end{aligned} \tag{3}$$

where *trend* is a linear deterministic trend and *const* is a constant term. $accdisaster_t$ is the accumulated sum of insurance claims for the municipality, $accdisaster_t = \sum_{t=1}^{T} disaster_t$. First, the bounds test is utilized by testing the null hypothesis of $\lambda_1 = \lambda_2 = \lambda_3 = 0$ against the alternative that one or more of the arguments are wrong. This is done through an F-test where the null hypothesis expresses that there is no long-run relationship between the variables (Pesaran et al., 1995, 2001).

All of the variables in levels may further be normalized on house prices in order to yield the relationship $\Delta lnHP_t = \cdots + \Pi(\ln HP_{t-1} + \beta_1 \ln accdisaster_{t-1} + \beta_2 trend) + \cdots + \varepsilon_t$ which will express the long run relationship between the variables in the system. This will be zero in the long run, $\ln HP_{t-1} + \beta_1 \ln accdisaster_{t-1} + \beta_2 trend = 0$. By normalizing on log house prices, this gives the long run relationship

$$\ln HP_{t-1} = -\beta_1 \ln accdisaster_{t-1} - \beta_2 trend \tag{4}$$

If the bounds test indicates cointegration, and β_1 is significant, we then have a measure of the long run effect of insurance claims related to natural disasters or water damages on the housing market. This effect is negative if $\beta_1 > 0$ ($-\beta_1 < 0$) and positive if $\beta_1 < 0$ ($-\beta_1 > 0$). No effect would then imply that risk is priced into the housing market in the long run and that the insurance market is well functioning, but a long run effect on the housing market could indicate that the perceived risk in the market is changing.

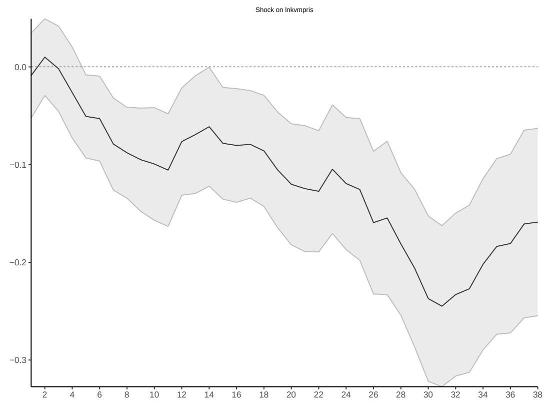
5 Results

In order to investigate the potential effect of natural disasters and water damages on the housing market, I have utilized the econometric tools presented in the previous chapter.

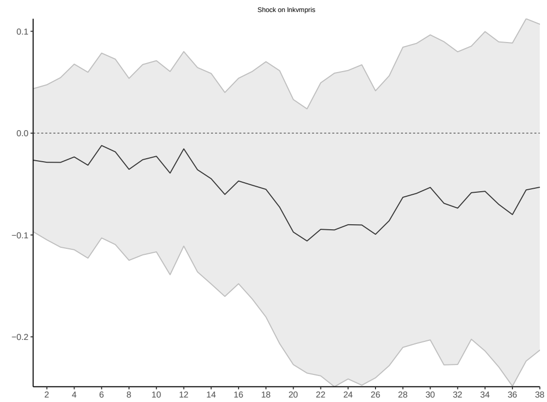
5.1 Local projections

I present the estimates of the panel local projection (LP) regressions graphically, from the estimates effect on (log) house price change from natural disasters and water damages for a horizon of one through 38 months. The results in the figures below presents the estimated β_h coefficients from (2) which measures the approximate percentage effect on house price growth, as well as 95 % confidence bands. I estimate the local projection model without any control variables and with included control variables included in order to investigate the effect of disasters on potential confounding factors.

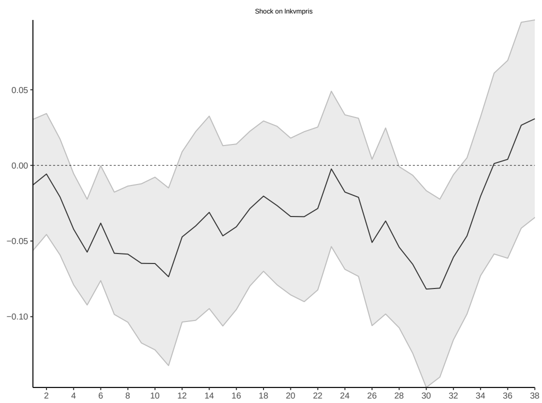
The sample used in the analysis contains a panel of monthly data on the municipality level (of 365 Norwegian municipalities), and runs from 2000 for natural disasters and 2008 for water damages. The control variables used are number of sales (to control for housing market activity), the unemployment rate (controlling for regional economic business cycles and the demand side), (log of) number of approved housing units (to control for changes on the supply side of the regional housing market), and net migration (to control for population changes). Lags, municipality fixed effects, year fixed effects and monthly dummies are also included. See (2) and the previous section for details.



(a) Natural disasters



(b) Water damages



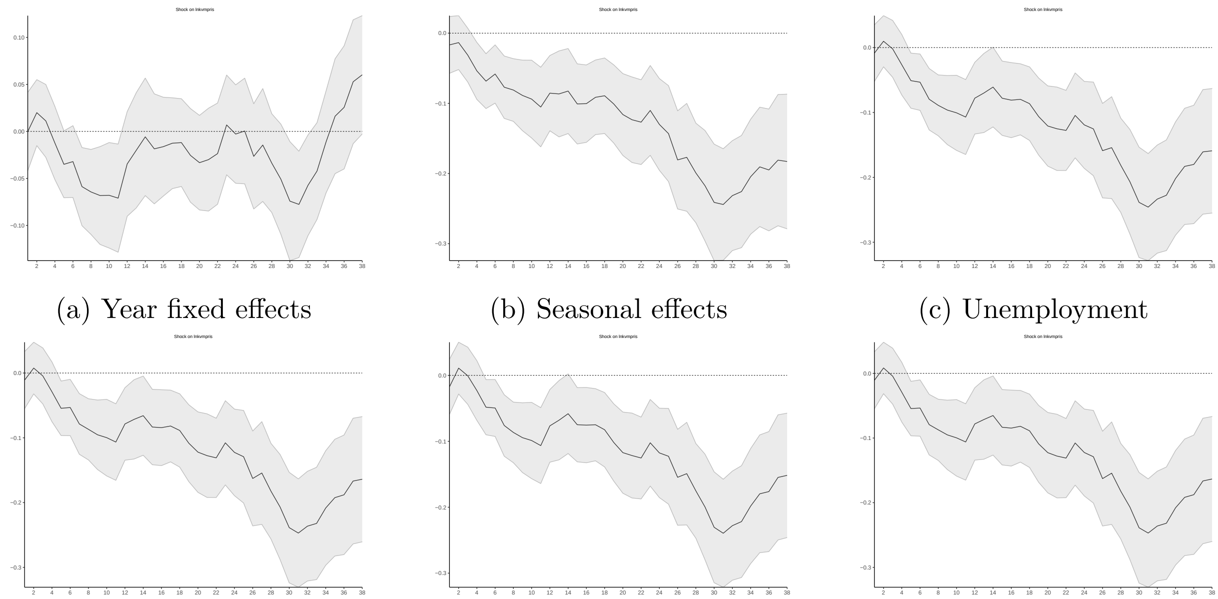
(c) Natural disasters, including controls

(d) Water damages, including controls

Figure 5: Local projection estimates. Means and 95% confidence bands.

While there are no significant effects on house prices from water damages, both with and without control variables, there are some effects from natural disasters. In the short run (from four to twelve months), there is a significant negative effect of natural disasters on house prices. This implies that even if insurance will cover the monetary damages to a home, housing markets are affected negatively by natural disasters. This negative effect is also significant when we control for demand and supply side effects, migration, seasonality and include municipality and year fixed effects. There also seems to be some signs of a negative long run effect, even if this is not as evident when we include control variables. This long run effect is investigated further in the estimated ARDL model in the next section.

I investigate the difference between the estimated effect with and without using control variables further by including each control separately. This then includes six local projection estimates where I include 1) year fixed effects 2) seasonal/monthly dummies 3) unemployment (demand side effects) 4) approved housing units (supply side effects) 5) number of sold homes and 6) net migration. All of the estimates include municipality fixed effects. The results are shown in Figure 6. Here, we see that the significant effect we found when not including control variables is mitigated only when including year fixed effects. This may imply that disasters that have affected the housing market the medium/long run are only present in certain years and that the damage influenced multiple municipalities.



(a) Year fixed effects (b) Seasonal effects (c) Unemployment

(d) Supply side (e) Number of sales (f) Net migration

Figure 6: Local projection estimates for natural disasters. Means and 95% confidence bands. One control variable included in each panel

There are no significant effects of water damages on house prices, even if there are some borderline significant negative effects in the medium run. Confidence bands seems to be larger for water damages than for natural disasters. This may be a result of the shorter sample that we have for water damages. The data also does not reflect as large a share of insurance claims in the country as the data on natural disasters. The potential long run effects of water damages are also investigated in an ARDL model.

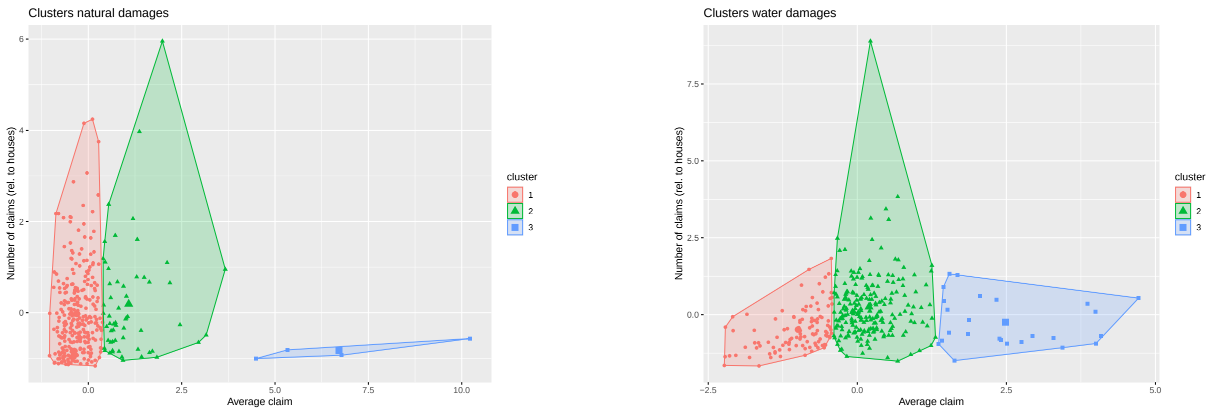
5.2 Clusters and cluster specific estimates

In order to investigate whether some types of municipalities are the cause of these effects while there are no effects in other municipalities, I divide the municipalities into groups using cluster analysis. I carry out a number of tests for the optimal number of clusters by using the NbClust package in R (Charrad et al., 2014) using data on annual average claim size for each municipality over the sample and the average of annual number of claims divided by number of houses. This will then provide a measure how severe each damage have been and the share of homes in a municipality that were damaged which says something about the scope of the damage. Hence, municipalities are separated based on how severe damages were and how many houses that were damaged as both of these affect the total damage in a municipality.

By plotting average claims against the share of homes being affected for all municipalities together with their cluster numbers (see Figure 7), we observe that number of claims (relative to amount of houses in the municipality) shows no particular pattern between the clusters. The average claim size is thus the most important divider between the municipalities according to the clustering. The summary statistics for each cluster (and in total) for average claim sizes is shown in Table 2. Histograms and maps for the distribution is in Appendix A, as well as details on the methods for determining the number of clusters.

Table 2: Summary statistics for average claims, in total and for each cluster

Natural disasters	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	n
Cluster 1	12 866	34 437	42 586	44 783	56 346	74 631	294
Cluster 2	75 278	83 359	93 520	105 052	117 111	217 493	58
Cluster 3	253 387	280 695	321 413	349 736	390 453	502 730	4
All	12 866	37 345	47 813	58 029	65 501	502 730	356
Water damages							
Cluster 1	2 984	23 439	31 368	28 893	36 494	40 803	107
Cluster 2	41 481	47 671	52 444	53 822	58 472	77 163	224
Cluster 3	78 243	81 997	98 497	101 720	118 658	148 480	25
All	2 984	38 593	48 780	49 693	57 290	148 480	356

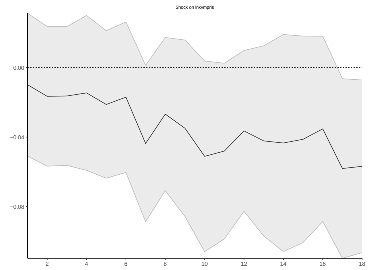


(a) Clusters natural damages

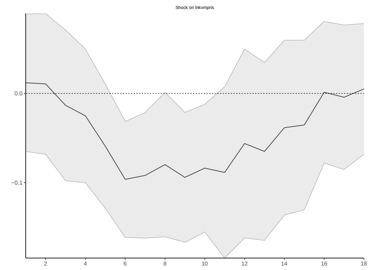
(b) Clusters water damages

Figure 7: Cluster number 1 (red), 2 (green) and 3 (blue). The vertical axis deviation from mean number of claims relative to number of houses and the horizontal axis the deviation from mean average claim size.

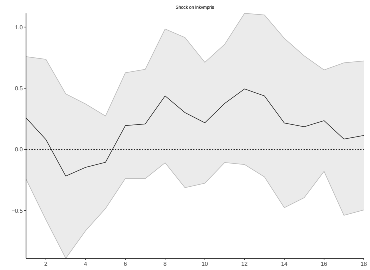
Since the number of municipalities is smaller for each cluster than when we used the whole sample, we are not able to estimate for the same horizon as in that case. Hence, I only estimate local projection up to a horizon of 18 months for each cluster. The results are presented graphically in Figure 8.



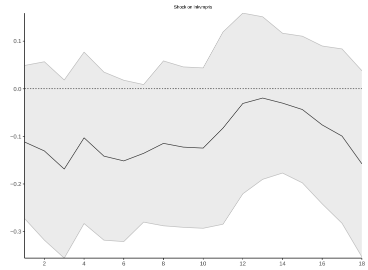
(a) Natural disasters, clust. 1



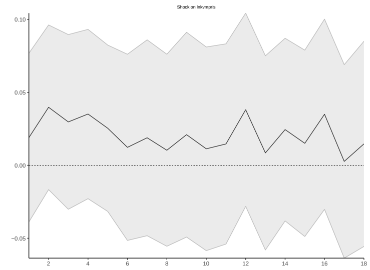
(b) Natural disasters, clust. 2



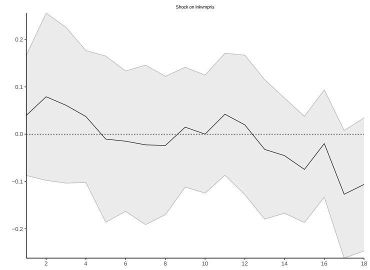
(c) Natural disasters, clust. 3



(d) Water damages, cluster 1



(e) Water damages, cluster 2



(f) Water damages, cluster 3

Figure 8: Local projection estimates for natural disasters and water damages. Separated by cluster number. Means and 95% confidence bands. All control variables included.

The local projection estimates for each cluster shows that the significant negative effect for natural disasters we found when looking at all municipalities only is shown in cluster 2. Hence, the negative effect on house prices from natural disasters is seen in municipalities that has had an average claim size between 75 278 and 217 493 NOK, all of which are above the third quartile for all municipalities of 65 501 NOK. Cluster 3 only has $n = 4$ municipalities, and we do not find a significant effect here. Including there four municipalties together with the 58 in cluster 2 does not alter the results, see Figure A.4. Hence, housing markets are affected from natural disasters only in municipalities with large average claims. This may indicate that in order for natural disasters to affect house prices, the damages must be severe or municipalities must have experienced a certain amount of damages in the past.

There is no significant effect from water damages on house prices within each cluster, but there is a borderline significant negative effect for cluster 3 after 17 months. There may therefore be a long run effect in municipalities with some severe water damages.

5.3 Long run effects

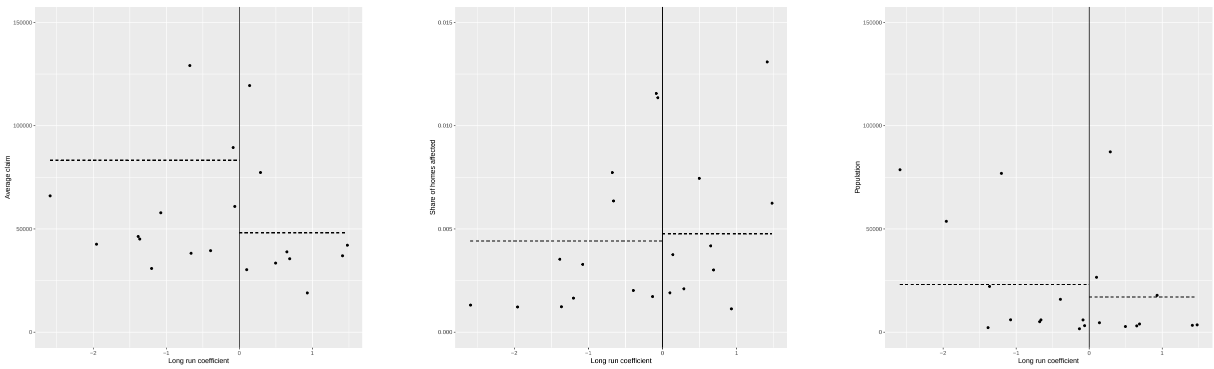
From the local projection estimates, it seems that there may be long-term effects on house prices from natural disasters and possibly also water damages in some municipalities. However, the estimates of long horizons in local projections may be inaccurate (Herbst and Johannsen, 2021). In order to investigate this further here, we look at cointegration effects between insurance claims and house prices.

By testing for cointegration and estimating the long run relationship between the (non-stationary) variables by using an ARDL model for each municipality, we are able to measure the long-run impact of natural diasters and extreme weather on house prices. The summary statistics from estimating the long run coefficient (if cointegration is found) are shown in Table 3. The estimated $-\beta_1$ express the long run effect of disasters on house prices. In addition to the distribution of $-\beta_1$, I also show the a summary of how many municipalities that had a significant long run effect in Table 3, together with whether to what extent the effect was positive or negative and how the significance was distributed across clusters.

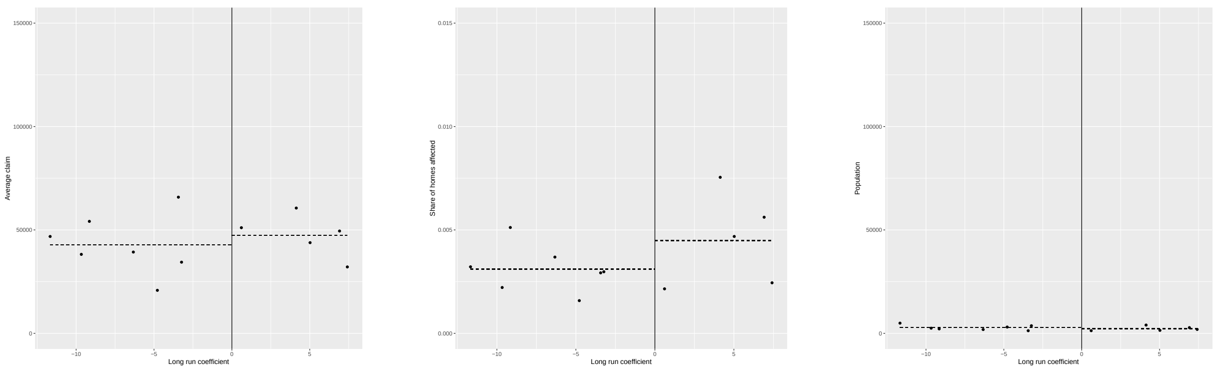
Table 3: Long run effects ($-\beta_1$ if cointegration is found)

	Natural disasters	Water damages
Min.	-2.4804	-2.8896
1st Qu.	-1.0061	-0.1652
Median	-0.0582	0.1251
Mean	**-0.1859**	**0.0458**
3rd Qu.	0.3970	0.3619
Max.	1.4417	2.2610
n no sign. effect	335	332
n sign.	**21**	**24**
n sign. pos.	11	8
n sign. neg.	10	16
n cluster 1	16	10
n cluster 2	4	14
n cluster 3	1	0

We do not observe any specific pattern related to which municipalities that have positive or negative long run effects. As seen in Figure 9, the average claim sizes, share of homes affected and population size do not show a specific pattern between municipalities that experience positive or negative effects. There is also an even distribution of positive and negative effects within each cluster. Since the number of municipalities with a significant effect is at most 21 and 24 out of 356 municipalities, we only have that only up to 6.7% of the municipalities experience a long run effect. This is only slightly larger than the significance level of 5% used in the analysis, indicating that many of the significant effects we find may be by chance and due to Type 1 errors.



(a) Average claim size (b) Avg. share homes affected (c) Average population size

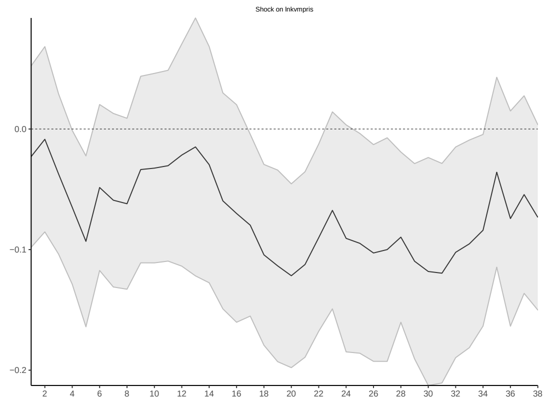


(d) Average claim size (e) Avg. share homes affected (f) Average population size

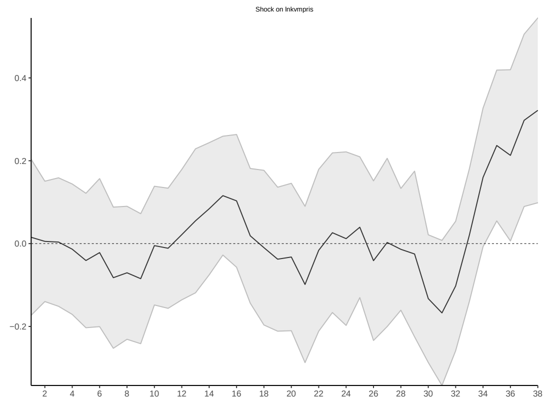
Figure 9: Significant long run effects ($-\beta_1$) between disasters and house prices at the horizontal axes with the vertical line representing an effect of 0. The dashed horizontal lines show the average of claim size (panel a and d), share of homes affeced (panel b and e) and population size (panel c and f). Panels (a), (b) and (c) are for natural disasters and panels (d), (e) and (f) for water damages.

5.4 Differentiating by type of damage

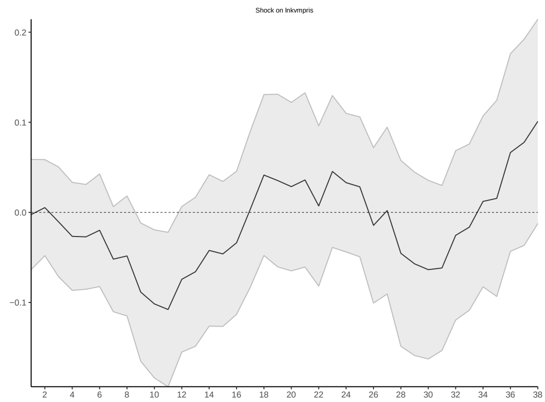
Since the natural diasters occuring in Norway over the sample can be divided into storms, floods, storm surges and avalanches, I perform local projection estimates and ARDL estimates for each of these four types of natural disasters. This will further separate the disasters into categories, such that it is possible to see whether some types of damages are more prone to affect the housing market than others. The results from local projections are shown in Figure 10.



(a) Storms



(b) Storm surges



(c) Floods

(d) Avalanches

Figure 10: Local projection estimates of natural disasters, by damage type. All control variables are included.

From the local projection results, only see significant negative effects for storms and floods, while there is a bordeline negative effect for avalanches. The negative significant effect from storms is present after five months and between 18 and 22 months, while the significant effect from floods is after 9-11 months. Hence, the results we found previously in cluster 2 and when looking at all municpalities seems to come from storms and floods. There also seems to be a long run positve effect from storm surges. However, the long run estimates may be inaccurate (Herbst and Johannsen, 2021), so we will rather investigate this in the ARDL model below. There is also a borderline significant negative effect from avalanches after 7 months. All of the significant effects are estimated to be around -0.1, implying that a 1% increase in disasters will lead to a 0.1% decrease in the average house price. This is in line with what we found when looking at all natural disasters and in cluster 2.

We also estimate ARDL models for all municipalities for each type of damage. The long run results are presented in table 4.

Table 4: Summary statistics of stimated beta coefficients if a sigificant effect is found

	Min.	Q1	Median	Mean	Q3	Max	Sign	pos	neg
Storm	-2.1716	-1.0448	-0.3975	-0.2462	0.5761	1.8784	26	11	15
Storm surge	-17.7885	-7.5724	-0.8834	-3.9672	1.3279	4.3317	12	5	7
Flood	-4.9008	-0.9007	0.1469	-0.3519	0.6994	3.2120	27	14	13
Avalanche	-12.9465	-2.8391	-1.1591	-1.8216	-0.2696	8.2126	27	6	21

Although there are some of the 356 municipalities that has a significant long run relationship between disasters and house prices, the number of counties are very small. We also see an even distribution among positive and negative long run effects from natural disasters on the housing market. For avlanches however, the relationship in the majority 21 of 27 municipalities with a significant long run relationship is negative. Even if only only 7.5% (27 of 365) of the municipalities show a long run effect, but the distribution between positive and negative effects are not as equal as it is for the other types of damages. Since avalanches may be considered at the highest risk of fatalities along with being the expensive on average, cf. Table 1, a negative long run effect on house prices may indicate that even if insurance covers damages, it will still alter the perceived risk and the valuation of homes in those areas.

6 Conclusion

I find some indications of both short and long run effects on house prices by insurance claims, which acts as a proxy for the size and extent of natural disasters and water damages. There seems to be a negative short run effect related to storms and storm surges, and in areas where the severity of the damages has been above average. There are also signs of negative long run effects on house prices by avalanches in some regions. For water damages, there does not seem to be a link between damages and the housing market.

The effects are not highly significant, which implies that there does not seem to be a strong impact from natural disasters on the housing market. This implies that the insurance market seems to work well by covering costs for rebuilding damaged homes. The lack of positive effects also implies that we do not see signs that the insurance market is helping to fund an increase in home values by the use of insurance payouts to upgrade homes.

Since almost all homes in Norway are insured with a relatively low risk premium, we should expect that the risk is priced into the housing market and that disasters that happen do not affect house prices. The short and long run effects on house prices found here will therefore indicate that risk is valued higher than what the insurance may cover. The frequently occuring storms and storm surges that we should expect more of in the future may therefore affect house prices negatively in affected areas, and the potentially fatal and often expensive damages from avalanches may have long run implications on housing markets.

As we expect more frequent and more severe natural disasters in the future, the results presented here may be indicative of future effects on regional housing markets and real economies. Focusing on how regions are affected by disasters is thus important from a policy perspective and for risk assessment.

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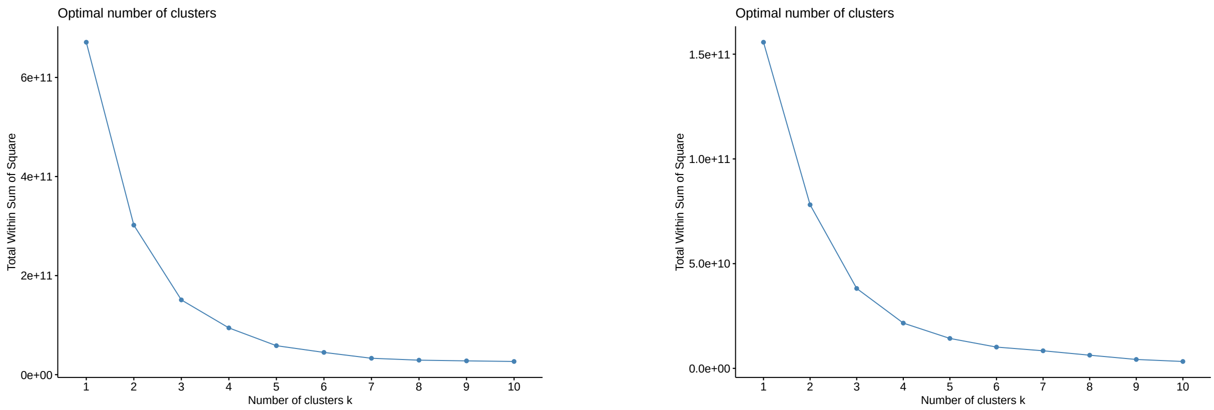
A Cluster analysis

For the indices that are calculated in order to determine the number of clusters, the majority of these propose two clusters for the natural disasters claims and three clusters for the water damage claims. In order to provide symmetry in our analysis, I use three clusters for both types of insurance claims. This is illustrated by the widely used elbow method shown in Figure A.1, which supports the choice of three clusters for both natural disasters and water damages.

The cluster analysis for natural disasters results in that the municipalities are divided into clusters 1, 2 and 3 with 294, 58 and 4 municipalities respectively. For water damages, the clusters consists respectively of 107, 224 and 25 municipalities. The third cluster for natural disasters only consists of 4 municipalities and only includes the most extreme cases, while the second cluster includes 58 municipalities who also all are well over the third quartile of total average claims. Both clusters 2 and 3 are thereby contains more extreme values than the average. For water damages, the largest cluster is cluster 2 with 224 municipalities spanning from below the mean to over the 3rd quartile, while the 25 most extreme observations are not equally relatively far from the mean compared to what we had for natural disasters. This shows that there are some municipalities that have very severe natural disasters, while the majority have relatively small average claims over the sample.

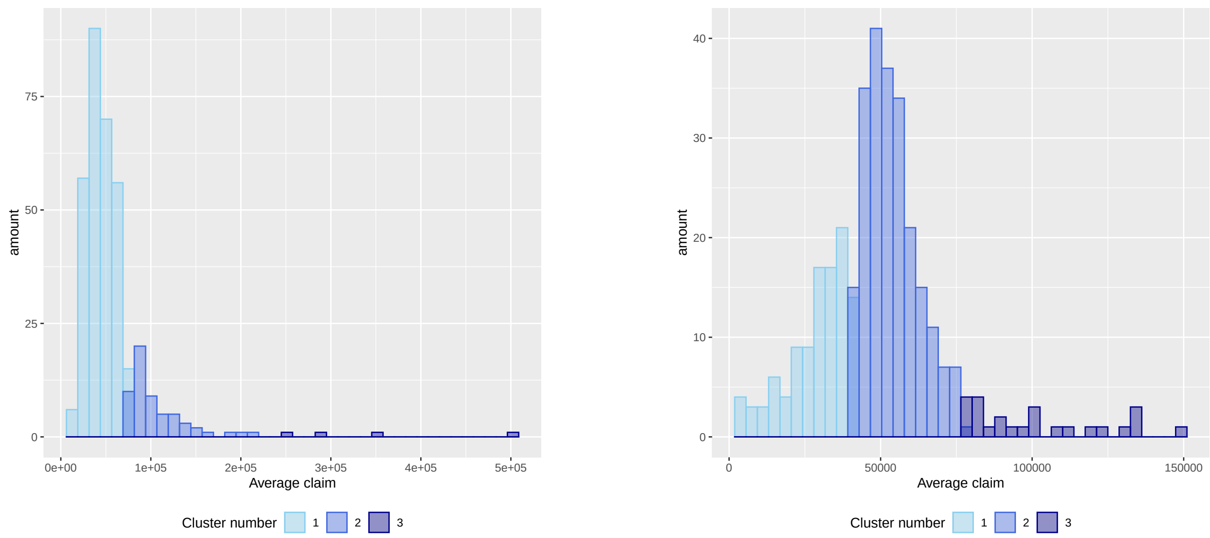


(a) Natural damages

(b) Water damages

Figure A.1: Elbow method to determine number of clusters

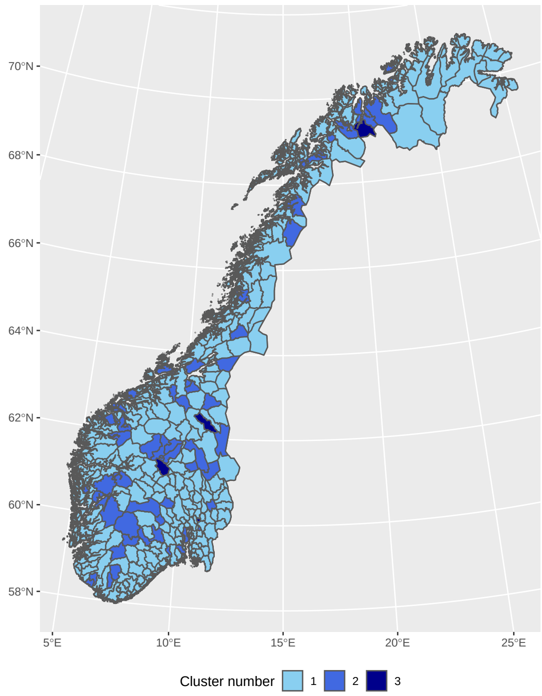
Average claims related to water damages seems to be more evenly distributed than for natural disasters as shown in Figure A.2. There does not seem to be a distinct pattern in the geographical distribution of cluster numbers as shown in the maps in Figure A.3



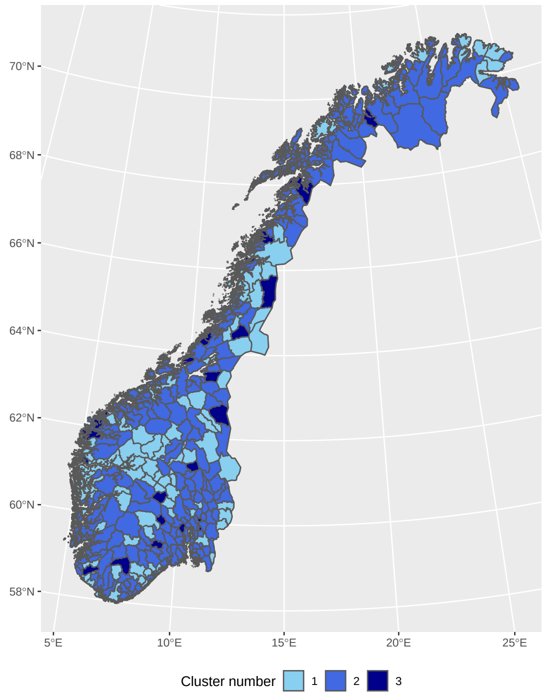
(a) Clusters natural damages

(b) Clusters water damages

Figure A.2: Histograms showing the distribution of average claims for each cluster



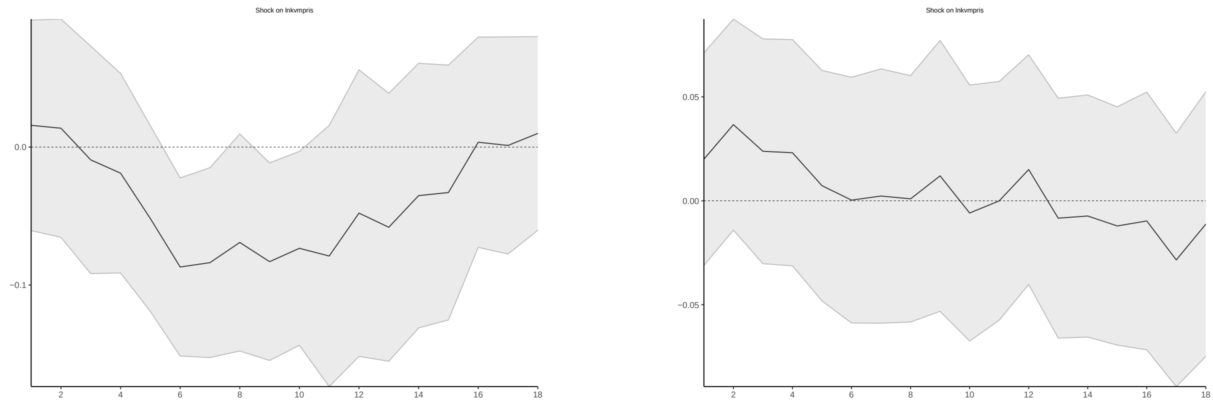
(a) Clusters natural damages



(b) Clusters water damages

Figure A.3: Maps showing the cluster of each municipality

Local projection estimates when combining clusters 2 and 3 are shown in Figure A.4.



(a) Natural disasters, clusters 2 and 3

(b) Water damages, clusters 2 and 3

Figure A.4: Local projection estimates for natural disasters and water damages when combining clusters 2 and 3. Means and 95% confidence bands. All control variables included.

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