Weathering the Storm: The Effects of Natural Disasters on Households under Universal Insurance*

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Abstract

We study the indirect economic consequences of natural disasters for households using administrative data from Norway. A unique feature of this setting is universal natural disaster insurance, which fully compensates direct damages and allows us to isolate indirect effects. Linking a municipality-level measure of disaster severity to population-wide administrative records on income, wealth, consumption, and housing transactions, we estimate household responses using a matched difference-in-differences design. We find that disasters cause persistent declines in income and consumption: four years after an event, cumulative income losses amount to about 20 percent of the average direct damages, while consumption falls by more than twice as much. The consumption response is concentrated among homeowners and is consistent with deleveraging and reduced spending caused by a steep decline in housing wealth.

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1 Introduction

The increasing frequency and severity of extreme weather events is a central consequence of climate change. Beyond their environmental impact, these events generate substantial economic costs, particularly for households located in affected regions. Projections suggest that the incidence of natural disasters will continue to rise, raising concerns about their broader economic consequences. Assessing these effects is crucial for understanding both the aggregate and distributional implications of climate change and for informing the design of effective policy responses.

In this paper, we use comprehensive administrative data from Norway to examine the economic consequences of natural disasters on households. The Norwegian setting is particularly well suited for this analysis: Natural disaster insurance is universal, mandatory, and provides nearly full coverage with minimal deductibles, so direct damages to housing and other assets are largely compensated. This institutional feature allows us to distinguish the indirect effects of disasters from their direct impacts. While direct effects reflect the destruction of physical assets, indirect effects operate through broader channels such as labor income, consumption, savings, and housing markets. The availability of linked administrative records at the individual level and insurance payouts in municipalities enables us to quantify these effects with precision and to assess their persistence over time.

To do so, we construct a municipality-level measure of disaster severity based on insurance payouts, which allows us to systematically identify the most damaging weather events in Norway between 1993 and 2023. Because natural disaster insurance is universal and nearly comprehensive, these data are free from the selection issues that arise in settings with heterogeneous coverage and provide a reliable measure of the immediate economic impact of each event. This approach not only captures large-scale disasters but also enables the study of smaller and more frequent events, thereby offering a broader perspective on the economic consequences of extreme weather. Our methodology is similar to Tran and Wilson (2023) and Boustan et al. (2020), but differs from studies that focus on individual large events, such as Hurricane Katrina in 2005 (Deryugina et al., 2018) or the 2004 Indian Ocean Tsunami (Frankenberg et al., 2023).

We then combine this classification with administrative records covering the entire Norwegian population to examine the effects of natural disasters on households in affected areas. The resulting dataset includes annual information from 2006 to 2018 on a broad range of variables, including income, wealth, geographic location, property transactions, and labor market outcomes, allowing us to track household responses across multiple dimensions. In addition, we use data on electronic transactions, which provide a near-complete measure of household consumption in Norway's largely cashless economy (Galaasen et al., 2024). These data allow us to study consumption dynamics in the aftermath of disasters, an aspect of household adjustment that has received limited attention in the existing literature due to data constraints.

To identify the effect of natural disasters, we treat the most severe weather events as natural experiments and compare households in affected municipalities with similar households in municipalities of comparable size that were not exposed. To ensure comparability, we follow Fagereng et al. (2024) and implement a high-dimensional near-neighbor matching method that incorporates a combination of exact and interval matching on household and municipality characteristics. This allows us to create a control group of households that are similar to those affected by the natural disaster. We then estimate the effects of the disasters on households using a difference-in-difference methodology which allows for staggered treatment.

We show that households exposed to a natural disaster experience lasting declines in both income and wealth. Over the four years following the event, cumulatively income falls by $720 and consumption by $1,460 — amounting to 16% and 33% of the *direct* economic damages, respectively. The negative effects persist, indicating that natural disasters can have lasting economic consequences beyond direct physical damages. We find little evidence of recovery in income or consumption even three years after the disaster. The income decline is driven by a gradual but persistent reduction in labor earnings, with no detectable change in financial income. The drop in gross wealth is entirely accounted for by housing: housing wealth falls steeply for affected households, reaching a peak decline of about $13,000 in the second year after the disaster.

Our evidence points to a central role for housing prices in transmitting disaster impacts to households. Using standard estimates of marginal propensities to consume out of income and housing price shocks, only around 20% of the observed decline in consumption can be attributed to lower income; the remainder is explained by the fall in housing wealth. Consistent with this mechanism, the consumption response is much smaller for households that do not own homes than for homeowners, while the income response is similar across the two groups. Following a disaster, homeowners also become less likely to purchase housing, and they reduce their outstanding debt.

The insurance payout data distinguish between household and firm policies, allowing us to assess the underlying mechanisms behind these effects. We find that the declines in income and consumption are concentrated in disasters where direct damages are borne primarily by firms. These events also coincide with short-run increases in unemployment, underscoring the importance of local labor markets in transmitting disaster impacts to households. By contrast, when damages mostly affect households, the income effects are smaller and statistically insignificant.

Our results demonstrate that households are substantially affected by natural disasters. Even under a universal insurance regime that fully compensates direct losses, indirect effects — including reduced labor income, depressed local housing markets, and consumption contractions — remain considerable. As emphasized in the household finance literature, liquidity constraints, precautionary savings motives and borrowing limits can hinder households from smoothing consumption in response to adverse shocks (Blundell et al., 2008). Although damages to property and other physical assets are fully insured, coverage does not extend to reductions in labor income or house prices in affected areas. Consequently, households experience persistent consumption declines due to the broader economic repercussions of natural disasters.

Finally, our estimates likely represent a lower bound of the economic impacts of natural disasters, given the near-universal coverage of the Norwegian insurance scheme. In settings with less comprehensive insurance, the effects on households would be expected to be even larger. These results highlight the central role of insurance in mitigating the economic consequences of climate-related events and emphasizes the importance of policy frameworks in promoting financial resilience among affected households.

1.1 Related literature

This paper relates to a large and growing body of literature studying the economic impact of natural disasters on the economy (see Cavallo and Noy, 2010; Klomp and Valckx, 2014; Botzen et al., 2019, for reviews). Our contribution to this literature is threefold. First and foremost, given the full reimbursement of the direct costs of natural disasters provided by the universal insurance scheme in Norway, our setting allows us to provide clean estimates of the indirect effects of natural disasters. In the Norwegian setting, any changes in income, wealth, savings, etc. observed after the disaster can only be an indirect consequence of the natural disaster given that insurance provides full compensation for the direct damages of the natural event. Our estimations show that indirect effects of natural disasters lead to a decrease in economic activity three years after the event, suggesting there is limited to no recovery after a natural disaster.[1]

Second, we rely on detailed administrative individual-level data that allows us to follow households affected by heterogeneous natural disasters over time for a large number of disasters. Due to data availability, previous studies analyzing the economic effects of natural disasters either relied on administrative data to follow individuals after a single large event (Gallagher, 2014; Deryugina et al., 2018), or used county-level aggregated data as outcome variables to analyze the impact of disasters of different magnitudes (Anttila-Hughes and Hsiang, 2013; Boustan et al., 2020). Our access to detailed administrative data over several natural events allows us to exploit heterogeneity across disasters and household characteristics to explore which events are most economically damaging, and which segments of the population are more severely affected. In addition, our access to the insurance payouts allows us to construct precise estimates of the economic magnitudes of each disaster in a municipality. Most of the studies in this literature rely on cost estimates of the damages provided by the local authorities (such as those provided by the EM-DAT, FEMA or SHELDUS databases), which can be biased for political reasons (e.g., to access emergency funds, see Garrett and Sobel, 2003; Botzen et al., 2019).

Third, through the detailed Norwegian administrative data we are able to analyze several outcome variables that to the best of our knowledge have not been explored previously in the literature – such as some sub-components of income (labor income and self-employment income), housing transactions, or within-county relocations. These variables allow us to shed new light on the mechanisms that households use to weather the effects of a natural disaster. For instance, we uncover new evidence on an increase in the likelihood of becoming self employed, as well as of an increase in self-employment income, following a natural event.

[1] Hsiang and Jina (2014) present four competing hypotheses about the long-term impact of natural disasters on economic output. The "creative destruction" hypothesis suggests that disasters may temporarily boost economic growth through increased demand for goods and services, international aid, and innovation. The "build back better" hypothesis posits that while initial growth may suffer due to the loss of lives and capital, the replacement of outdated assets with modern units can lead to long-term growth. The "recovery to trend" hypothesis argues that growth should initially decline but eventually rebound to pre-disaster levels. Finally, the "no recovery" hypothesis asserts that disasters permanently lower economic growth by destroying productive capital and durable goods.

We also build on the results by Boustan et al. (2020), who find that severe disasters increase county out-migration rates in affected counties, by showing that fully insured individuals tend to relocate within the affected municipality after a natural disaster. In related and complementary work, Kivedal (2023) relies on the same insurance payments data as we do to show that natural disasters depress regional house prices. We complement his study to show that affected households are less likely to accomplish a housing purchase.

Of particular interest is our unique access to card payments data, which in a cashless society as Norway provide us with reliable measures of consumption. Previous studies focusing on consumption have relied on survey information to measure expenditures (Sawada and Shimizutani, 2008; Bui et al., 2014). Benmir et al. (2021) propose a model in which environmental externalities increase households' willingness to consume goods. There is evidence that climate change and associated phenomena, including pollution, increase the consumption of electricity and other goods such as air conditioning, air purifiers, and medicine (e.g., Abel et al. (2018); Deschenes et al. (2017); and Ito and Zhang (2020)). We find persistent albeit small effects on consumption in a fully insured society, which suggest that the indirect economic consequences of natural disasters are substantial.

Our paper also contributes to the literature that estimates the impact of temperature fluctuations on economic growth. Several papers in this literature estimate mild medium-term effects of increases in the global temperature, as well as minimal or even positive effects on countries at high latitudes such as Norway (see e.g. Dell et al., 2012, 2014; Burke et al., 2015; Kahn et al., 2021; Nath et al., 2024, and the references therein). More recent studies have revised these estimates upward showing that the impact is generally negative, and can be several times larger than previously thought (Bilal and Känzig, 2024; Kotz et al., 2024; Neal, 2023). To the extent that natural disasters will become more frequent with higher temperatures, our estimates are consistent with the latter set of estimates, by showing that even with full insurance, and in high latitudes, the indirect economic consequences of natural disasters are overall negative.

1.2 The Norwegian insurance scheme

In Norway, any physical asset insured against fire damage (such as real estate and movable property) is also automatically covered for natural damage, unless the loss is already covered by another insurance policy. Fire insurance is included in standard home insurance, which is held by the vast majority of homeowners. The natural damage insurance scheme is administered by the Norwegian Natural Perils Pool (NASK), which all companies providing fire insurance are required to join. Member companies conttribute to a joint fund used to compensate policyholders when natural damage occurs. Since its introduction in 1980, the program has undergone minimal changes, making the data consistent and comparable over time (Finans Norge, 2024). Natural damage is defined in Section 4 of the Natural Damage Compensation Act as damage directly caused by a natural disaster, such as flood, landslide, storm, storm surge, earthquake or volcanic eruption.

Premiums are uniform across the country, regardless of geographical location or exposure to extreme weather risks. The rate is set as a per-mill charge on the insured fire value, currently set to 0.07 (updated annually). This uniform pricing reflects the principle of solidarity –a core aspect of the scheme since its inception–which ensures that the risk associated with natural damage is distributed among all residents. By contrast, in many other countries, natural disaster insurance must be purchased separately and may be unavailable or prohibitively expensive in high-risk areas (see e.g. Sastry et al., 2023; Keys and Mulder, 2024).

Coverage extends not only to households but also to firms insuring property or other objects against fire damage. For companies, insured items such as machines, tank farms, or other similar assets are also automatically insured against natural damage if they are insured against fire, subject to some exceptions. Neither households nor firms, however, are insured under this scheme for losses on motor vehicles or boats. In such cases, damages may be covered by regular insurance. If no such coverage exists, households and firms may apply for compensation through the government's natural damage compensation scheme, which covers objects such as agricultural and forestry land, roads, bridges, and concrete quays (Landbruksdirektoratet, 2023).

2 Data

We rely on several comprehensive and detailed data sources to analyze the economic impact of natural disasters on Norwegian households. These include insurance payouts from Finance Norway, supplemented with qualitative information gathered from The Norwegian Water Resources and Energy Directorate (NVE), The Norwegian Meteorological Institute (MET), and local newspapers. We complement these data with Norwegian administrative records from Statistics Norway, providing extensive demographic, income, and labor market data. Finally, electronic transaction data from Nets Branch Norway, the Norwegian retail clearing institution, offers granular insights into household consumption. Combining these datasets enables us to conduct a detailed analysis of household economic outcomes in response to natural disasters.

2.1 Insurance payout data

This dataset, provided by Finance Norway, contains records of all insurance claims related to natural damages for all municipalities in Norway between 1993 and 2023. From this dataset we obtain the date and municipality of each claim, along with the total compensation amount paid by the insurance company (including both paid compensations and provisions for reported damages). We also obtain the cause of the incident (storm, storm surge, flood, landslide, or other). Finally, we obtain a classification of the type of property that was damaged. Prior to 2010, the data was categorized into three broad categories: real estate, agriculture, and other. However, post-2010, the categorization became more detailed, distinguishing between different types of real estate, manufacturing, business, municipality, and agriculture insurance types. These classifications allow us to determine which sectors of the economy were most affected by each event. The data on insurance payouts due to natural damages is available through the Natural Perils Pool, see Section 1.2.

2.2 Norwegian administrative records

We access detailed information on individuals' wealth, income, and their demographic information from Statistics Norway (Statistisk Sentralbyrå, or SSB). The data cover the entire population of Norway aged 16 and over for the period 2005-2018. Demographic information includes the individuals' age, gender, education, place of residence, and family status. Income and wealth data are based on financial reporting from assets and liabilities of each household, as reported to the Norwegian Tax Authority ("Skatteetaten") for tax assessments, and thus are highly reliable. Income variables correspond to the cumulative total over a calendar year and comprise several income categories, including labor income, capital income, income from self-employment, pensions, and all government transfers, as well as taxes paid. Wealth variables correspond to the balance sheet positions as of the beginning of each fiscal years, and they are available for several asset classes, including liquid assets (deposits, cash, listed and non-listed stocks, and mutual funds), debt, and housing wealth. The main component of liquid assets are bank deposits. Debt includes primarily mortgage debt, but also other debt obligations including car loans, consumer debt, and student loans. We aggregate individual data to the household level using information on the composition of households, also provided by SSB. For research purposes each individual is anonymized, and assigned a unique identification number that allows us to link the data to information on households' consumption, obtained from electronic transaction data, as described below. In our study, all our wealth and income variables in levels are reported in 2018 US dollars (USD).

2.3 Electronic transaction data

We collect information about households' consumption from electronic transactions for the years 2006 to 2018 (Galaasen et al., 2024). The data is provided by the Norwegian retail clearing institution, Nets Branch Norway, and it consists of weekly-level data for all debit card transactions cleared by BankAxept (the Norwegian payment system owned by Norwegian banks), plus all online wire transfers cleared by the Norwegian Interbank Clearing System (NICS). This dataset, spanning from 2006 to 2018, categorizes expenditures into 24 different consumption categories and includes information on the location of spending. All debit card payments in domestic physical terminals are cleared by BankAxept, while payments abroad, online or mobile payments are processed through VISA or Mastercard. Debit card is the dominant means of card payment in Norway during our sample period, accounting for 9 out of 10 card transactions and around 71% of all transactions value (Aastveit et al., 2020).

3 Research Design

To assess the economic impacts of natural disasters on Norwegian households, we employ a differences-in-differences approach combined with coarsened matching. Our treatment group consists of the residents in municipalities experiencing a natural disaster. To identify these municipalities, we construct a municipality-level severity metric for natural damage.

While our event study focuses on the period 2006–2018 due to data restrictions related to the electronic transaction records (as discussed in Section 2.3), we classify all natural disaster events over a 30-year period from 1993–2023 using our proposed severity metric, as we consider this to be of public interest.

3.1 A severity metric for natural disasters

To obtain a systematic classification of all natural disasters that occurred in Norway between 1993 and 2023, we rely on data from insurance payouts covering damages due to natural disasters. Figure 1 contains total insurance payouts in Norway for each year since the scheme was established in 1980. The figure shows that payouts have increased over time, with 2011 (with several major floods) and 2023 (with the extreme weather “Hans”) standing out as particularly severe years. This trend has also been highlighted by other sources, e.g., Finans

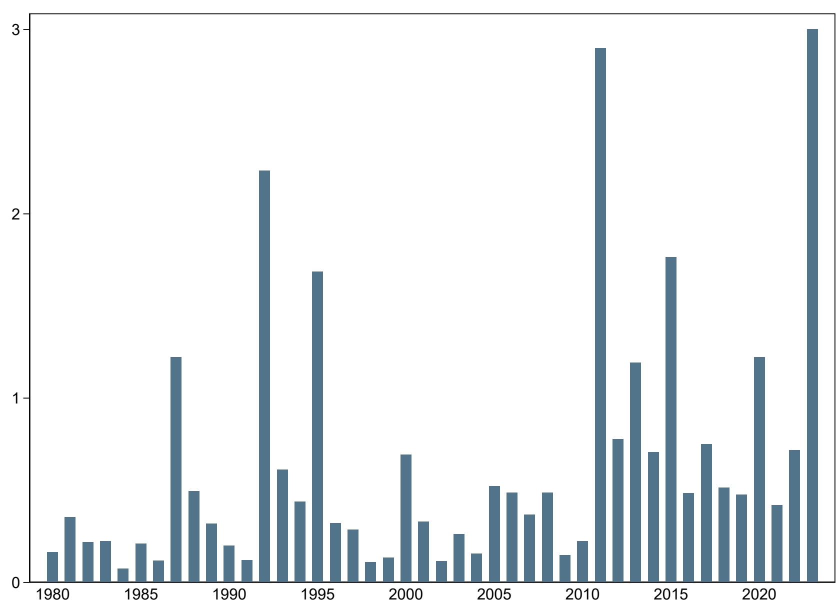


Figure 1: Insurance Payouts Due to Natural Disasters (1980 – 2023). 2018 Billion NOK.

Norge (2024).

To construct the severity metric, we normalize the sum of insurance payouts due to natural damages for each municipality and year by dividing it by total labor income in the municipality. This provides a measure of the event's impact relative to the size of the local economy. We use a broad labor income measure, which includes professional income, salary income, net business income, sickness, and parental benefits. The normalization allows us to compare events across municipalities of varying sizes, and it works as a deflator. This approach provides a more accurate and informative proxy for the economic severity of natural disasters than for instance total municipality insurance payouts, which would be biased towards highly populated cities. The severity metric is robust to alternative normalizations such as dividing by income after tax (which includes pension payments) or to considering insurance payouts per capita, underscoring the reliability of our chosen approach. Appendix A.1 discusses these issues in more detail.

We identify the occurrence of natural disasters in a given municipality and year if the sum of insurance payouts in that particular municipality exceed 5 percent of labor income. Figure 2 displays the distribution of insurance payouts as share of labor income across all

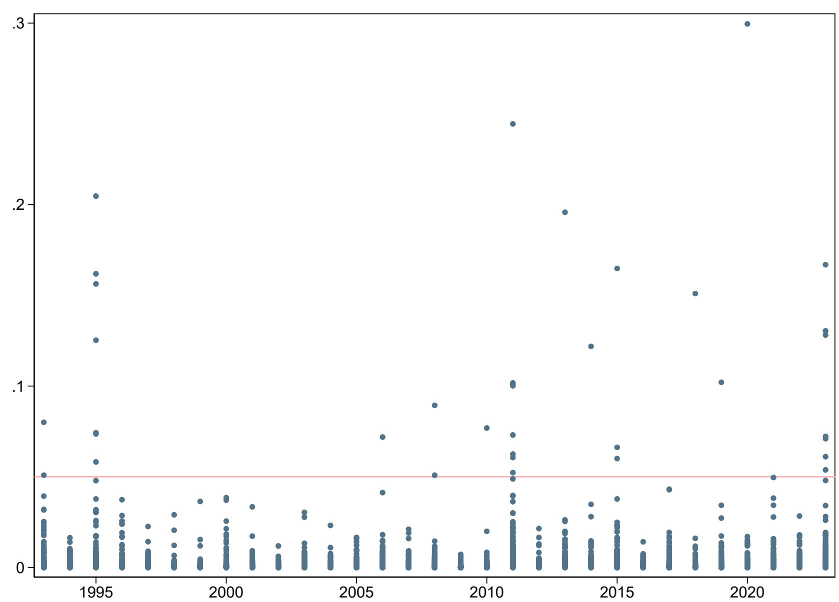


Figure 2: Scatterplot of Total Insurance Payouts as a Share of Labor Income (1993–2023).

Note: Each dot in the scatterplot represents an observation for one municipality in a given year. The red line indicates where insurance payouts are equal to 5% of labor income.

municipality-year observations in the period 1993–2023. The figure shows that this distribution is highly skewed. Notably, only 0.34 percent of the observations have insurance payouts greater than or equal to 5 percent of labor income, placing these cases well within the top 1 percent of the distribution.

By using a threshold of 5% of insurance claims relative to local labor income, we identify 38 natural disasters in Norway between 1993 and 2023, see Table 1. Figure 3 depicts the number of natural disasters occurring in Norway each year during the same time period. Consistently with the increase in insurance payouts through time in Figure 1, we also observe that the number of natural disasters has increased over time.

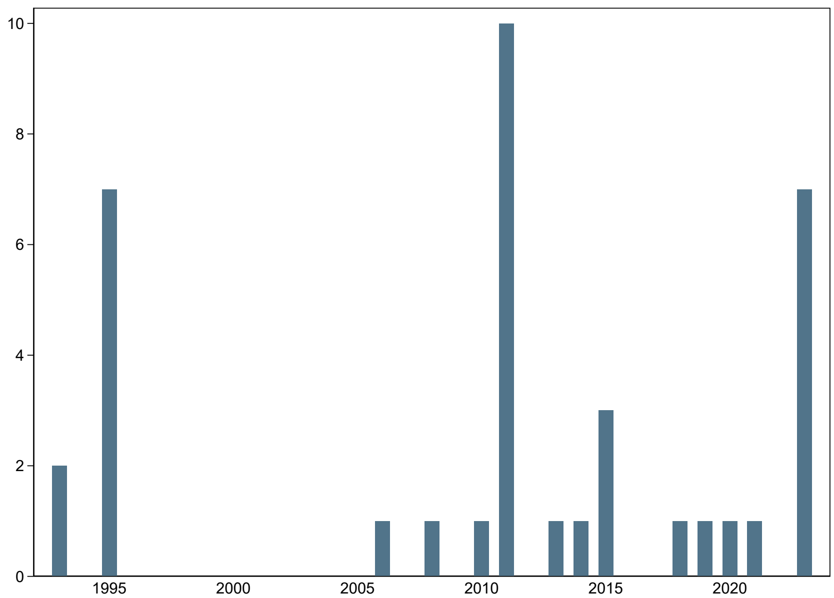


Figure 3: Number of Natural Disasters in Norway 1993-2023

To ensure that our classification is meaningful, we have manually verified each of the events using qualitative information on natural events from The Norwegian Water Resources and Energy Directorate (NVE), extreme weather warnings from The Norwegian Meteorological Institute (MET) and articles from local newspapers. These insights help contextualize the insurance data, providing a clearer picture of the severity and impact of each event.

As a further robustness check, to ensure that the insurance payouts are substantial relative to what is typical for each municipality, we have considered various alternative criteria and methods of measurement, such as deviations of insurance payouts from the average or median payout in the municipality, deviations as share of standard deviation, etc. We found that

Table 1: List of Natural Disasters classified using our proposed Severity Metric (1993–2023)

	Municipality	Year	Month and Day	Payouts as share of labor income	Verified Natural Disaster Type
1	Gjerdrum	2020	Dec 30th	29.9	Landslide, quick clay slide
2	Holtålen	2011	Aug 16th	24.8	Flood, 200-year flood
3	Stor-Elvdal	1995	June 1st	20.5	Flood, "Vesleofsen"
4	Nord-Fron	2013	May 22th	20.1	Flood, 200-year flood
5	Halden	2023	April 27th	16.8	Landslide, rockslide
6	Lund	2015	Dec 5th	16.7	Flood, Extreme Weather "Synne"
7	Åsnes	1995	June 2nd	16.2	Flood, "Vesleofsen"
8	Trysil	1995	June 1st	15.6	Flood, "Vesleofsen"
9	Skjåk	2018	Oct 14th	15.2	Flood
10	Sør-Aurdal	2023	Aug 9th	13.8	Extreme Weather "Hans"
11	Nesbyen	2023	Aug 8th	13.2	Extreme Weather "Hans"
12	Sør-Odal	1995	June 4th	12.5	Flood, "Vesleofsen"
13	Aurland	2014	Oct 28th	12.2	Flood, "Oktoberflommen"
14	Værøy	2019	Feb 16th	11.1	Storm
15	Værøy	2011	Nov 26th	10.6	Extreme Weather "Berit"
16	Moskenes	2011	Nov 26th	10.6	Extreme Weather "Berit"
17	Røst	2011	Nov 26th	10.1	Extreme Weather "Berit"
18	Lyngen	2010	Sep 03rd	8.5	Landslide, earth and clay
19	Flakstad	1993	Feb 03rd	8.0	Storm
20	Nord-Fron	2011	June 10th	7.8	Flood
21	Flå	2023	Aug 8th	7.6	Extreme Weather "Hans"
22	Ål	2023	Aug 8th	7.5	Extreme Weather "Hans"
23	Åmot	1995	May 30th	7.4	Flood, "Vesleofsen"
24	Ringebu	1995	June 2nd	7.4	Flood, "Vesleofsen"
25	Høylandet	2006	Feb 1th	7.2	Flood
26	Kvinesdal	2015	Dec 6th	6.8	Extreme Weather "Synne"
27	Nord-Aurdal	2023	Aug 8th	6.6	Extreme Weather "Hans"
28	Ringebu	2011	Jun 11th	6.5	Flood
29	Bjerkreim	2015	Dec 6th	6.4	Extreme Weather "Synne"
30	Vanylven	2011	Dec 25th	6.2	Extreme Weather "Dagmar"
31	Ringebu	2023	Aug 9th	5.9	Extreme Weather "Hans"
32	Øyer	1995	June 2nd	5.8	Flood, "Vesleofsen"
33	Flakstad	2011	Nov 26th	5.45	Extreme Weather "Berit"
34	Tokke	2021	Oct 4th	5.3	Flood
35	Loppa	1993	Feb 1th	5.09	Storm
36	Værøy	2008	Oct 25th	5.09	Extreme Weather "Ulrik"
37	Stryn	2011	Dec 25th	5.08	Extreme Weather "Dagmar"
38	Sel	2011	June 10th	5.07	Flood

All events have payouts as share of labor income larger or equal to 5 percent.
The number of payouts in a municipality in a given year is at least 15.

the choice of method does not affect the outcome: events that are large relative to labor income in a municipality are also large relative to what historically has been typical for the municipality. Therefore, this measure is robust and effective as an indicator of the severity of natural disasters.

The events are well spread geographically, as illustrated in Figure 4. The map outlines municipal boundaries and uses a red color scale to indicate natural disaster; a light red means a disaster occurred, while a darker red shows that a municipality has experienced multiple

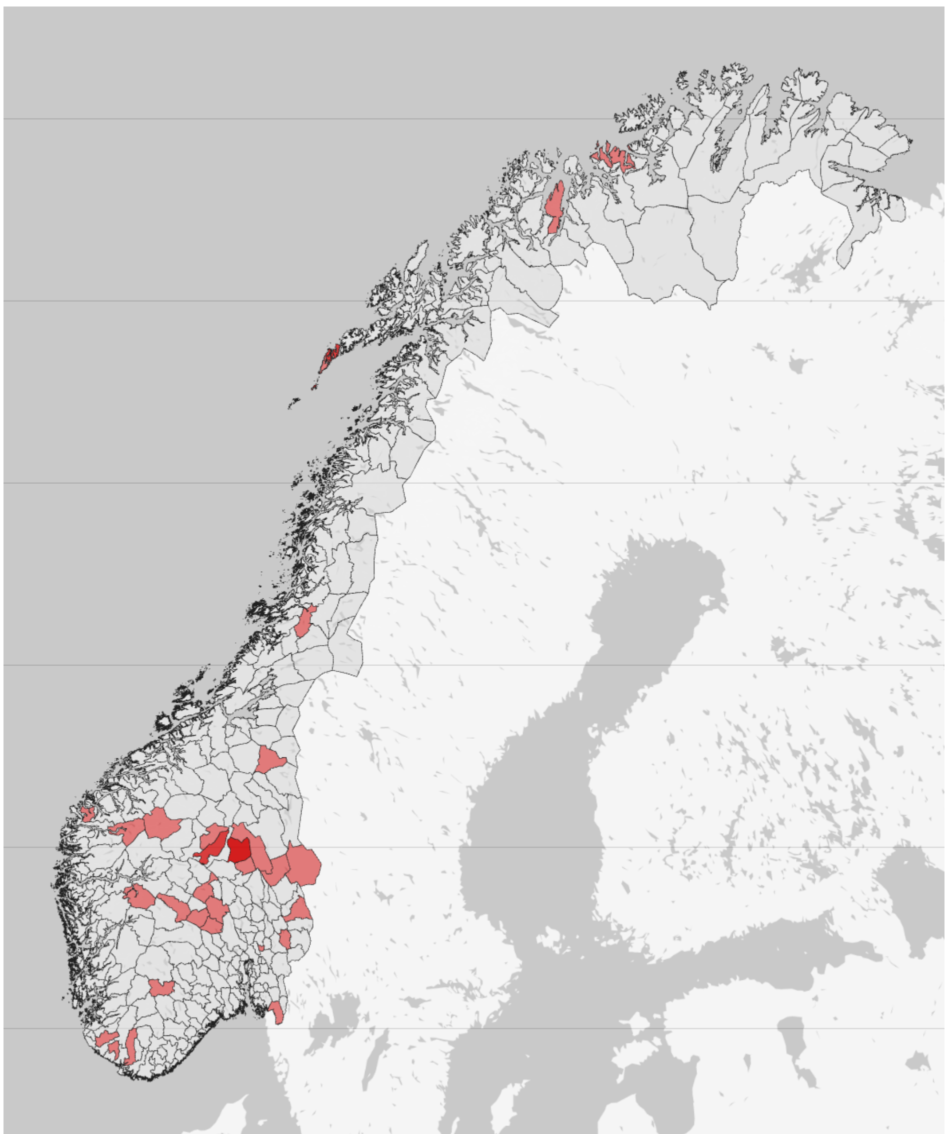


Figure 4: Map of Natural Disasters in Norwegian Municipalities (1993–2023)

Note: Red shading indicates that a natural disaster occurred in a municipality according to our measure. Darker red signifies that the municipality experienced multiple events.

events. The largest event during the 30-year period we are examining, was a quick clay slide in the municipality of Gjerdrum in Dec 2020, where insurance payouts amounted to approximately 30 percent of the labor income in that year, see Table 1. Prolonged precipitation and snowmelt in the weeks preceding the event increased the water content in the soil, weakening the stability of the quick clay. Two additional landslides also rank among the most severe natural disasters in our dataset. However, floods and extreme weather events constitute the majority of recorded disasters.

As explained in Section 2, matching natural disaster information with administrative records and electronic transaction data for our main analysis limits our sample to the years 2006 to 2018, which reduces the number of sample events to 19. Table 2 presents summary statistics for affected and not affected municipalities, respectively. Affected municipalities are on average smaller in terms of population, consisting of about 2,500 residents (median $\approx$ 2,040), whereas not affected municipalities average around 11,600 residents (median $\approx$ 4,125). These differences are primarily due to the inclusion of larger cities in the latter group – the vast majority of Norwegian municipalities are small. The ten most populous municipalities account for 36 percent of the total population in Norway, while approximately 70 percent of municipalities have fewer than 10,000 inhabitants.

The average age is quite similar between the two groups, and education levels are also quite comparable: affected municipalities report that about 17 percent of residents have higher education, compared to roughly 21 percent in not affected municipalities. When it comes to financial indicators, affected municipalities report notably lower labor income, total gross wealth, and debt compared to their not affected counterparts, also when we consider median values instead of averages. For instance, the median labor income in affected areas is approximately 65 million USD, while not affected municipalities average around 123 million USD. the median total gross wealth is about 293 million USD for affected areas, whereas not affected municipalities report a median of roughly 615 million USD. Debt and total consumption follow the same pattern. These differences highlight that affected municipalities consistently exhibit lower median financial metrics, even as the overall dispersion is greater in the not affected group – likely due to the presence of urban areas. This also underscores the need for a more sophisticated matching method to identify households that are comparable to those residing in affected municipalities.

When it comes to insurance payouts, we see from Table 2 that the two groups are comparable when excluding the years in which the natural disaster occurred (see Total Payouts

Table 2: Summary Statistics for Affected and Not Affected Municipalities

Affected Municipalities					
	Mean	Median	St.dev.	Min	Max
Population	2501.59	2043.00	1635.65	473.54	5519.46
Age	49.79	52.00	16.09	26.08	78.92
Higher Education	0.17	0.17	0.03	0.11	0.24
Labor Income	72.23	64.91	47.13	15.39	169.69
Total Gross Wealth	344.41	293.11	243.37	63.82	870.01
Debt	118.86	106.81	82.74	22.34	263.01
Total Consumption	56.24	50.10	36.30	10.24	121.61
Total Payouts incl. Events	735.60	539.48	669.62	152.68	2944.93
Total Payouts excl. Events	153.73	107.06	207.96	23.25	927.20
Not Affected Municipalities					
	Mean	Median	St.dev.	Min	Max
Population	11649.67	4125.08	32806.79	167.62	499905.15
Age	49.82	49.54	15.87	19.69	91.00
Higher Education	0.21	0.20	0.06	0.12	0.48
Labor Income	407.32	123.14	1316.09	6.12	20497.82
Total Gross Wealth	2359.74	615.42	9100.90	23.45	147177.58
Debt	861.63	225.06	2948.51	9.75	46173.33
Total Consumption	251.96	90.33	688.34	3.53	10317.57
Total Payouts	230.09	117.76	358.12	2.55	2920.47

Notes: All monetary values are in real USD (2018 prices).
Labor income, total gross wealth, and debt are in millions, while payouts are in thousands.
Higher education indicates the share of individuals in a municipality who have attained either a lower or higher university degree.
Based on data for the population of Norway aged 16 and over.

including and excluding the events), and there is no indication that affected municipalities generally receive higher insurance payouts than non-affected ones. This highlights that the events we are analyzing are large not only in relation to the local economy but also when compared to historical data, and it supports the use of these events as natural experiments.

3.2 Control group

We follow Fagereng et al. (2024) to find counterfactual control households for each of the treated households using high-dimensional near-neighbor matching. This matching procedure requires that each household residing in an affected municipality is paired with a group of households that are similar in observable characteristics, but have never resided in a municipality that has experienced a natural disaster. Specifically, we require that the control households have never resided in a municipality where insurance payouts have exceeded 2 percent of labor income. This ensures that control households have not been exposed to events that were almost as severe as those classified as disasters but did not meet the 5 percent threshold. This set of eligible households is the initial set of "potential controls" (4.5 million households).

Using detailed administrative records, we select a control group from the dataset of potential controls. Given that weather events are spatially correlated, we employ exact dismatching at the county level to ensure that control households are not indirectly affected by a natural disaster in another municipality that lies in the same county.[2] Dismatching at the county level allows us to account for impacts that may spill over municipal boundaries within the same county.

Then, we use coarsened exact matching (CEM) to find the closest controls for each treated household. CEM is a statistical technique used to improve the estimation of causal effects by reducing the imbalance of covariates between treated and control groups. This method involves coarsening (i.e. temporarily categorizing) key variables into broader groups to simplify the matching. Each unit in the treatment group is matched with one or more control units that share the same or similar coarsened values. The primary advantage of CEM is that it reduces model dependence and potential estimation error by matching exactly on coarsened covariates, thus limiting the influence of extreme weights often associated with propensity score matching.

Our matching procedure requires exact matching as of year-end of the year previous to the natural disaster for the following discrete variables: home ownership, ownership of risky assets, self-employment status, and an indicator for whether a household has children below the age of 18. We also match on maximum household education. Education is a categorical variable representing the highest level of educational attainment. It is divided into four categories: individuals who have not completed upper secondary education (coded as 1), those who have completed upper secondary education (coded as 2), those with a bachelor's degree (coded as 3), and those with a master's degree or higher (coded as 4). When matching,

[2]Norway is geographically divided into 15 counties and 357 municipalities as of January 1, 2024 (356 municipalities as of January 1, 2020, which is the municipality division utilized in this study). Municipalities are often responsible for local services and administration, while counties emcompass several municipalities and coordinate broader regional policies.

we use the highest education level within the household. Control households are included only if their maximum education level matches the highest education level of a treated household.

Additionally, we apply interval matching by selecting control households whose head (eldest member) is as close in age as possible to the head of the treated household within a ± 5-year range. We also match on total consumption, household income after tax, debt level, and liquid assets within a $\pm 20\%$ range. Furthermore, we match on municipality population size within $\pm 30\%$, or $\pm 10,000$ inhabitants for small municipalities. This final criterion ensures that treated households and their respective control households reside in municipalities of comparable size.

We match with replacement, meaning that the same household can appear as a control for more than one treated unit, and we allow each treated household to be matched to multiple control households, enhancing the robustness of our analysis. The number of control households per treated household ranges from 1 to 1,558, with a highly skewed distribution. Notably, 76.6 percent of treated households have fewer than 100 control matches.

Utilizing the principles of CEM, each treated household i associated to a matching group m is allocated to a unique bin, indexed by $i(m)$, and assigned a weight of 1. All control households within the same bin receive a distinct weight specific to that bin. If any of these control households also serve as controls for another treated household in a different bin, they will have a different weight that is unique to the new bin. The weighting mechanism for matched control members, where weights can range from fractions to values equal to or greater than 1, ensures that the distribution of the control group's characteristics is normalized to ensure similarity to the treatment group. The weights $w_{i(m)}$ are given by:

$$w_{i(m)} = \frac{N^T_{i(m)}/N^C_{i(m)}}{N^C/N^T},$$

Here, $N^T_{i(m)}$ represents the number of treated households in bin $i(m)$, which in our case is always equal to 1, as each treated household has its own bin. Similarly, $N^C_{i(m)}$ denotes the number of control households within the corresponding bin, while N^C and N^T indicate the total number of matched control and treated households across all bins.

We impose balancing and restrict our sample to treated and control households that we can observe continuously for at least four years prior to the event and two years after. Additionally, we winsorize consumption, income, and wealth outliers at the 1st and 99th percentiles. After matching and cleaning the data we are left with 7646 unique treated households and 84 645 unique controls. Table 3 contain summary statistics of the final

Table 3: Summary Statistics for Treated and Control Households

Treated Households				
	Mean	St.dev.	Min	Max
Age of Household Head	60.92	15.49	19.00	101.00
Maximum Household Education	1.75	0.83	0.00	4.00
Share of Households with Children	0.23	0.42	0.00	1.00
Share of Homeowners	0.79	0.41	0.00	1.00
Income after tax	43027.16	16139.29	17199.40	83722.64
Self-employment income	463.89	1661.75	-460.05	6721.78
Housing Wealth	115190.54	87644.99	0.00	407949.59
Debt	47159.41	58793.84	0.00	224389.26
Deposits + Securities	43701.57	48203.20	830.55	211188.05
Total Consumption	31542.50	19542.37	411.24	82047.86
Control Households				
	Mean	St.dev.	Min	Max
Age of Household Head	67.06	16.85	19.00	102.00
Maximum Household Education	1.48	0.74	0.00	4.00
Share of Households with Children	0.22	0.42	0.00	1.00
Share of Homeowners	0.77	0.42	0.00	1.00
Income after tax	36190.14	13651.63	17199.40	83722.64
Self-employment income	57.49	600.67	-460.05	6721.78
Housing Wealth	122947.52	95425.79	0.00	407949.59
Debt	33517.18	53416.54	0.00	224389.26
Deposits + Securities	42335.35	37805.96	830.55	211188.05
Total Consumption	23706.43	16314.48	411.24	82047.86

Notes: All monetary values are in real USD (2018 prices).

sample of treated and control households, respectively, as of the start of the year of the natural disaster.

The tables indicate that the matching process results in a similar distribution between treated and control households. Over 75 percent of households are homeowners, while slightly more than 20 percent have children. Most households are not self-employed and tend to have low education levels and higher ages. Financially, the average household has a disposable income of approximately 43,000 USD, with total consumption around 31,500 USD. Housing wealth is around 115,190 USD, while debt levels average 47,160 USD. Additionally, deposits and securities are roughly equal to the amount of debt.

To ensure the robustness of our results, we have applied several alternative matching strategies (see the Appendix). For instance, instead of using variables from time -1, we have matched on pre-period averages to account for longer-term trends. Additionally, given our focus on relocations after the natural disaster, we have also experimented with exact matching on the population growth decile of the municipality. This approach makes intuitive sense, as it ensures that treated and control households reside in municipalities with comparable population growth. However, these alternative specifications does not alter our main findings. The primary effect of these adjustments is a reduction in the number of treated households, which in turn slightly lowers the precision of our estimates. Overall, our results remain robust across these different matching approaches.

3.3 Event study

We use a simple differences-in-differences specification on the set of matched households

$$Y_{i,m,t} = \sum_{\substack{k=-4 \\ k \neq -1}}^{3} \beta_k \mathbb{1}_{i,k,t} T_i + \sum_{k=-4}^{3} \delta_k \mathbb{1}_{i,k,t} + \eta_m + \epsilon_{i,t} \tag{1}$$

$Y_{i,m,t}$ represents the different outcome variables (income, wealth, consumption, etc) for each household i in a given calendar year t belonging to matching group m. The dummy variable T_i denotes whether the household i is treated, i.e. they lived in the municipality affected by a natural disaster at the time of the disaster; the treatment does not change over time. $\mathbb{1}_{i,k,t}$ is an indicator variable that takes the value one k years relative to the event year. δ_k gives the time effects that affect both treated and controls, while β_k is the coefficient of interest capturing differences between treated and controls over time, relative to the baseline period -1. η_m are matching group fixed effects. The error term is represented by $\epsilon_{i,t}$ and clustered at the matching group level m. We run this regression on the sample of matched treatment and control households, using the CEM weights.

4 Results

We now present our estimation results. We start by estimating the size of the direct damages due to the natural disasters. Figure 5 shows the estimated increase in insurance payouts related to natural damages per household in affected municipalities (treated households) relative to households non-affected municipalities. The black line shows the estimated dynamic treatment effects relative to the year immediately before the disaster ($t = -1$). Period 0 along the horizontal axis corresponds to the event year. The figure shows that insurance payouts increase sharply by around $\$4,000$ in the year of the disaster. Since the Norwegian insurance scheme provides full coverage of damages related to natural disasters, Figure 5 provides an estimate of the direct economic effects of the events in our dataset.

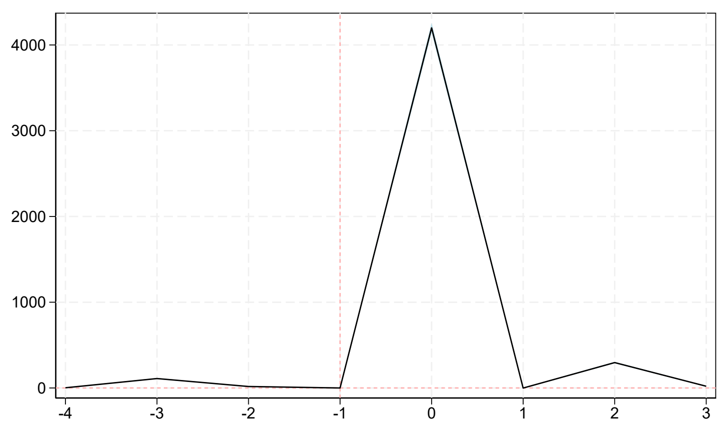


Figure 5: Direct damages per household.

Notes: Estimated effect of natural disasters on insurance payouts related to natural damages, per household in affected municipalities. Year 0 is the event year. Real USD in 2018 Prices. Shaded areas show 90% and 95% confidence bands.

4.1 Confirming treatment assignment

While payouts related to natural disasters in Figure 5 are only observed at the municipality level in our dataset, we do observe total transfers from insurance companies at the household level. Figure 6 shows the effect of natural disasters on transfers from insurance companies to households. In this and all the following figures, the black line shows the estimated dynamic treatment effects relative to the year immediately before the disaster ($t = -1$), where $t = 0$ corresponds to the event year. The shaded areas show 90 and 95 percent confidence intervals. The figure indicates that the difference between treated – residents of municipalities affected by a natural disasters – and control households is not statistically different from zero in the years prior to the natural disaster. After the disaster, we find a sharp increase in insurance payments concentrated among treated households, providing a validation of our empirical design. Since the treatment is assigned at the municipality level, this confirmation is particularly important, reinforcing the credibility of our identification strategy.

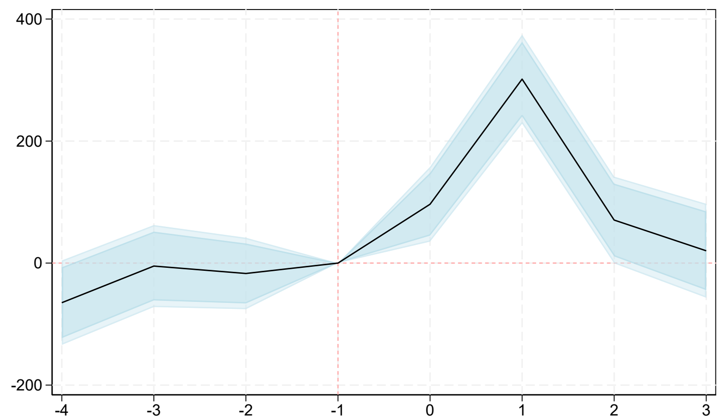
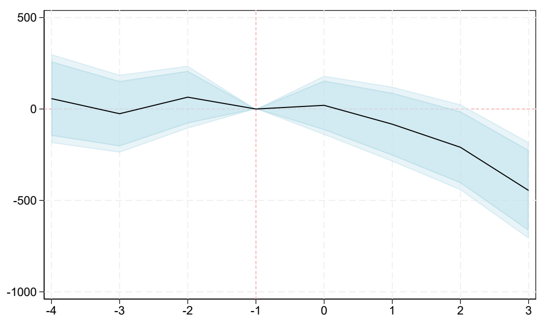


Figure 6: Validation of treatment. Transfers from insurance companies to households.
Notes: Estimated effect of natural disasters on transfers from insurance companies to households. Year 0 is the event year. Real USD in 2018 Prices. Shaded areas show 90% and 95% confidence bands.

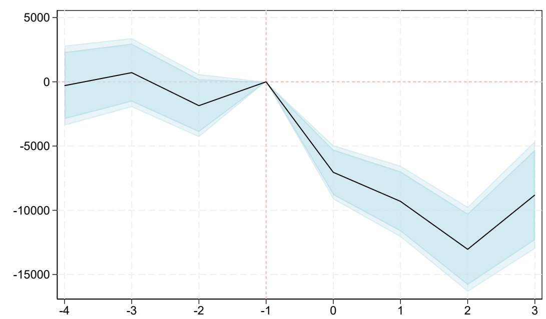
Most households affected by natural disasters allow the insurance company to manage the entire reconstruction or repair process, including contractor payments. While households may opt to receive a direct payout instead, this option is typically chosen only for small damages, such as losses to movable property. When the insurance company manages repairs, the full value of direct damages appears in Figure 5, but not in the payouts made directly to households shown in Figure 6. Consistent with this, we find that payments received by treated households account for only about 10% of the total damages covered by insurance.

4.2 Main results

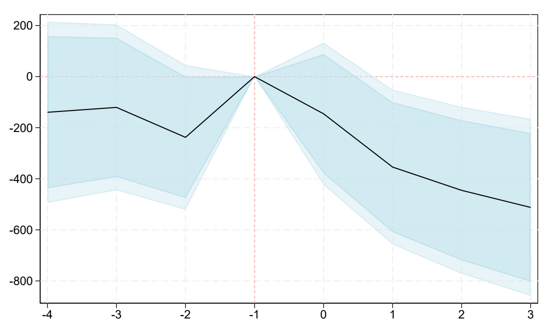
Figure 7 shows the dynamic effect of natural disasters on household post-tax income, wealth and consumption. Each subgraph shows the results for a separate dependent variable. As before, period 0 along the horizontal axis corresponds to the event year. The figure shows that the difference between treated – residents of municipalities affected by a natural disasters – and control households is not statistically different from zero in the years prior to a natural disaster (parallel trends). This validates that our matching method is able to match households that are similar along the relevant dimensions. As shown in panel (a) of Figure 7, the income of treated households declines gradually following the natural disaster and remains depressed in subsequent years. By year 3, the income of treated households is \$446 lower than comparable households in the matched control group, relative to their pre-disaster difference. This suggests that natural disasters have long-lasting effects on income. Panel (b) of Figure 7 shows analogous estimates for household net wealth. Treated households experience an immediate relative decline of \$7,934 in the year of the disaster. The effect peaks in year 2, reaching a maximum gap of \$13,039 for treated households relative to households in the control group.



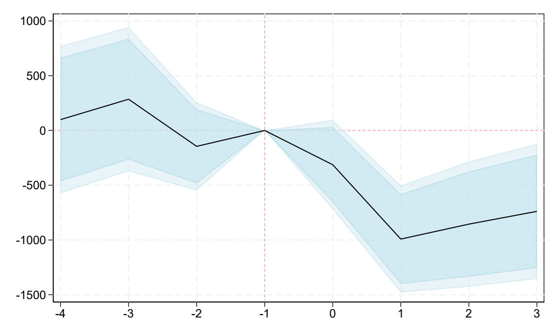
(a) Income After Tax



(b) Net Wealth



(c) Consumption, unadjusted



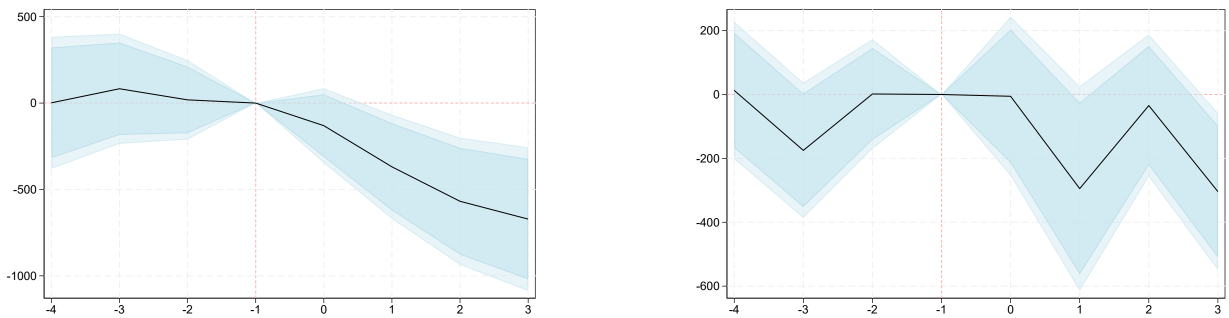
(d) Consumption, adj. for insurance transfers

Figure 7: Effect of natural disasters on income, net wealth and consumption.
Notes: Estimated effects of natural disasters on households. Year 0 is the event year. Real USD in 2018 Prices. Shaded areas show 90% and 95% confidence bands.

Consumption also declines gradually following a disaster, as shown in panel (c) of Figure 7. The fall in consumption largely mirrors the dynamics of income, but the consumption response is even stronger, especially during the first three years. Notably, the cumulative response of income in years 0 – 3 is approximately \$718, while consumption drops by \$1,457. In fact, this likely understates the relative consumption response. The reason is that the dependent variable in Figure 7 (c) includes spending on reconstruction of damaged property for the minority of directly affected households who choose to hire contractors themselves rather than let the insurance company handle the process. Hence, the estimated consumption response is due to a combination of indirect effects and direct effects for a small subset of households. In Appendix Figure A2, we plot estimates of the effect on income and consumption for the subset of households in our sample who receive payments from insurance companies in either year 0 or year 1. While the income response is similar to that in the full sample, the consumption response is substantially smaller in the subsample, in particular in the event year and the following year, suggesting the presence of a positive direct effect. In panel (d) of Figure 7, we plot the estimated response of an alternative consumption measure that adjusts for the transfers from insurance companies to households, which we observe at the household level. The assumption is that all of the additional transfers from insurance companies received by treated households relative to households in the control group in years 0 – 3, shown in Figure 6, are spent on replacing and repairing damaged property. As such, the effect is likely to be an upper bound on the direct consumption response due to a natural disaster. Panel (d) shows that the indirect effect on consumption likely is larger than the total effect shown in panel (c). Together, panels (c) and (d) suggest that the indirect effect on consumption is two to three times as large as the effect on income.

To understand how large the estimated indirect effects of natural disasters on income and consumption are, we can compare them to the direct economic damages measured by the insurance payouts related to natural disasters, shown in Figure 5. The cumulative effect on income over the four post-event years constitutes 16% of the direct damages, while the consumption response constitutes 33% when measured using unadjusted consumption and 46 percent when measured using consumption adjusted for insurance transfers to households.

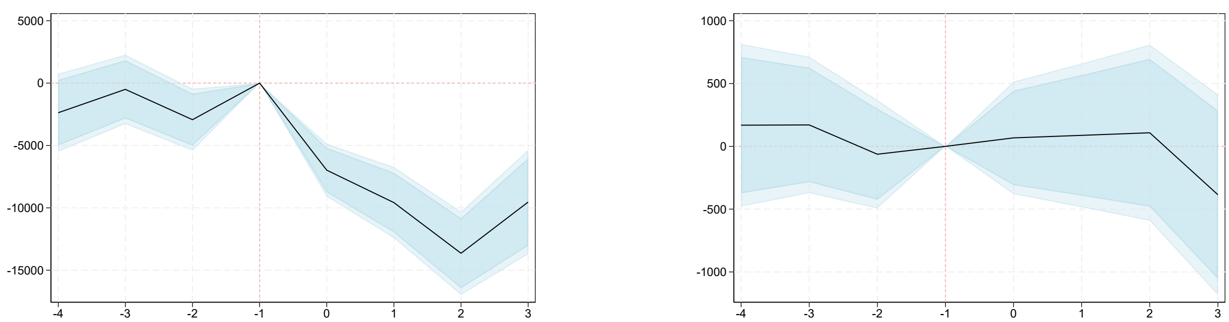
We now consider how the components of income and wealth react following a natural disaster. In Figure 8, we show separately the effect on labor income and capital income. As expected, there is no significant effect on capital income, which consists of dividend payments and interest income. Labor income follows a similar dynamic as total income after tax. However, due to the role of the tax system in cushioning any fall in labor income into disposable income, the former drops by more than the latter. We find no significant effect on the likelihood of being unemployed or being self-employed.



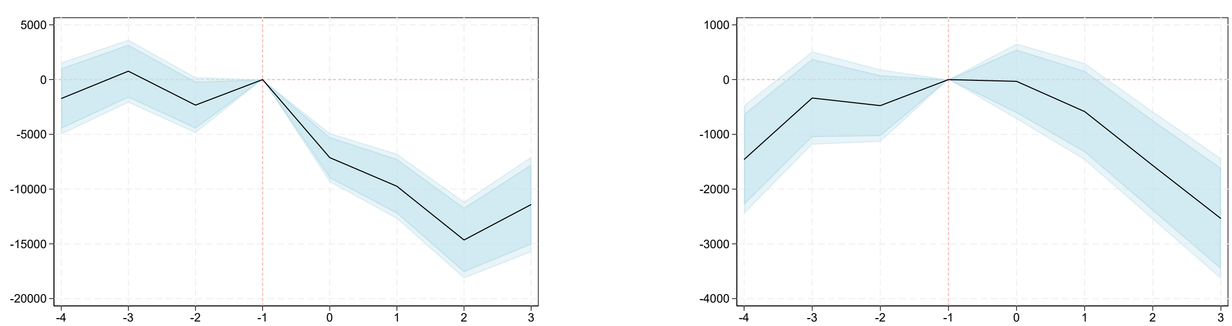
(a) Labor Income **(b)** Capital Income

Figure 8: Effect of natural disasters on components of income.

Notes: Estimated effects of natural disasters on households. Year 0 is the event year. Real USD in 2018 Prices. Shaded areas show 90% and 95% confidence bands.



(a) Housing Wealth **(b)** Financial Wealth



(c) Total Gross Wealth **(d)** Debt

Figure 9: Effect of natural disasters on components of household wealth.

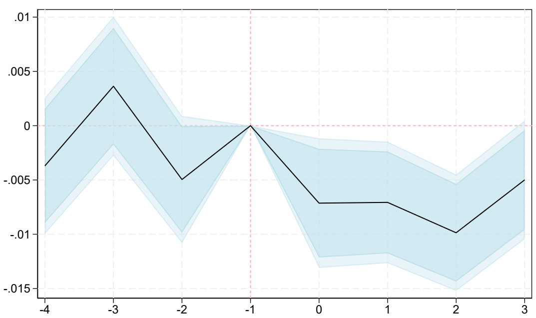
Notes: Estimated effects of natural disasters on households. Year 0 is the event year. Real USD in 2018 Prices. Shaded areas show 90% and 95% confidence bands.

In Figure 9 we show the response of the components of net wealth: housing wealth (a) and gross financial wealth (b) –which together constitute total gross wealth (c)– and debt (d). We find no significant effect on financial wealth, mirroring the result for financial income. Instead, all of the steep fall in gross wealth is due to housing wealth, which falls for treated households relative to non-treated households in the year of the disaster and continues falling in the following two years, reaching a peak effect of $13,641$ in year 2.[3] The fall in housing wealth for treated households is consistent with the findings by Kivedal (2023). Using the same dataset of insurance claims as us, he estimates a negative effect of natural disasters on regional house price indices in Norway.

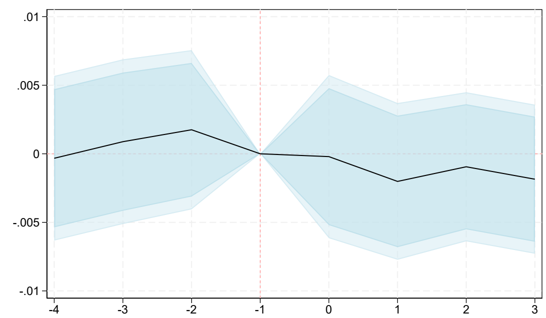
The value of housing wealth held by homeowners in municipalities affected by a natural disaster is determined by a combination of price changes for existing housing and activity in the housing market by the residents of the affected areas. In Figure 10 panel (a)-(b) we plot the effect of natural disasters on the probability of buying and selling new housing, respectively. Treated households buy less new housing following a disaster, with the likelihood increasing by 0.7 percentage points on average for the four post-event years. When we split the sample into existing homeowners and non-owners, we find that this effect is concentrated among owners. We find no significant effect on housing sales for either group. We also consider how the likelihood to relocate either inside the municipality or to a different municipality changes as a result of a disaster.

Table 4 shows estimates of the average treatment effects over the for several outcome variables over the four years following the natural disaster. Column 1 shows the average effects for the full sample, and the sample is split by home-ownership status in columns 4–5. Estimates show that non-owners become significantly more likely to move within their municipality, while homeowners do not. These results are consistent with a lock-in effect for owners whose home loses value as a result of the natural disaster. For instance, Bojeryd (2024) investigates the effect on moving patterns on Norwegian households following a negative regional shock, and finds substantial differences in migration rates between renter and low housing-wealth homeowners, and higher housing-wealth homeowners.

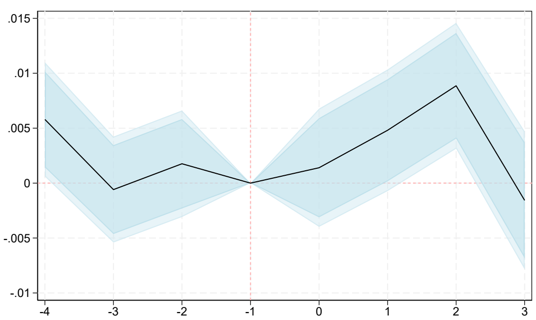
[3]Starting with the 2010 tax year, Statistics Norway implemented a new method for calculating the value of housing for tax purposes. Before 2010, the tax value of a house was based on the price of the house when first constructed, updated annually using a common adjustment factor for all residential properties in Norway. As of 2010, each residential property is assigned its own market value every year, based on predicted values from hedonic regression (size, location, type of house etc.). As explained in Appendix A.4, we adjust the housing values from tax returns using a machine learning algorithm based on all housing transactions to better account for the market value of housing wealth in all years.



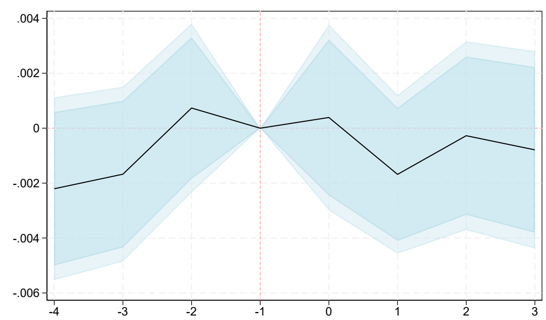
(a) Housing Transactions: Purchases



(b) Housing Transactions: Sales



(c) Moves Within Municipality



(d) Moves to New Municipality

Figure 10: Effect of natural disasters on housing transactions and relocations.
Notes: Estimated effects of natural disasters on households. Year 0 is the event year. Changes in probability. Shaded areas show 90% and 95% confidence bands.

Panel (d) of Figure 9 shows a significant negative effect on debt held by treated households.[4] Treated households who experience a fall in the value of their home might choose to increase savings in order to pay off their mortgage more quickly and hence lower their loan-to-value ratio, or they might choose to take on less new debt tied to new mortgages. The latter is consistent with the fall in purchases of new housing by existing homeowners. The former is consistent with a larger drop in consumption relative to disposable income for treated households.

More generally, we can ask whether the estimated effect on consumption is consistent with the estimated effect on income and wealth for treated households. In the empirical literature, estimated marginal propensities to consume (MPC) out of large, unexpected and temporary income shocks are typically in the range of $20 - 50\%$. For instance, using variation due to

[4]The estimated effect on debt should be interpreted with caution, as we find a significant increase in the debt held by treated households relative to non-treated households in the years prior to a natural disaster.

the onset of unemployment for Norwegian workers, Fagereng et al. (2024) estimate an MPC of 40%. Using this estimate, only around 20% (72$ on average over four years) of the effect on consumption for treated households is due to the effect on income after tax. In order to

Table 4: Average effects of natural disasters

	Baseline	Event Type		Household Type	
Outcome	(1)	Firm event (2)	HH event (3)	Homeowner (4)	Renter (5)
Income after tax	-180**	-361**	-101	-169*	-230
	(87)	(158)	(104)	(100)	(169)
Net wealth	-9550***	-19675***	-5156***	-11047***	-3379
	(1304)	(2397)	(1550)	(1544)	(2171)
Consumption	-365***	-711***	-215	-401***	-232
	(125)	(236)	(148)	(145)	(250)
Labor income	-435***	-695***	-323*	-469***	-313
	(139)	(254)	(166)	(162)	(254)
Capital income	-160*	-244	-124	-199*	-13
	(88)	(165)	(104)	(108)	(100)
Self-employed	0.002	0.005	0.001	0.002	0.002
	(0.002)	(0.003)	(0.002)	(0.002)	(0.005)
Unemployed	-0.001	0.009*	-0.006	-0.002	0.002
	(0.003)	(0.005)	(0.004)	(0.004)	(0.005)
Housing wealth	-9934***	-19348***	-5848***	-11651***	-2906
	(1315)	(2373)	(1578)	(1551)	(2267)
Financial wealth	-31	-228	54	-186	575
	(268)	(505)	(317)	(293)	(649)
Gross wealth	-10730***	-20398***	-6534***	-12329***	-4137*
	(1368)	(2487)	(1635)	(1607)	(2420)
Debt	-1181***	-1134*	-1201***	-1258***	-863
	(381)	(676)	(462)	(441)	(741)
House buy	-0.007***	-0.002	-0.010***	-0.009***	-0.003
	(0.002)	(0.004)	(0.003)	(0.003)	(0.003)
House sell	-0.001	0.000	-0.002	-0.002	0.001
	(0.002)	(0.004)	(0.003)	(0.003)	(0.005)
Move within	0.003	0.006	0.003	0.001	0.011*
	(0.002)	(0.004)	(0.003)	(0.002)	(0.006)
Move out	-0.001	-0.002	0.000	-0.002	0.006**
	(0.001)	(0.003)	(0.002)	(0.002)	(0.003)

Notes: Estimated effects of natural disasters on households. Average effect in year 0 to 3, where year 0 is the year of the disaster. Real USD in 2018 Prices. Standard errors in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

account for the rest of the consumption effect, our estimates imply an MPC out of housing wealth changes of around 3%.[5] This number is in line with the literature on consumption responses to exogenous movements in house prices, which typically find MPCs lower than 5%. For instance, the benchmark estimate by Guren et al. (2021) is 3.3 cents on the dollar. Hence, our estimated consumption response is consistent with the responses of income and wealth. Further underlining the importance of housing wealth for the consumption response, Table 4 shows that while the point estimate of the income response is slightly larger for renters than for homeowners, the consumption response is only about half the size for the former group.

4.3 Firm and household events

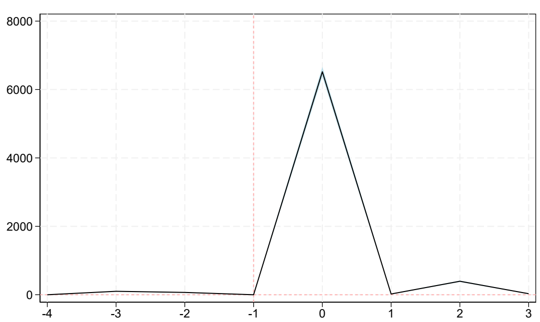
We now split the events by type to explore the economic mechanisms driving our results. Specifically, we divide the sample into events that mostly affected the property of firms and those that mainly affected the property of households, based on the type of insurance policy covering the damage – either business or household insurance. If the fraction of damage covered by business insurance relative to the total damage exceeds 50 percent, the event is classified as predominantly affecting firms, see Appendix A.2.

Columns 2-3 of Table 4 shows that only the former type of events have significant negative effects on income and consumption. In the case of firm events, the effect on income after tax is \$361 on average in the years following an event, while the effect on consumption is \$711. Figure 11 shows that the direct damages covered by insurance are around twice as large – when measured per household in the affected municipalities – for events classified as firm events.[6] However, the indirect effects through income, consumption and wealth are $3-4$ times as large for firm events. In addition, we find that the likelihood of being unemployed increases significantly and sharply for treated households in the year following a firm event. This indicates that these natural disasters affect the labor income of households at least partially through the damage it does to employers in the affected municipalities.

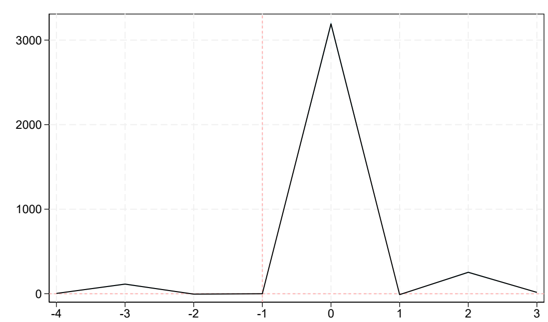
TO BE COMPLETED.

[5]To get to this number, we assume that 40% (72\$) of the average yearly effect on income after tax transmits to consumption. Then the remaining consumption response equals 2.9% of the average effect on housing wealth (0.029×9934).

[6]The insurance payments to households are smaller for the firm events than for the household events.



(a) Firm events



(b) Household events

Figure 11: Insurance payouts per household, firm and household events.

Notes: Estimated effect of natural disasters on insurance payouts related to natural damages, per household in affected municipalities. Year 0 is the event year. Real USD in 2018 Prices. Shaded areas show 90% and 95% confidence bands.

5 Preliminary conclusions

This paper examines the economic impact of natural disasters on households in Norway, a country with a unique universal insurance scheme that provides full coverage for property in the event of natural disasters. Even in this setting, natural disasters generate persistent declines in household income, consumption, and wealth. The income drop reflects sustained reductions in labor earnings, while the wealth effect is driven by steep falls in housing values that induce deleveraging and disproportionately depress consumption among homeowners. Disasters with damages concentrated on firms lead to short-term spikes in unemployment and sharper household losses, revealing the central role of local labor markets.

These findings contribute to debates on the sustainability and design of disaster insurance as natural disasters become more frequent and severe. Internationally, rising insurance costs and reduced coverage in high-risk areas highlight the challenges of maintaining broad protection against climate-related disasters. Norway's insurance scheme substantially mitigates immediate, direct losses, yet significant indirect effects — via depressed local housing markets and reduced labor earnings — remain. This indicates that insurance alone cannot fully protect household welfare in the wake of disasters.

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Appendix

A Appendix

A.1 Robustness of the severity metric

Table A1: Ranking of Natural Events by Different Metrics.

Municipality	**Year**	**Payouts as share of labor income**	**Payouts as share of income after tax**	**Payouts per capita**
Holtålen	2011	1	1	1
Nord-Fron	2013	2	2	2
Lund	2015	3	3	3
Skjåk	2018	4	4	4
Aurland	2014	5	5	5
Værøy	2011	6	8	8
Moskenes	2011	7	6	7
Røst	2011	8	7	6
Lyngen	2010	9	9	12
Nord-Fron	2011	10	10	11
Høylandet	2006	11	12	18
Kvinesdal	2015	12	13	10
Ringebu	2011	13	15	14
Bjerkreim	2015	14	11	9
Vanylven	2011	15	14	13
Flakstad	2011	16	18	19
Værøy	2008	17	16	20
Stryn	2011	18	17	16
Sel	2011	19	19	22

The number of payouts in a municipality in a given year is at least 15.

A.2 Categorizing natural disasters by damage type: Firm- vs. household-related events

Using the insurance payout data from Finance Norway (see Section 2.1), we can differentiate between damages covered by business insurance and those covered by household insurance. We calculate the fraction of damage covered by business insurance relative to the total damage. If this ratio exceeds 50 percent, the event is classified as predominantly affecting firms, and the indicator variable "Firm Damage" is set to 1; otherwise, it is set to 0. Using this method, we identify 8 events as firm-related, with the remaining 11 events classified as household-related, see Table A2.

Table A2: Natural Disasters by Largest Impact: Firm vs. Household Events.

Municipality	**Year**	**Payouts as share of labor income**	**Fraction of Firm-related Damage**	**Firm Damage Dummy**
Holtålen	2011	24.8	0.69	1
Nord-Fron	2013	20.1	0.035	0
Lund	2015	16.7	0.87	1
Skjåk	2018	15.2	0.32	0
Aurland	2014	12.2	0.20	0
Værøy	2011	10.6	0.63	1
Moskenes	2011	10.6	0.43	0
Røst	2011	10.1	0.53	1
Lyngen	2010	8.5	0.021	0
Nord-Fron	2011	7.8	0.17	0
Høylandet	2006	7.2	0.71	1
Kvinesdal	2015	6.8	0.30	0
Ringebu	2011	6.5	0.81	1
Bjerkreim	2015	6.4	0.65	1
Vanylven	2011	6.2	0.44	0
Flakstad	2011	5.45	0.35	0
Værøy	2008	5.09	0.37	1
Stryn	2011	5.08	0.44	0
Sel	2011	5.07	0.30	0

A.3 Identification of natural disaster event dates

Table 1 in Section 3.1 represents a list of natural disasters classified using our proposed Severity Metric for the 30-year period from 1993 to 2023. To determine the exact date of each natural disaster in this Table, we identify the day on which the municipality experienced the highest insurance payouts. From Figure A1, we observe that the spike is clearly centered around 1-2 days.

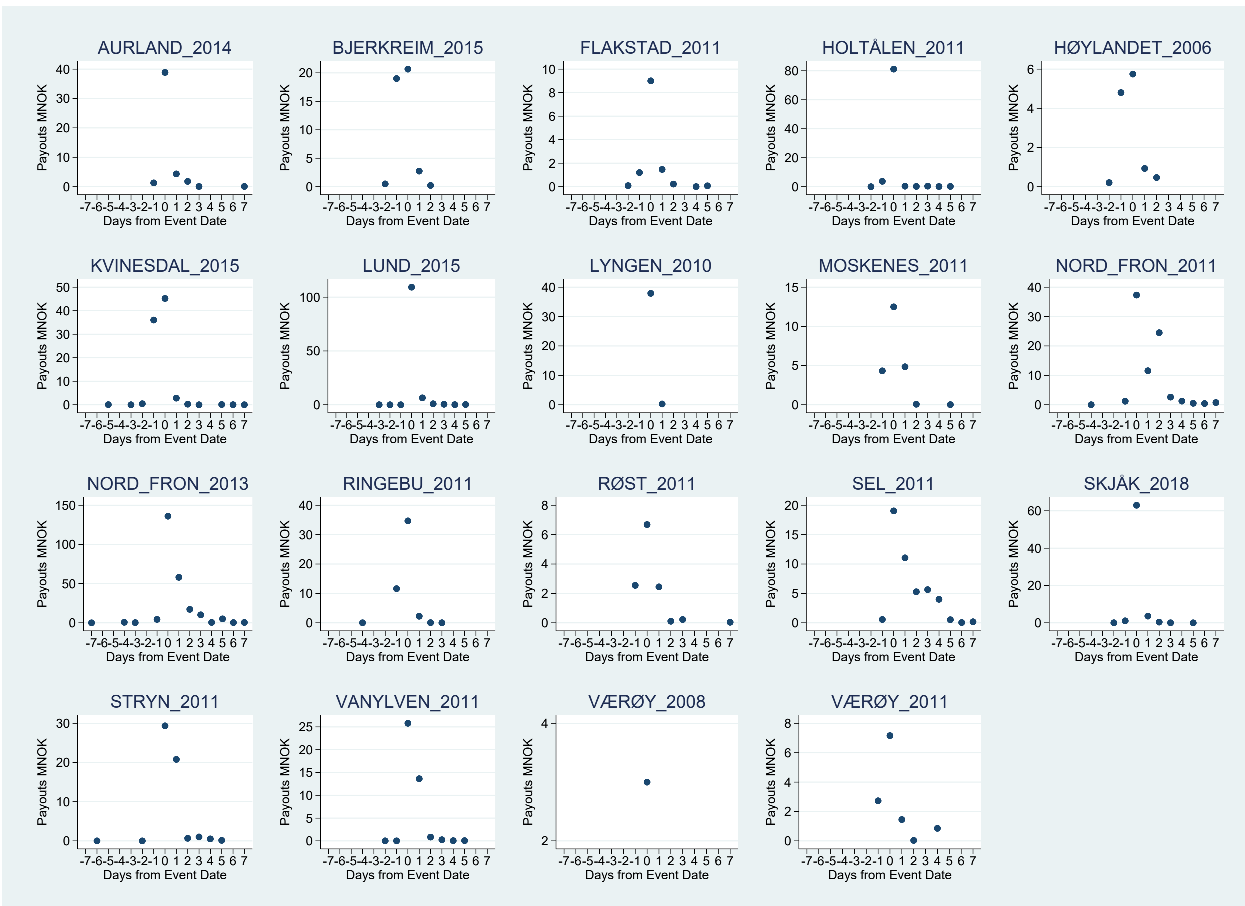
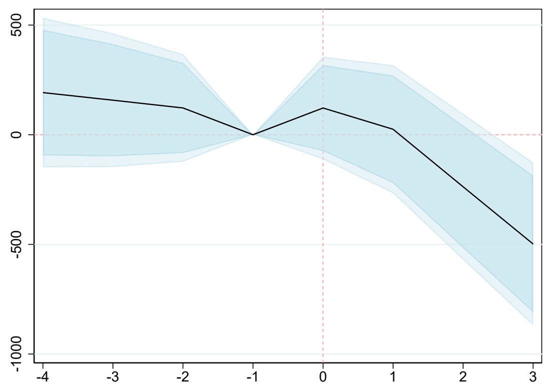


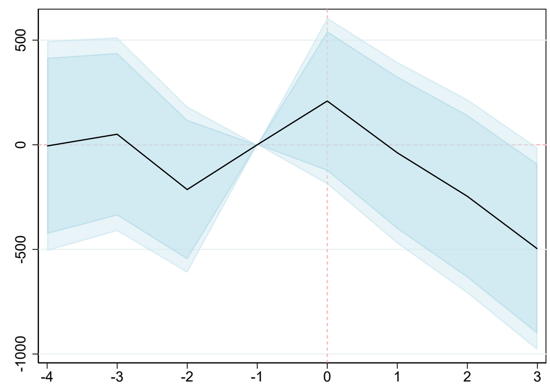
Figure A1: Insurance Payouts Around Event Dates (±7 Days)

A.4 Adjustment of Housing Wealth with Municipal Weights

To correct for the systematic undervaluation of housing wealth in the tax data, we apply adjustment factors that link the tax-assessed values to estimated market values from the machine learning model in Fagereng et al. (2020). For each year and municipality, the ratio of the estimated market value to the reported tax value is computed at the household level. The median of these ratios within a municipality is used as the adjustment weight. Reported housing wealth in the tax data is then scaled by this weight to approximate market values.



(a) Income after tax



(b) Consumption

Figure A2: Insurance payouts per household, firm and household events.

Notes: Effect of natural disasters on income and consumption. Subset of treated households who receive positive transfers from insurance companies in year 0 or 1. Year 0 is the event year. Real USD in 2018 Prices. Shaded areas show 90% and 95% confidence bands.