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

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Abstract

We estimate the economic effects of natural disasters using comprehensive Norwegian administrative data on household income, wealth, consumption, housing transactions, and relocations. The existence of universal and full insurance coverage against direct damages from natural disasters in Norway allows us to obtain clean estimates of the indirect effects of the disasters. Our findings show that natural disasters have an indirect negative and persistent effect on labor income and consumption driven by economic damages to local firms. Affected households compensate for their loss in income by increasing self employment. Housing wealth, housing purchase transactions, and debt levels fall for homeowners. Moreover, non-homeowners become more likely to relocate after a disaster.

JEL classification:
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1 Introduction

As climate change intensifies, extreme weather events are becoming an increasingly urgent global concern. These events pose not only environmental risks but also significant economic challenges, particularly affecting those residing in regions that experience a natural disaster. Projections indicate that extreme weather events will continue to increase in both frequency and severity, further complicating the economic landscape that households must navigate. Understanding the economic implications is essential, as it will provide policymakers with insights into the potential macroeconomic and distributional effects of climate change.

This paper uses rich and extensive data from Norway to explore the economic impact of natural disasters on households under full insurance. Focusing on Norway allows us to disentangle the direct and indirect economic effects. While the direct effects include damages to real estate and other physical assets directly caused by the events, the indirect effects extend beyond the directly impacted households, influencing broader economic factors such as local labor markets, savings behavior, and regional economic development. The Norwegian insurance scheme is universal, mandatory, and provides nearly full coverage with minimal deductibles, ensuring that direct damages are largely compensated. This unique institutional setting enables us to credibly isolate the indirect effects on various economic outcomes.

We start by introducing a municipality-level severity metric for natural damages, which allows us to systematically classify the most severe weather events (or "natural disasters") that occurred in Norway between 1993 and 2023. Given Norway's universal insurance coverage, we leverage detailed and comprehensive records of insurance payouts related to natural disasters, which are not subject to the selection bias seen in other countries with varying levels of coverage. As a result, this data provides a reliable measure of the immediate economic impact, and allows us to accurately identify the events that caused the largest economic damage. Moreover, this approach enables us to examine a broader range of smaller-scale events, which can provide insights into more frequently occurring extreme weather events. This is in line with the methodologies used by Tran and Wilson (2023) and Boustan et al. (2020), but contrasts with studies focusing on a single large event, such as the Hurricane Katrina in 2005 (Deryugina et al., 2018) or the 2004 Indian Ocean Tsunami (Frankenberg et al., 2023).

Secondly, we combine this classification with administrative records for the entire Norwegian population to examine the effects of natural disasters on households living in the affected areas. We construct a dataset that contains high-quality information on a broad

range of variables, including income, wealth, geographic location, property transactions, and labor market outcomes, at a yearly frequency from 2006 to 2018. This gives us a good understanding of how households are affected. Additionally, we have at hand data on electronic transactions which, due to Norway's near-cashless economy, provides an ideal basis for studying household consumption (Aastveit et al., 2020). This allows us to explore the effects on consumption behavior of affected households, thereby contributing to the existing literature on the economic impacts of climate-related events, which has until now seen limited focus on consumption due to data limitations.

To identify the effect of natural disasters, we treat the most severe weather events as natural experiments and compare the economic outcomes of households residing in a municipality hit by an extreme weather event to similar households in a municipality of comparable size (in terms of population) that was not affected. To ensure comparability between households, we follow Fagereng et al. (2024) and employ a high-dimensional near-neighbour matching method built on a coarsened matching approach that incorporates both exact and interval matching. To estimate the effects of the natural disasters on households, we use a difference-in-difference methodology which allows for staggered treatment.

Our results indicate that affected households experience a persistent decline in both income and consumption following a disaster. The indirect effect on income accumulated over the 4 years following a disaster is around 720 USD, in 2018 constant prices. This corresponds to approximately 20 percent of the direct damages that a household in an affected municipality on average experiences. While the direct consumption response is positive for households that receive insurance payouts and must spend on reconstructing damaged objects or replacing items, the indirect consumption response is negative – amounting to approximately 2000 USD over four years, about 2.8 times the income response. Our results suggest that this is due to households paying down existing debt more quickly or taking on less new debt, likely driven by increased uncertainty and more precautionary saving behavior.

While affected households become more likely to move to a different location both inside and outside the affected municipality, this effect is limited to non-homeowners. We further uncover that the effects on income and consumption are concentrated among homeowners, while results for non-homeowners are both smaller and not statistically significant. The lower disposable income is due to a drop in labor income. Furthermore, we find that homeowners are less likely to buy a house, and that their debt level drops following the disaster.

Moreover, the insurance payout data distinguish between various types of policies. This

enables us to assess whether the events primarily impacted households or firms. Our findings indicate that the negative effects on income and consumption are concentrated in events where damages were most severe for firms, and we observe a short-term increase in unemployment benefits. While we also observe a decline in income following events primarily affecting households, this effect is not statistically significant.

Despite Norway's extensive insurance scheme, our results indicate that households are significantly affected by natural disasters. As the household finance literature highlights, liquidity constraints, precautionary savings motives, and borrowing limitations can prevent households from maintaining their consumption levels after a shock (Blundell et al., 2008). In our case, these challenges are further compounded by increased debt repayments by households, likely declines in housing wealth, and adverse impacts on their employers. While damages to property and other physical assets are fully insured, the coverage does not extend to reductions in labor income or declines in housing values. Consequently, households experience consumption declines due to broader economic repercussions that follow a natural disaster.

The natural damage insurance scheme is characterized by broad public support, yet it has been criticized for failing to incentivize individuals to adapt after experiencing a disaster and referred to as "the world's biggest complacency trap" (Gjuvsland, 2014). On one hand, it is possible that the economic effects following a natural disaster are not substantial enough to prompt relocation. On the other hand, our results on housing purchases and relocations align with a lock-in effect for homeowners whose home loses value (Bojeryd, 2024), which may counteract any incentives to move.

Our estimates likely represent a lower bound of the economic impacts given the insurance scheme in place, as the effects on households would be expected to be more severe in contexts with less inclusive insurance. This underscores the critical role of insurance in mitigating the economic consequences of climate-related events and emphasizes the importance of policy frameworks in ensuring financial stability for 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

[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.

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. 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, such as real estate and movable property, insured against fire damage is also covered for natural damage, provided that the damage is not covered by another insurance policy. Fire insurance is typically included in standard home insurance policies, which are held by the vast majority of homeowners. The natural damage insurance scheme is administered by the Norwegian Natural Perils Pool (NASK), which all insurance companies providing fire insurance are required to join. These companies accumulate funds to compensate policyholders when natural damage occurs. Since data collection commenced in 1980, the program has undergone minimal changes, making the figures representative for the entire period (Finans Norge, 2024). Natural damage is defined in the Natural Damage Compensation Act Section 4, and is understood as damage directly caused by a natural disaster, such as flood, landslide, storm, storm surge, earthquake or volcanic eruption.

The premium is uniform across the country, regardless of geographical location or exposure to extreme weather risks, and is calculated as a per mille rate of the fire insurance sum, currently set to 0.07 (updated annually). This uniform pricing is based on the principle of solidarity, a core aspect of the scheme since its introduction in 1980, ensuring that the risk associated with natural damage is distributed among all residents of the country. In contrast, many other countries require individuals to purchase separate natural disaster insurance, and coverage is sometimes unavailable in high-risk areas.

The natural disaster insurance also extends to companies that have insured property or other objects against fire damage. Any physical items such as machines, tank farms, and other similar assets, that are covered under an asset insurance policy for fire damage are also automatically insured against natural damage, with some exceptions. Neither households nor companies are insured against damage on objects such as motor vehicles or boats, which are not covered under this scheme but may be protected by regular insurance. If there is no regular insurance coverage for the damaged property, one may apply for government natural damage compensation. Examples of areas and objects that can be covered by the state compensation scheme include agricultural land, forestry land, roads, bridges, and concrete quays (Landbruksdirektoratet, 2023).

2 Data

The project utilizes 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. Additionally, we use 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 individual consumption patterns. Together, the datasets enable a thorough examination of household economic outcomes in response to natural disasters.

2.1 Insurance Payout data

This dataset is provided by Finance Norway and contains comprehensive 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 insurance claim occurrence, along with the total compensation amount paid by the insurance company, including paid compensations and provisions for damages that have occurred and been reported. 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 will allow us to determine which sectors of the economy have been 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 that experience a natural disaster. To identify these municipalities, we introduce 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

The first contribution of this paper is to obtain a systematic classification of all natural disasters that occurred in Norway between 1993 and 2023. We base this classification 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

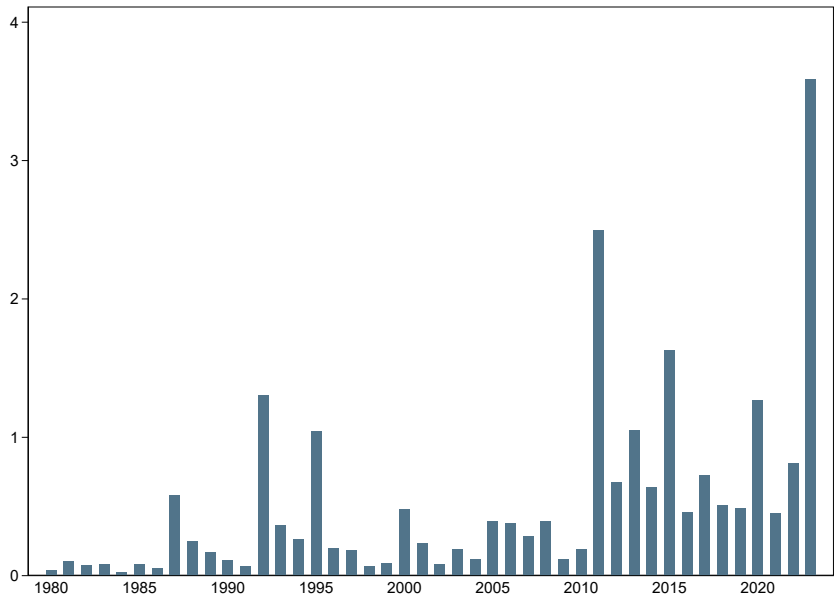


Figure 1: Insurance Payouts Due to Natural Disasters (1980 – 2023). Billions of NOK.

trend has also been highlighted by other sources, e.g., Finans Norge (2024).

To construct the severity metric, we begin by calculating the sum of insurance payouts due to natural damages for each municipality and year. We then normalize the insurance payouts by total labor income in the municipality, providing 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, as this would disproportionately emphasize areas with high population density, such as cities. The severity metric is robust when we normalize using income after tax (which includes pension payments) or consider insurance payouts per capita, underscoring the reliability of our chosen approach, see Appendix 6.1.

We classify that a municipality is hit by a natural disaster in a given 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 municipality-

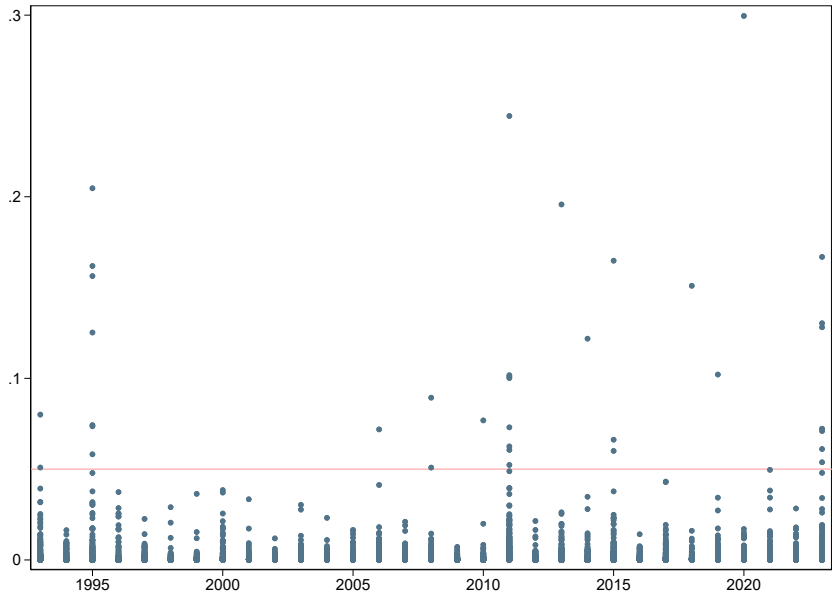


Figure 2: Scatterplot of Total Insurance Payouts as a Share of Labor Income (1993–2023).

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.

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.

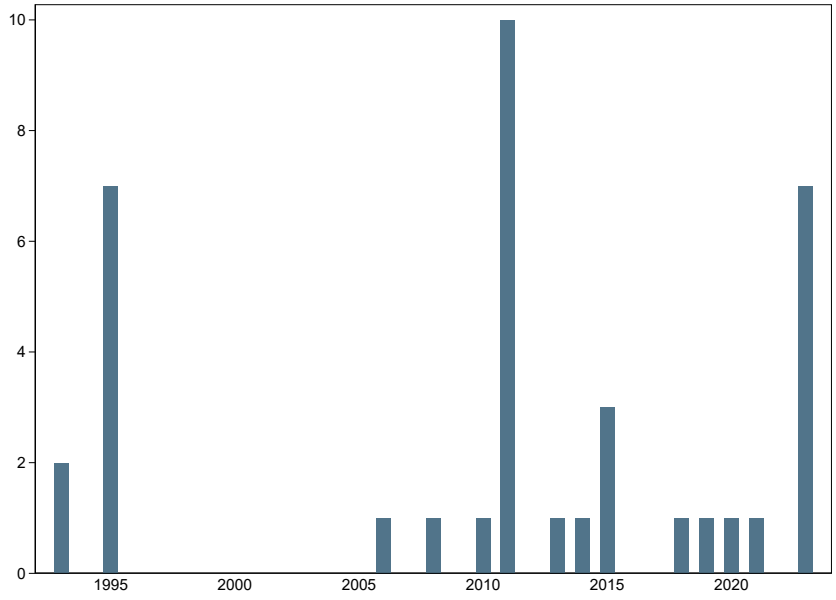


Figure 3: Number of Natural Disasters in Norway 1993-2023

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, jord- og leirskred
19	Flakstad	1993	Feb 03rd	8.0	Storm
20	Nord-Fron	2011	June 10th	7.8	Flood, storflom
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, "flommen i Nord-Trøndelag"
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, storflom
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

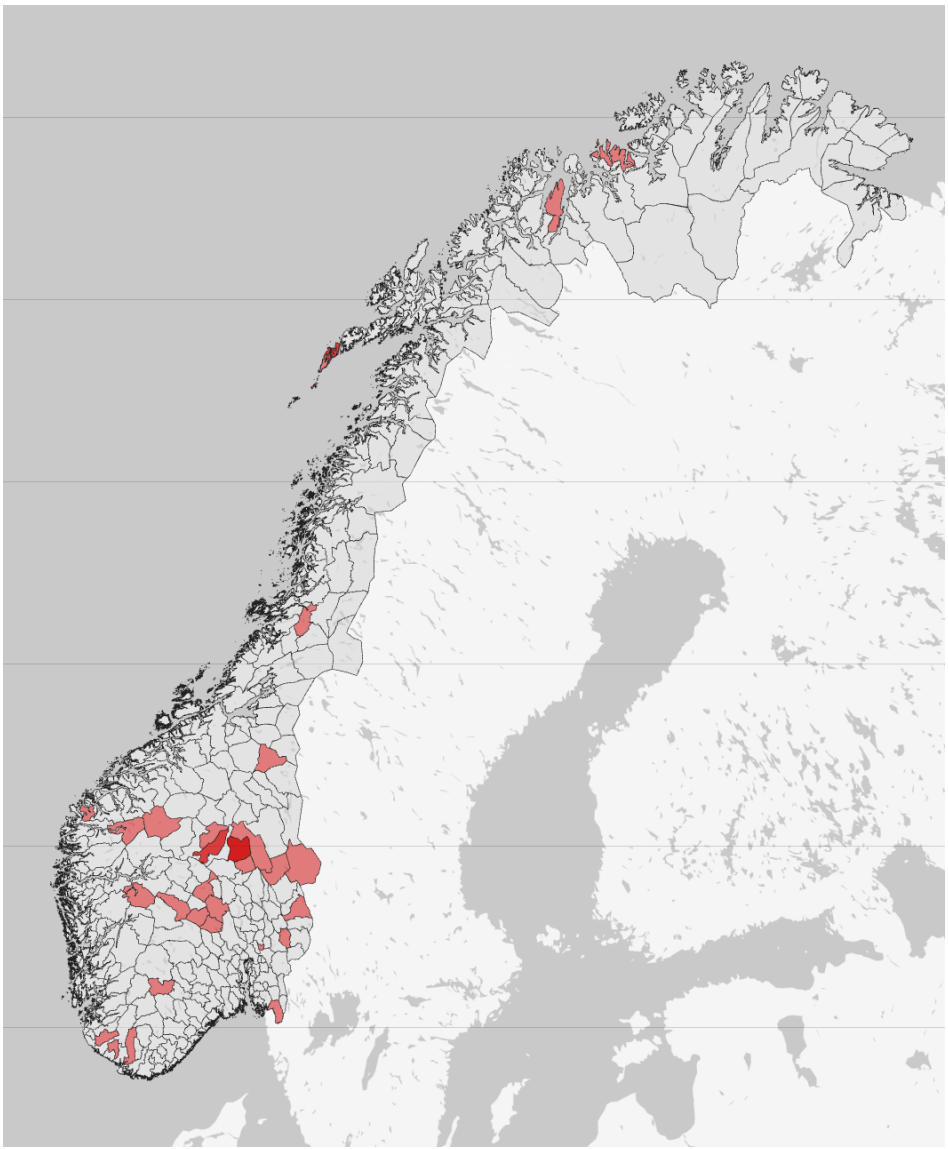


Figure 4: Map of Natural Disasters in Norwegian Municipalities (1993–2023)

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 above 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 limits our sample to 19 events. Table 2 present 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). It is important to note that while the average population in the not affected group is notably higher, this is primarily due to the inclusion of larger cities – 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 in stead 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 com-

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.

parable when excluding the years in which the natural disaster occurred (see Total Payouts 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 (see Appendix XXX), 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 here 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

[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.

degree (coded as 3), and those with a master's degree or higher (coded as 4). When matching, 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 $\pm$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 natural disaster 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

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).

households and 84 645 unique controls. Table 3 contain summary statistics of the final 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, several alternative matching strategies have been tested, see 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

In Figures 5-9 we present our main estimation results for the matched sample of households. Shaded areas show 90 and 95 percent confidence intervals. Each subgraph corresponds to a separate dependent variable, and period 0 along the horizontal axis corresponds to the event year. As explained in Section 3.3, we normalize the effect on treated households to be zero in the year prior to the event. For most outcome variables, the difference between treated, i.e residents of municipalities affected by a natural disasters, and control households is not statistically different from zero prior to the event. This validates that our matching method is able to match households that are similar along the relevant dimensions.

4.1 Confirming Treatment Assignment

Figure 5 provides clear evidence that the treatment effectively captures affected households. The panel illustrates transfers from insurance companies to households, showing a marked increase following the natural event. This indicates that insurance payouts were concentrated among impacted households. These patterns provide a robust validation of our empirical design. The sharp rise in insurance payouts confirms that treated households were indeed affected, supporting our classification in distinguishing between impacted and non-impacted households. Since treatment is assigned at the municipality level, this confirmation is par-

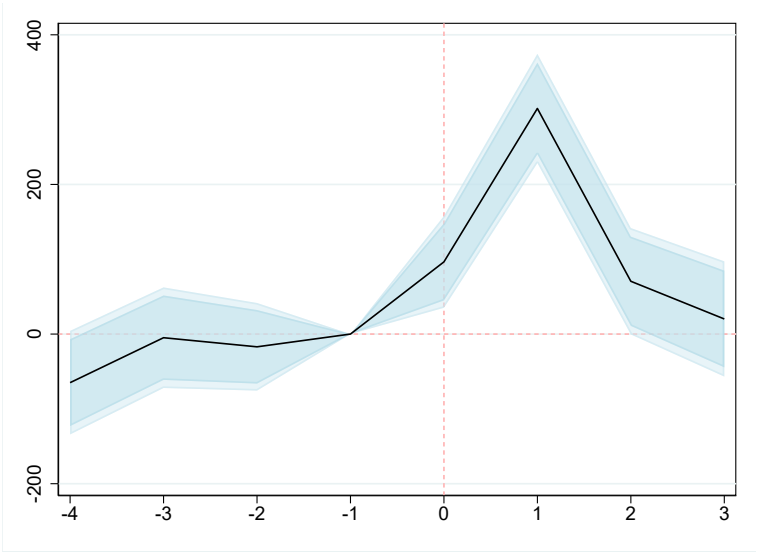


Figure 5: Validation of treatment. Transfers from insurance companies to households, Real USD in 2018 Prices.

ticularly important, reinforcing the credibility of our identification strategy before moving to further analyses.

It is important to note that households facing severe damages to their homes will most often allow the insurance company to handle contractors and oversee the entire reconstruction or repair process. In such cases, the transfers do not appear in household-level data, as the insurance company directly pays the contractors for the work performed. This is a common practice for larger damages, although households have the option to receive the payouts themselves. For smaller damages, it is more common for insurance payouts to be transferred directly to households, as reflected in Figure 5. This explains why the amount we observe here peaks at 300 USD, while average payouts per household in affected municipalities are approximately 4,000 USD, see Figure 6. It also makes sense that we see a peak in average insurance payouts in year zero, as it is the date of damage occurrence that is recorded, while the actual transfers from insurance companies typically follow with a lag of about one year when they are deposited into the household's account.

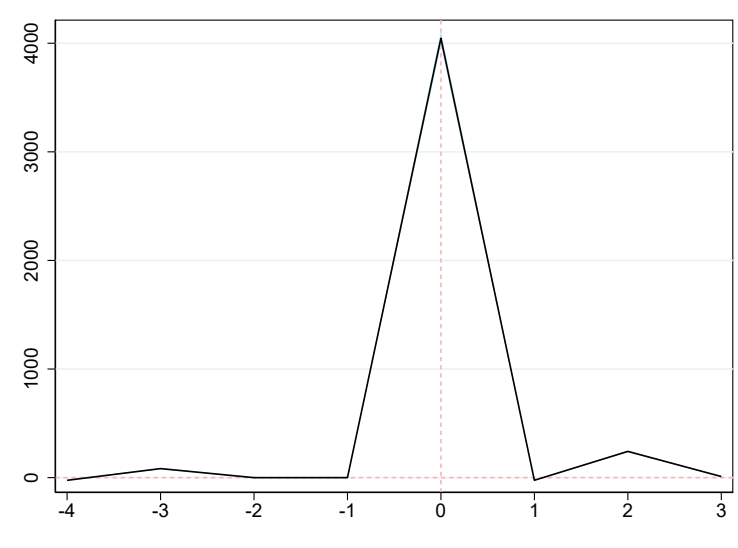


Figure 6: Insurance Payouts per Household, Real USD in 2018 Prices.

4.2 Main results

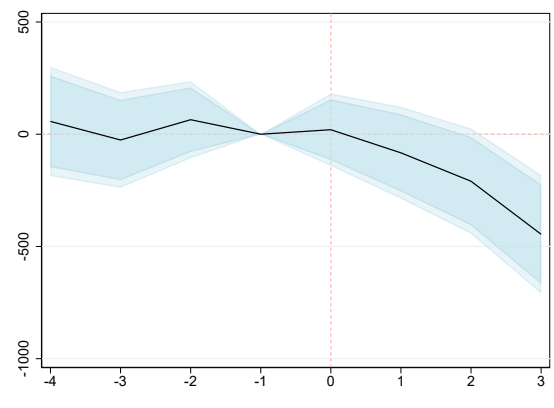
We first present the effect of natural disasters on household income and labor market participation. As shown in panel (a) of Figure 7, household income drops in the year of the disaster and continues to fall during the subsequent three years. This suggests that natural disasters have long-lasting effects on income. As shown in panel (b), labor income falls by

even more than total income. Part of the reason is that self-employment income increases, although this effect is not statistically significant from zero. At the same time, panel (d) shows that we find no significant effect on unemployment, suggesting that most of the labor income effect is on the intensive margin.

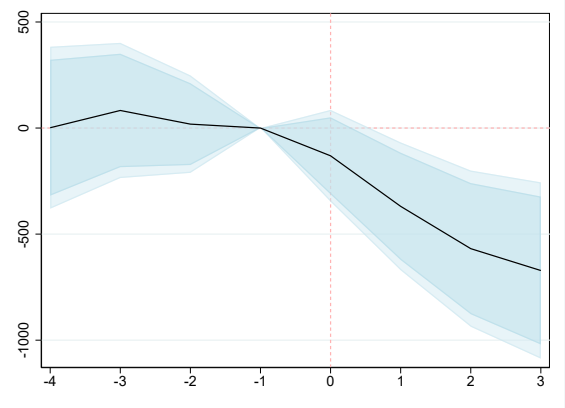
As shown in panel (e) of Figure 7, consumption drops in the year of the disaster and continues to fall in the subsequent three years. The fall in consumption largely mirrors the dynamics of income, but consumption responds even stronger to the natural disaster, especially in the first three years. Notably, the cumulative response of income in years $0-3$ is approximately 720 USD, while consumption drops by around 1460 USD. In fact, this likely understates the relative consumption response. The reason is that the dependent variable in Figure 7 (e) includes spending on reconstruction of damaged property for those households who choose to hire contractors themselves rather than let the insurance company handle the process. Hence, the consumption response in panel (e) is a combination of indirect effects and direct effects for a (small) subset of households. To get a back-of-the-envelope number for how much consumption excluding reconstruction falls, we can assume 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 5, are spent on reconstruction. That gives an additional cumulative fall in consumption of 490 USD. Hence, panel (f) estimates the indirect consumption response, suggesting that the real indirect consumption effect is as strong as 2.8 times the income response.

What might account for a larger response of consumption than income for treated households? To answer this question, in Figure 8 we show the response of total net wealth as well as its sub-components: gross financial wealth, debt and housing wealth. First consider financial wealth. As shown in panel (a), we find no effect on gross financial wealth such as deposits and securities. On the other hand, treated households reduce their stock of debt gradually following the disaster, with a peak yearly effect of close to 3400 USD in year 3. This debt response, shown in panel (b), is qualitatively consistent with a stronger effect on consumption than income, with treated households either paying down existing debt more quickly or taking on less new debt.

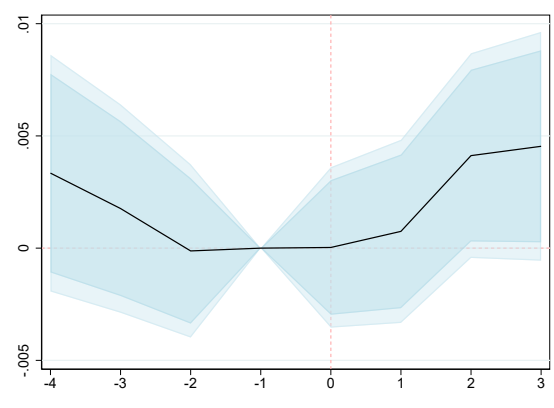
In panel (c) of Figure 8 we show the estimated response of housing wealth, which appears to fall by around 4490 USD within the year of the disaster and ends at 12000 USD in year 3. However, we also find a large difference in the path of housing wealth for treated and control households one year *prior* to the disaster. This is due to a particular problem with



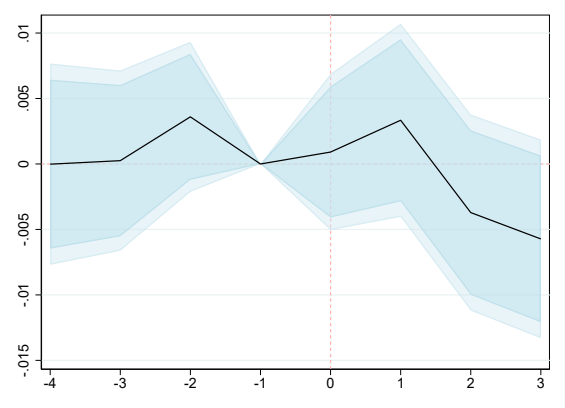
(a) Income After Tax



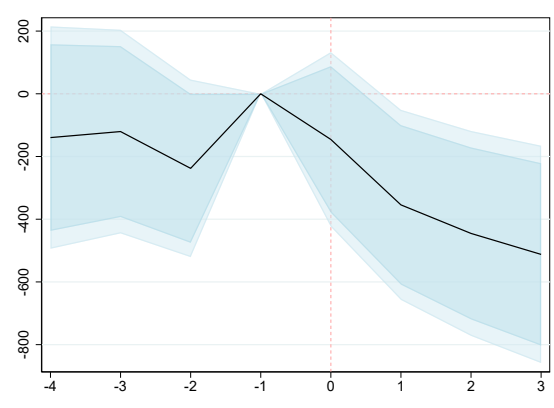
(b) Labor Income



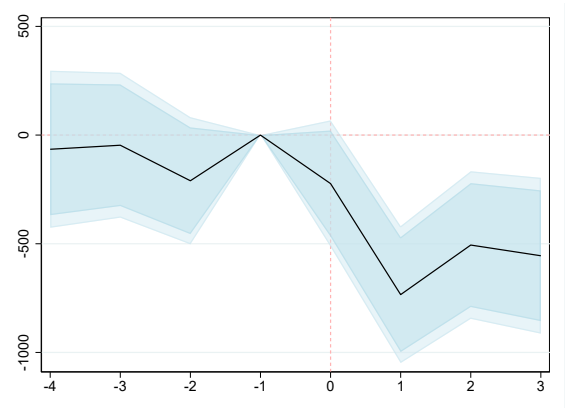
(c) Self Employment



(d) Unemployment

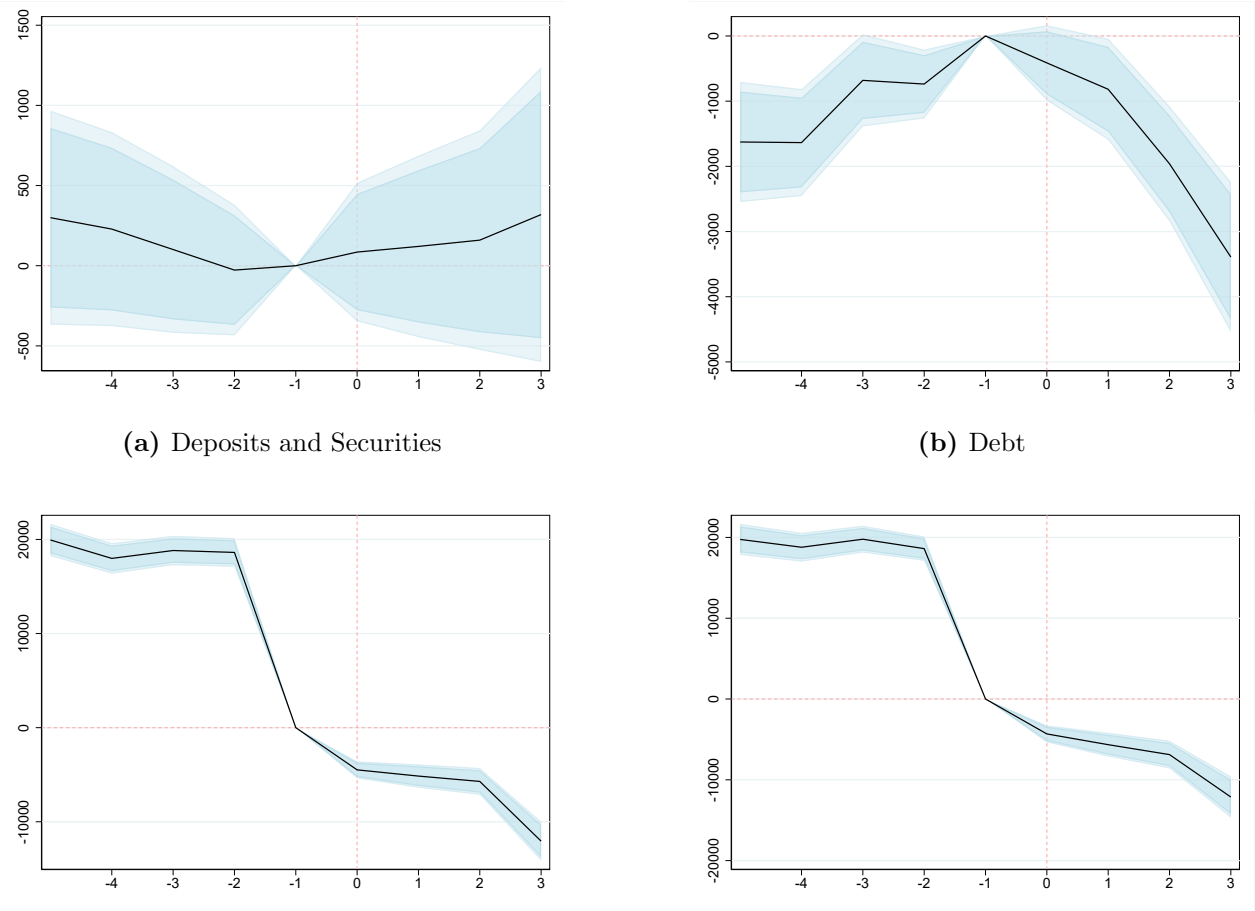


(e) Total Consumption



(f) Total Consumption excl. Insurance Transfers

Figure 7: Income Variables and Total Consumption, Real USD in 2018 Prices.



(a) Deposits and Securities

(b) Debt

(c) Housing Wealth

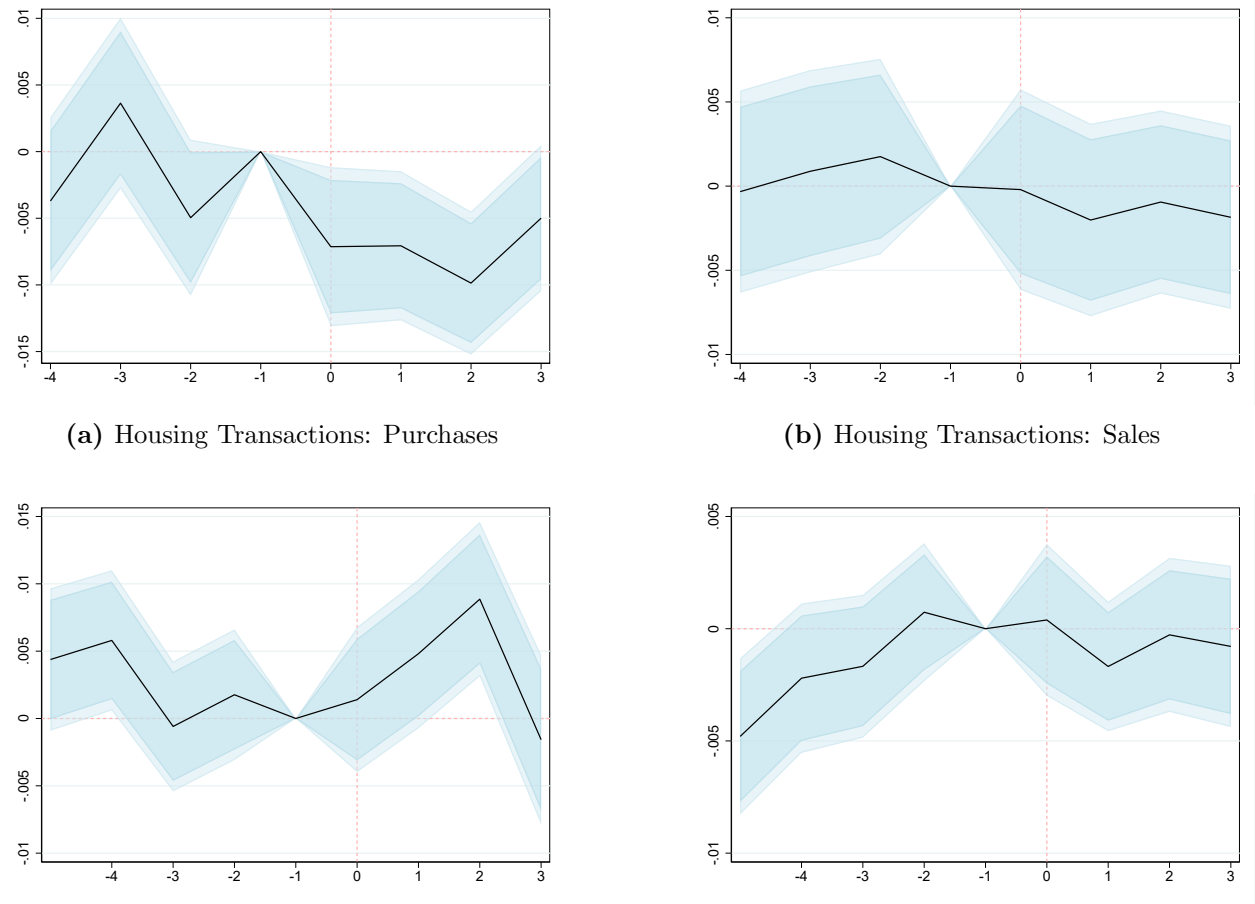
(d) Total Gross Wealth

Figure 8: Wealth Variables, Real USD in 2018 Prices.

the measurement of housing wealth in our dataset. As shown in Figure 3, the majority of the natural disasters in our dataset occur in year 2011. 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 annualy using a common adjustment factor for all residential properties in Norway. As of 2010, each residential property is assigned an its own market value every year, based on predicted values from hedonic regression (size, location, type of house etc.). Despite matching on total wealth, households in the control group on average had housing wealth that was classified as having a relatively higher value after the reform, compared to households in the treated group.

Despite this problem in our dataset, there are two reasons to expect the relative fall in housing wealth for treated households between year -1 and the subsequent years to be

credible. First, using the same dataset of insurance claims as us, Kivedal (2023) estimates the effect of natural disasters on regional house price indices, which are not subject to the same valuation issues. This particular study finds negative short run effects from natural disasters such as storms and storm surges, and negative long run effects from landslides. Second, the fall in housing wealth for treated households is consistent with the response of debt and to consumption relative to income. Treated households who experience a fall in the value of their home, potentially due to a perceived higher risk of living in an area that has recently been affected by a natural disaster, might choose to cut consumption in order to pay off their mortgage more quickly in order to lower their loan-to-value ratio, or they might choose to take on less new debt. To explore the latter effect, we estimate how the natural disasters affect the likelihood of transacting in the housing market, see Figure 9. Treated households



(a) Housing Transactions: Purchases

(b) Housing Transactions: Sales

(c) Moves Within Municipality

(d) Moves to New Municipality

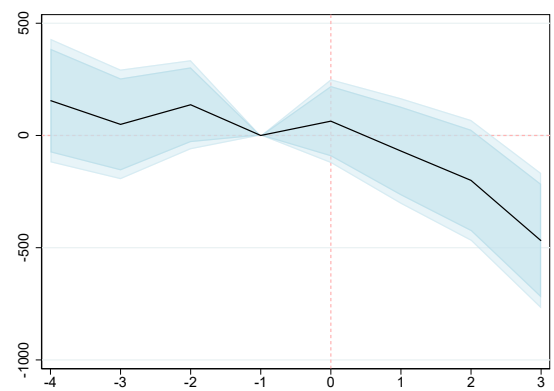
Figure 9: Housing Transactions and Relocations, Real USD in 2018 Prices.

buy less new housing following the disaster, while we find no effect on housing sales.

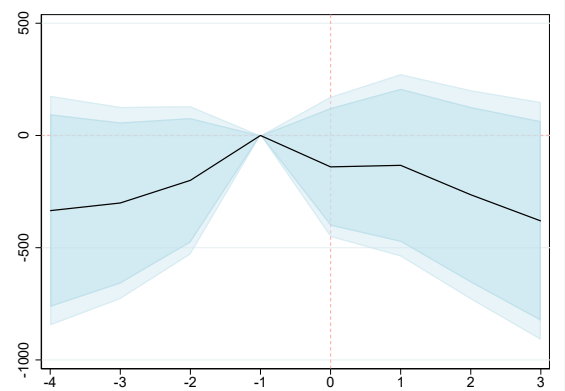
Next, we split the sample into homeowners and non-owners. This allows us to explore further to what extent transmission happens through the housing market by lowering the value of housing in affected areas. The results are shown in Figure 10. While a small sample of non-owners means that the estimated effects for this group are mostly not statistically different from zero, our point estimates indicate that the consumption response is smaller than the income response for non-owners and larger than the income response for owners. The income response is similar across the two groups. We also find no effect on the debt of non-owners. These results are consistent with the strong consumption response in Figure 8 being mostly driven by homeowners lowering their stock of debt.

In Figure 11, we show the responses of the likelihood to relocate either inside the municipality or to a different municipality. We find 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.

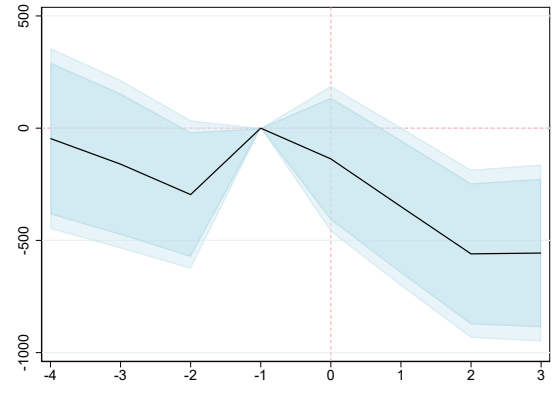
We now split the events by type. Specifically, we divide the sample into events that mostly affected the property of firms and those that mainly affected the property of households, based on the type of insurance policy covering the damage – either business or household insurance. If the fraction of damage covered by business insurance relative to the total damage exceeds 50 percent, the event is classified as predominantly affecting firms, see Appendix 6.2. Strikingly, Figure 12 shows that only the former type of events have significant negative effects on income and consumption. For firm damage events, income drops by 1500 USD cumulatively over years $0-3$, while consumption drops by 2900 USD. In addition, we find that the likelihood of being unemployed increases significantly and sharply in the year of the disaster and the subsequent year for events affecting firms. This indicates that natural disasters mainly affect the labor income of households through the damage it does to employers in the affected municipalities.



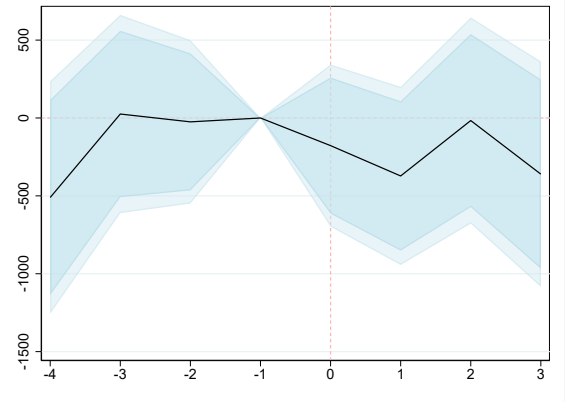
(a) Homeowners: Income After Tax



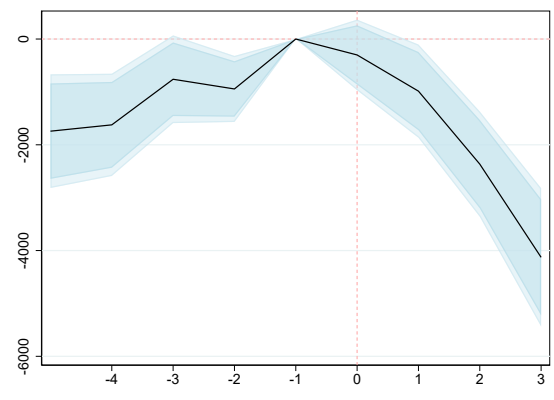
(b) Non-owners: Income After Tax



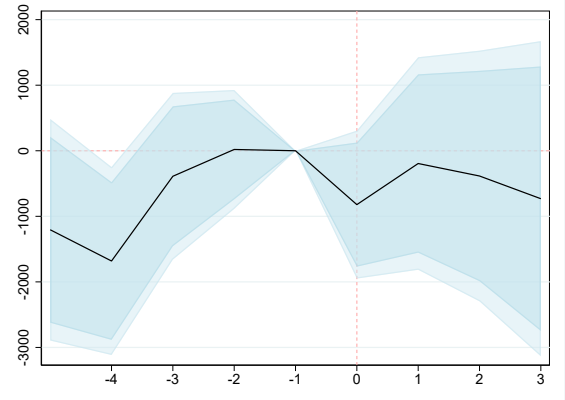
(c) Homeowners: Total Consumption



(d) Non-Owners: Total Consumption

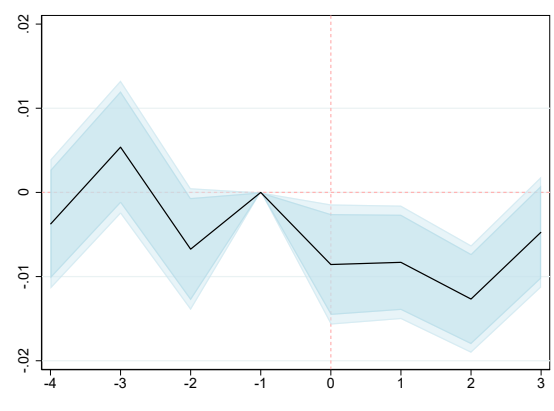


(e) Homeowners: Debt

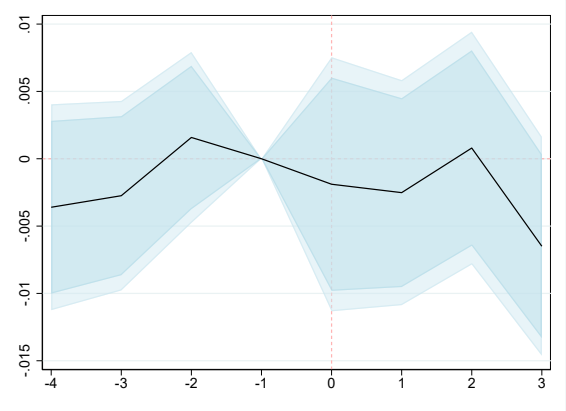


(f) Non-owners: Debt

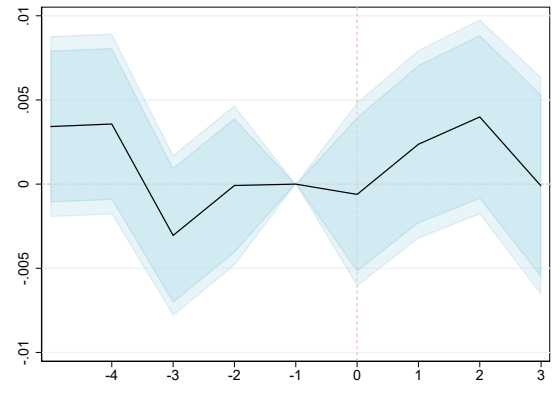
Figure 10: Homeowners vs Non-owners: Income After Tax, Total Consumption and Debt, Real USD in 2018 Prices.



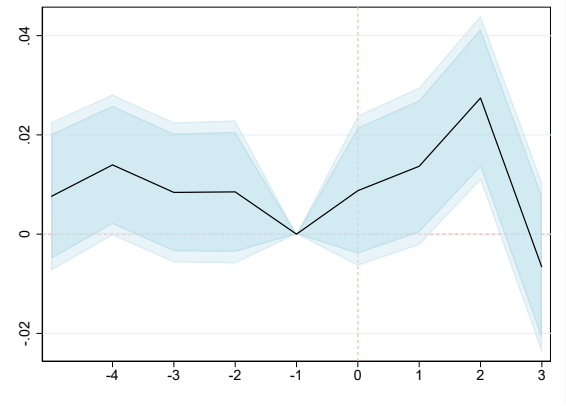
(a) Homeowners: Housing Purchases



(b) Non-Owners: Housing Purchases

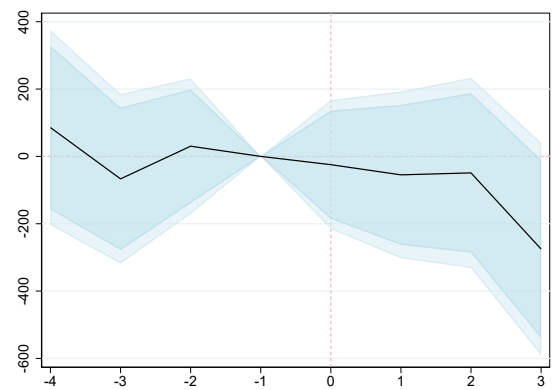


(c) Homeowners: Moves Within Municipality

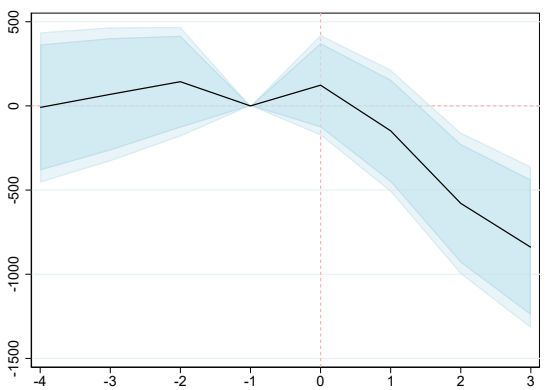


(d) Non-owners: Moves Within Municipality

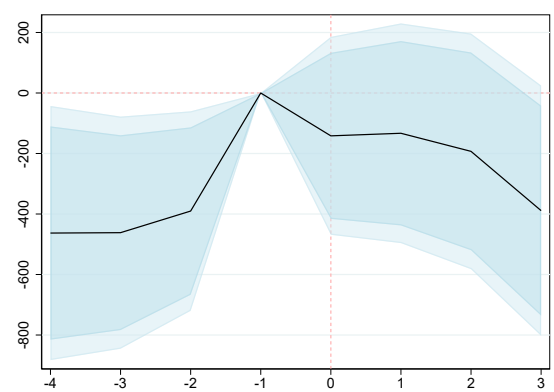
Figure 11: Homeowners vs Non-owners: Housing Purchases and Relocations, Real USD in 2018 Prices.



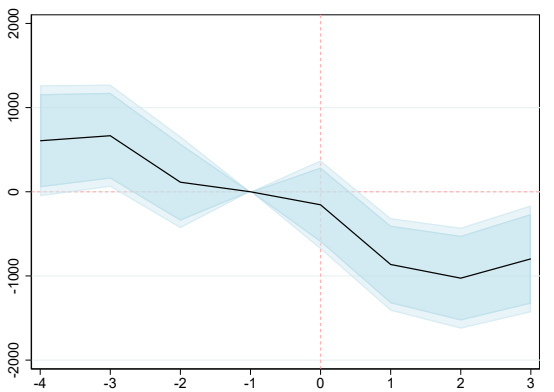
(a) Household Damage: Income After Tax



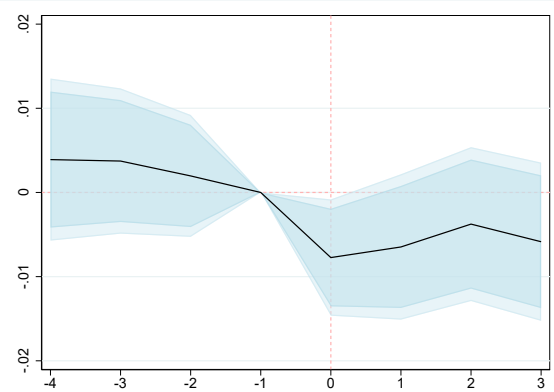
(b) Firm Damage: Income After Tax



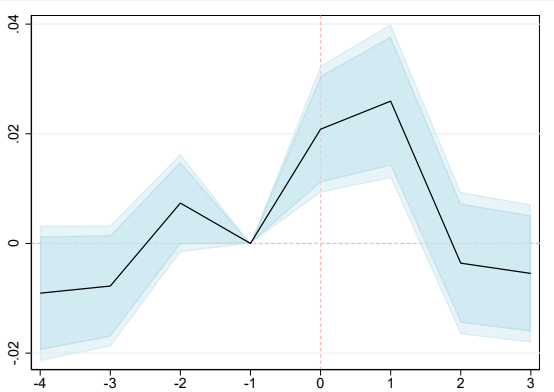
(c) Household Damage: Total Consumption



(d) Firm Damage: Total Consumption



(e) Household Damage: Unemployment



(f) Firm Damage: Unemployment

Figure 12: Household vs Firm Damage: Income After Tax, Total Consumption and Unemployment, Real USD in 2018 Prices.

5 Preliminary conclusions

This study 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, including real estate and personal belongings, in the event of natural disasters. Leveraging extensive administrative and insurance data, we analyze both direct and indirect effects of natural disasters on household income, consumption, labor market outcomes, and mobility. Our findings indicate that affected households experience a decline in income and consumption, particularly among homeowners, with the reduction in disposable income primarily driven by lower labor earnings. Additionally, affected households are less likely to buy a house and experience a decrease in debt levels. While relocation is more common following a disaster, this effect is concentrated among non-homeowners.

A key insight from our analysis is that the negative economic effects are most pronounced when firms, rather than households, are most exposed to damages. In these cases, there are signs of an increase in short-term unemployment benefits.

Despite these effects, the overall economic impact appears moderate, due to the mitigating role of Norway's comprehensive insurance system. The effects on firms may be more pronounced because other parts of businesses are not insured in the same way as households. For instance, infrastructure damage is not covered under this insurance scheme, and while state aid is available, the application process can be time-consuming, potentially leading to broader economic disruptions.

Our findings contribute to ongoing debates regarding the sustainability of disaster insurance schemes, particularly 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. Our results underscore the critical role of insurance in mitigating the economic consequences of climate-related event and may guide broader policy discussions on financing climate resilience.

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Appendix

6 Appendix

6.1 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.

6.2 Categorizing Natural Disasters by Damage Type: Firms 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

6.3 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.

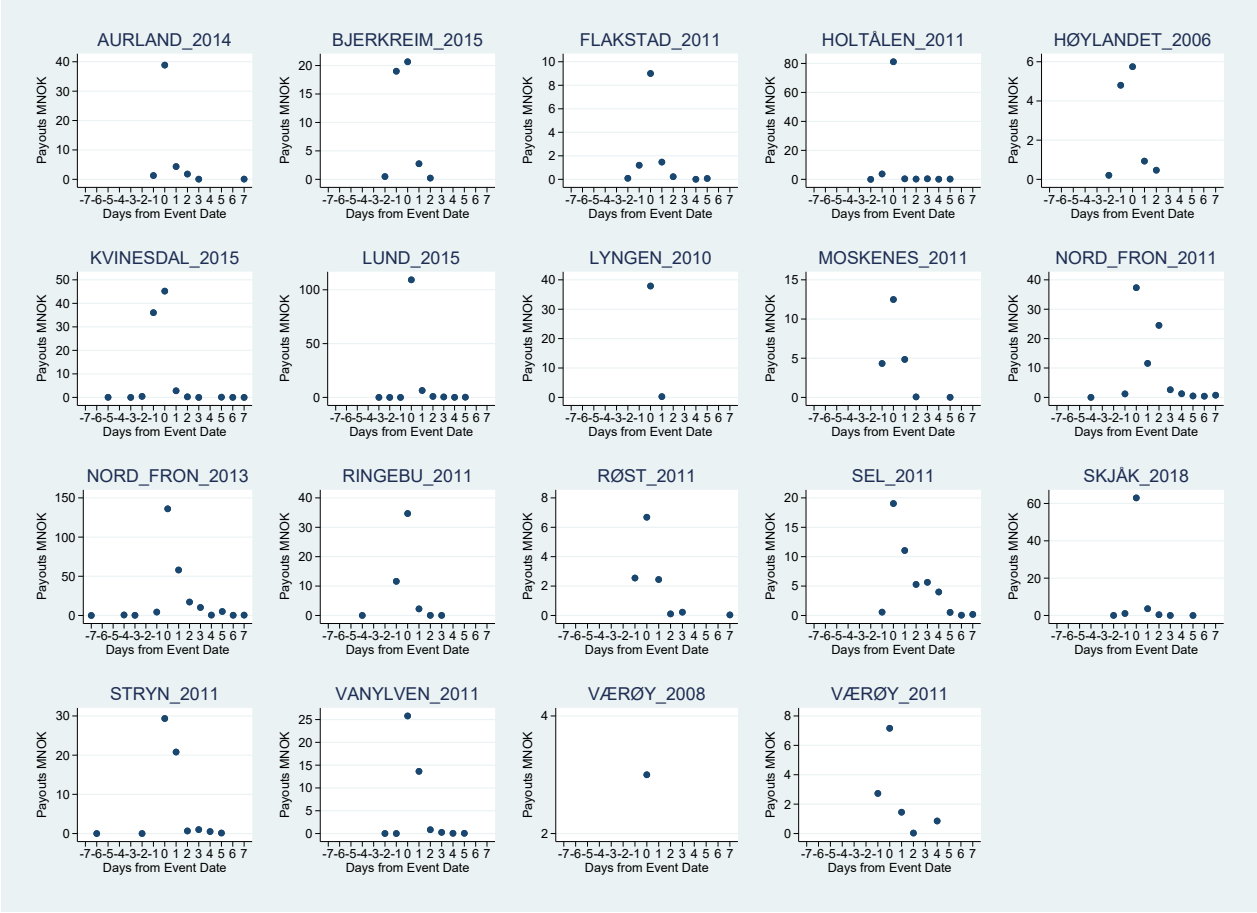


Figure A1: Insurance Payouts Around Event Dates (±7 Days)

6.4 Heterogeneity Analysis by Age



(a) Income After Tax **(b)** Labor Income **(c)** Self Employment **(d)** Unemployment **(e)** Consumption

(f) Total Wealth **(g)** Housing Wealth **(h)** Debt **(i)** Deposits + Sec. **(j)** Housing Purchases

(k) Housing Sales **(l)** Moves New Muni **(m)** Moves Within

Figure A2: Heterogeneity Analysis by Age: Less than 60 Years. All Outcome Variables. Real USD in 2018 Prices.



(a) Income After Tax **(b)** Labor Income **(c)** Self Employment **(d)** Unemployment **(e)** Consumption

(f) Total Wealth **(g)** Housing Wealth **(h)** Debt **(i)** Deposits + Sec. **(j)** Housing Purchases

(k) Housing Sales **(l)** Moves New Muni **(m)** Moves Within

Figure A3: Heterogeneity Analysis by Age: 60 Years or Above. All Outcome Variables. Real USD in 2018 Prices.

6.5 Heterogeneity Analysis by Homeownership Status



(a) Income After Tax **(b)** Labor Income **(c)** Self Employment **(d)** Unemployment **(e)** Consumption

(f) Total Wealth **(g)** Housing Wealth **(h)** Debt **(i)** Deposits + Sec. **(j)** Housing Purchases

(k) Housing Sales **(l)** Moves New Muni **(m)** Moves Within

Figure A4: Heterogeneity Analysis by Homeownership Status: Homeowners. All Outcome Variables. Real USD in 2018 Prices.



(a) Income After Tax **(b)** Labor Income **(c)** Self Employment **(d)** Unemployment **(e)** Consumption

(f) Total Wealth **(g)** Housing Wealth **(h)** Debt **(i)** Deposits + Sec. **(j)** Housing Purchases

(k) Housing Sales **(l)** Moves New Muni **(m)** Moves Within

Figure A5: Heterogeneity Analysis by Homeownership Status: Non-owners. All Outcome Variables. Real USD in 2018 Prices.

6.6 Heterogeneity by Damage Type: Firms vs. Households



(a) Income After Tax **(b)** Labor Income **(c)** Self Employment **(d)** Unemployment **(e)** Consumption

(f) Total Wealth **(g)** Housing Wealth **(h)** Debt **(i)** Deposits + Sec. **(j)** Housing Purchases

(k) Housing Sales **(l)** Moves New Muni **(m)** Moves Within

Figure A6: Heterogeneity Analysis by Damage Type: Household-related Damage. All Outcome Variables. Real USD in 2018 Prices.



(a) Income After Tax **(b)** Labor Income **(c)** Self Employment **(d)** Unemployment **(e)** Consumption

(f) Total Wealth **(g)** Housing Wealth **(h)** Debt **(i)** Deposits + Sec. **(j)** Housing Purchases

(k) Housing Sales **(l)** Moves New Muni **(m)** Moves Within

Figure A7: Heterogeneity Analysis by Damage Type: Firm-related Damage. All Outcome Variables. Real USD in 2018 Prices.