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

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November 19, 2025

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 consumption data and administrative records on income, wealth and housing transactions, we estimate household responses using a matched difference-in-differences design. We find that disasters cause persistent and substantial declines in household consumption: four years after an event, the cumulative drop in spending amounts to more than 40 percent of the average direct damages. Standard estimates of marginal propensities to consume imply that only a small portion of this contraction can be attributed to lower income, while the bulk is explained by a steep and persistent decline in housing wealth. These results suggest significant and long-lasting welfare costs of natural disasters on affected households, even when direct physical damages are completely insured.

*All authors declare that they have no relevant or material financial interests that relate to the research described in this paper. We thank Steffen Andersen, Christian Brinch, Jon Frost, Gazi Kabas, Carlos Madeira, Gisle Natvik, Parinitha Sastry, Ragnar Torvik, and participants in seminars and conferences at the IBRN, NBER, CEPR, NYU Stern School of Business, Norges Bank and BI for useful comments. The views expressed are those of the authors and do not necessarily reflect those of Norges Bank.

JEL classification: D14, D31, E21, Q54
Keywords: Climate Economics, Natural Disasters, Consumption, Household Finance, Insurance

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 *indirect* economic effects of natural disasters on households. In the spirit of Hallegatte (2015) and Botzen, Deschenes, and Sanders (2019), we distinguish between the direct effects of the disasters, defined as damages on households' physical assets occurring as an immediate consequence of the event itself, and the indirect effects, understood as higher-order losses incurred by households due to the broader repercussions of the event in the local area. Indirect effects thus include damages to firms, the infrastructure, or to local amenities that lead to a reduction in production or trade, impact individuals' mobility, or affect the demand for local goods and services.

The Norwegian setting is particularly well suited for estimating the indirect costs of natural disasters. In Norway, insurance against natural disasters is automatically included in all fire insurance policies and covers physical assets such as real estate and movable property.[1] The take-up rate for such coverage through standard property insurance policies is virtually universal, with more than 99% of households covered against fire and hence against natural disasters. In addition, insurance against natural disasters –which is managed by a national fund, the Norwegian Natural Perils Pool– provides full compensation for damages, covering replacement costs with minimal deductibles.[2]

Our data and institutional setting provides three benefits relative to the existing literature. First, because natural disaster insurance is universal and comprehensive,

[1]The insurance applies to private dwellings, commercial and municipal assets, and agricultural property.

[2]In our sample, deductibles amount to only about 2% of insurance payouts due to natural damages.

our data are free from the selection issues that arise in settings with heterogeneous coverage across households. Second, observed insurance payouts at the municipality level provide a precise and reliable measure of direct physical damages, sidestepping the need for proxies or survey-based assessments. Third, near-complete insurance coverage ensures that any subsequent changes in household consumption, income, wealth or other household-level observables reflect the indirect consequences of disasters. The availability of linked administrative and electronic spending records at the individual level, combined with detailed insurance data at the municipal level, enables us to quantify these effects precisely and to assess their persistence over time.

To do so, we construct a municipality-level measure of disaster severity based on private insurance payouts, which allows us to systematically identify the most damaging weather events. 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, Kahn, Rhode, and Yanguas (2020), but differs from studies that focus on individual large events, such as Hurricane Katrina in 2005 (Deryugina, Kawano, and Levitt, 2018) or the 2004 Indian Ocean Tsunami (Frankenberg, Sumantri, and Thomas, 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 during this period. Because Norway was already a largely cashless economy in these years, debit card and bank transfer data capture the vast majority of household spending and thus offer a highly reliable measure of consumption (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.

Understanding how household consumption responds to natural disasters is vital for assessing the welfare effects of these events.

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 find that household consumption drops substantially in the aftermath of natural disasters, with affected households reducing their cumulative spending by nearly $\$1,460$ over four years - a drop equivalent to 33% of the *direct* economic damages. This decline in consumption is notably larger than the corresponding decline in post-tax income, which falls by about $720 (16% of direct damages) over the same period. There is little evidence of recovery in either consumption or income for at least three years after the disaster, underscoring lasting economic consequences that extend well beyond direct physical damages.

To understand why consumption contracts so much, we decompose the response using standard marginal propensities to consume (MPCs) from the literature. The decline in income - driven primarily by a gradual reduction in labor earnings - can only account for roughly 20% of the observed fall in consumption. The rest of the consumption response can be explained by a pronounced decline in housing wealth: affected households see housing values fall by as much as $\$13,000$, and standard MPC estimates imply this wealth shock can account for the majority of the spending contraction. Consistent with this channel, we find that the drop in consumption is concentrated among homeowners –the group directly exposed to changes in housing prices– whereas renters' spending is largely unchanged, even though the income response is similar across both groups. Homeowners also become less likely to purchase new homes, and they reduce their outstanding debt in the years following a disaster.

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. These results point to substantial and long-lasting welfare effects of natural disasters on households, even in a context where the direct economic damages are fully insured.

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.[3]

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).

[3]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.

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. 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 property insurance, which is held by the vast majority of homeowners. For example, in 2025 the total number of insurance policies for real estate objects (houses[4] and cabins) reported by Finance Norway was 1,744,450, and the number of properties of the same type reported by Eiendomsverdi AS was 1,749,352, implying that virtually all properties of these kinds are insured. Coverage is also comprehensive: in our sample, deductibles amount to only about 2% of the direct damages due to natural disasters.

This near-universal coverage stands in stark contrast to many other countries. In the United States, for example, property insurance is generally required only for mortgaged properties, and a considerably smaller share of households hold active policies. In Norway, by contrast, insurance coverage appears to be the norm rather than merely a condition for obtaining a loan. This pattern is also reflected in other types of insurance. For instance, the number of contents insurance policies reported by Finance Norway was 2,574,377, while the total number of property units reported by Eiendomsverdi AS, including apartments in cooperatives and joint ownerships, was 2,600,326. These figures further illustrate that insurance coverage is close to universal among Norwegian households.

The natural damage insurance scheme is administered by the Norwegian Natural Perils Pool (NASK), which all companies providing fire insurance are required to join.

[4]The category "houses" includes detached, semi-detached, and row houses.

When a natural disaster occurs, each member company pays compensation to its policyholders and subsequently settles its claims through the Pool, in proportion to its market share. 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 natural perils risk. The rate is set as a per-mill charge on the insured fire value, currently set to 0.08 (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).

In addition to natural disasters as defined above, weather-related water damages may also occur. These damages typically result from extreme weather events such as heavy rainfall and are most prevalent in urban areas where drainage capacity is limited. Finance Norway includes these damages in its climate reports as part of the broader category of extreme weather events. Unlike natural perils covered by the natural disaster insurance scheme, such weather-related water damages are covered by the water damage insurance component included in standard property insurance policies, for which insurance companies are allowed to vary premiums.

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 disasters and extreme weather events for all municipalities in Norway between 1993 and 2023. We use data on insurance payouts due to natural damages from The Norwegian Natural Perils Pool, and insurance payouts due to weather-related water damages from The Water Damage Statistics. From these datasets 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, heavy rain, or other). Finally, the datasets distinguish between insurance policies covering households and those covering commercial activities. This allows us to determine which sectors of the economy were most affected by each event.

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. Extending the classification over a longer horizon allows us to place recent events in historical context and to document how the frequency and intensity of natural disasters have evolved over time, which is of independent public and policy interest.

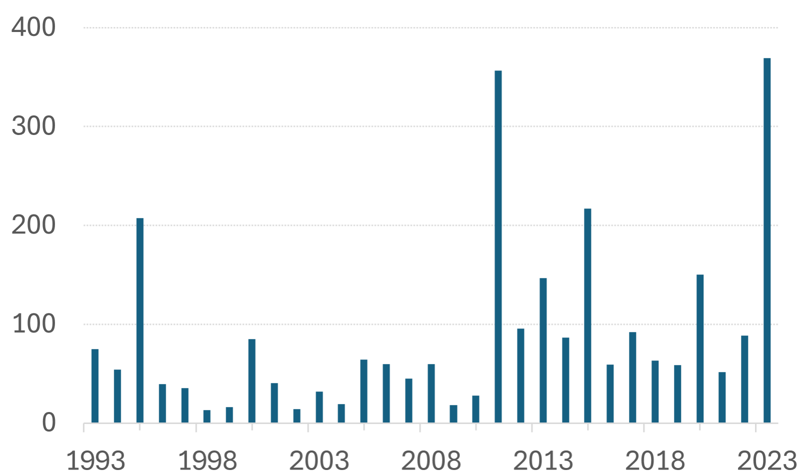
3.1 A severity metric for natural disasters

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 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 measure of 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 exceeds 5 percent of labor

Figure 1: Insurance payouts due to natural disasters.

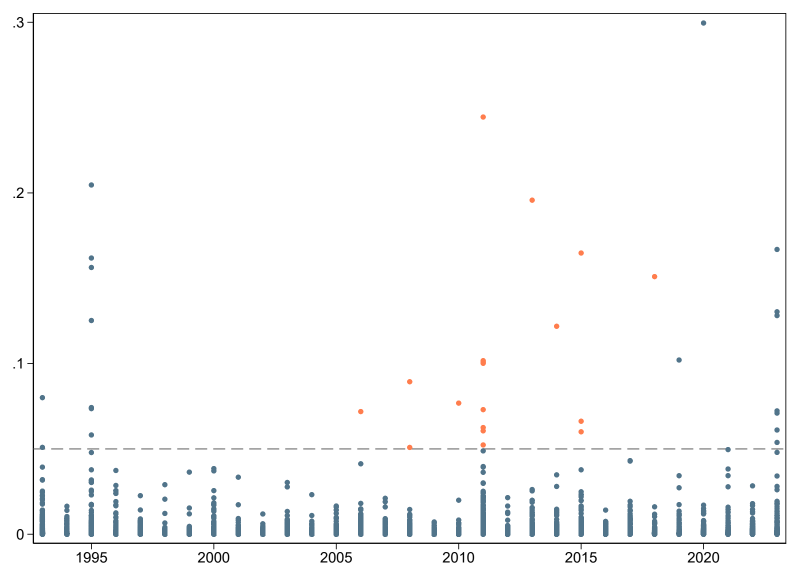


Note: This figure shows the total amount of insurance payouts covering damages due to natural disasters in Norway each year from 1993 to 2023, stated in 2018 Million USD. The bars in orange correspond to the years covered by our ultimate sample with household-level outcome variables. Data are aggregated from individual records of insurance claims related to natural damages from The Norwegian Natural Perils Pool (NASK) and from weather-related water damages from The Water Damage Statistics (VASK). Data have been provided by Finance Norway. Amounts correspond to the total compensation paid plus provisions for reported damages.

income. Figure 2 displays the distribution of insurance payouts as share of labor income across all 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. The orange color indicates the events that are included in the final analyzed sample. Consistently with the increase in insurance payouts through time in

Figure 2: Insurance payouts in municipality as share of labor income.



Note: This figure shows a scatterplot of the ratio of total insurance payouts to total labor income in each Norwegian municipality and year, for the period 1993–2023. Each dot in the scatterplot represents an observation for one municipality in a given year. Dots in orange color indicate the natural disaster events that are included in our sample. The horizontal dashed line at the 5% level indicates the threshold above which an event is classified as a natural disaster. The source of data are individual records of insurance claims related to natural damages from The Norwegian Natural Perils Pool (NASK) and from weather-related water damages from The Water Damage Statistics (VASK). Labor income data is provided by Statistics Norway (SSB).

Table 1: **Natural disasters classified using our proposed severity metric.**

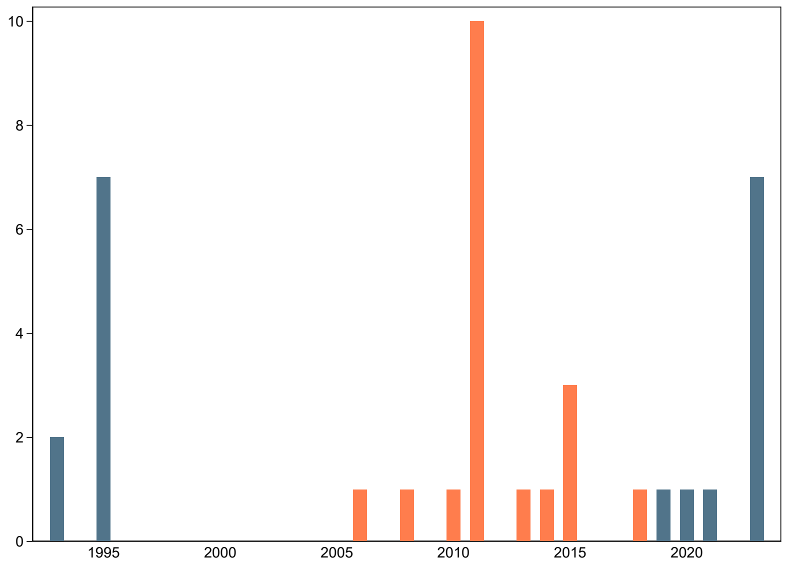
	Municipality	Year	Date	Payouts to labor income	Verified natural disaster type
1	Gjerdrum	2020	Dec 30^{th}	29.9	Landslide, quick clay slide
2	Holtålen	2011	Aug 16^{th}	24.8	Flood, 200-year flood
3	Stor-Elvdal	1995	June 1^{st}	20.5	Flood, "Vesleofsen"
4	Nord-Fron	2013	May 22^{th}	20.1	Flood, 200-year flood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

Note: This table contains a list of all natural disasters occurring in Norway during the period 1993–2023. Natural disasters as municipality events where total insurance payouts to labor income exceeded 5 percent of local labor income. We restrict to municipalitiesin which the number of payouts in a given year is at least 15. Natural disasters have been ranked according to the share of payouts to local labor income. Events in blue correspond to the natural disasters contained in our ultimate sample with household-level outcome variables.

Figure 1, we also observe that the number of natural disasters has increased over time.

To ensure that our classification is meaningful, we have manually verified each of

Figure 3: Number of natural disaster events, 1993–2023.



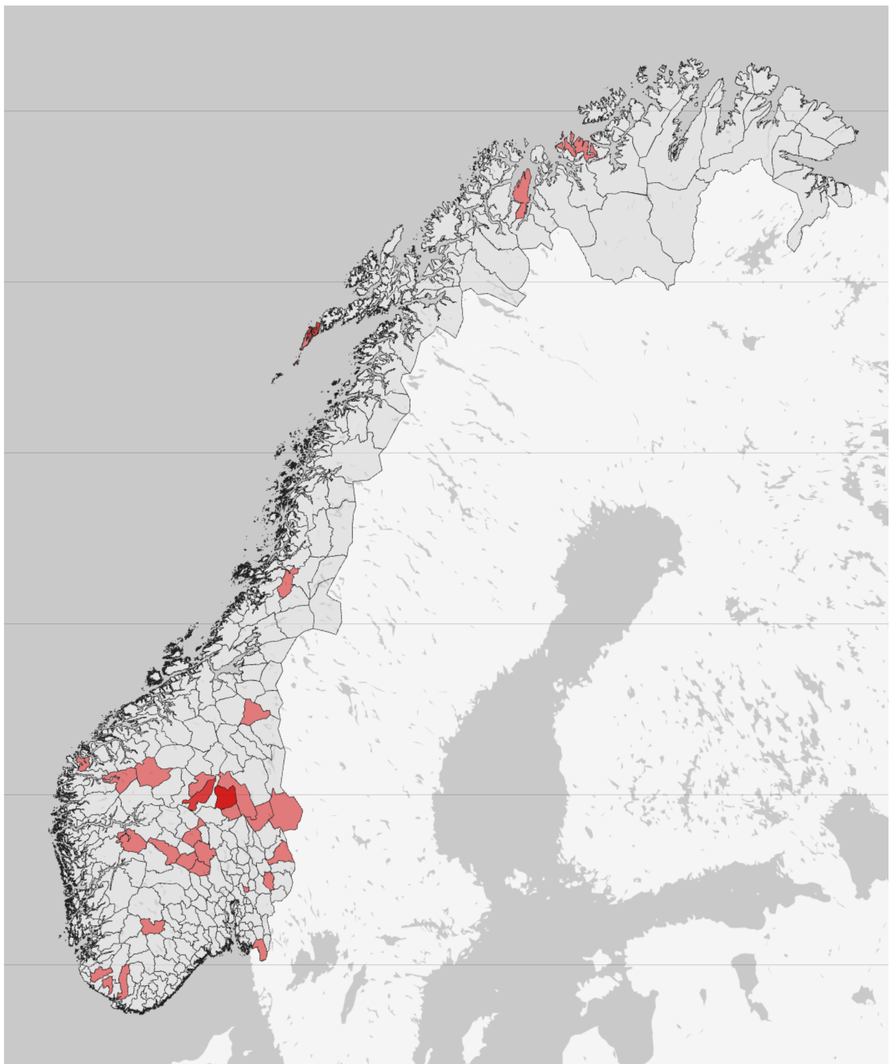
Note: This figure summarizes the number of natural disasters occurring in each year in Norway during years 1993–2023. Natural disasters are defined as those municipality events where total insurance payouts exceed 5 percent of local labor income. Bars in orange color indicate the natural disaster events that are included in our sample with household-level outcome variables.

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. It also allows us to classify the type of natural disasters that are associated with each event, as shown in Table 1.

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 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;

Figure 4: Map of natural disasters in Norwegian municipalities, 1993–2023



Note: This maps indicates the geographical distribution of natural disasters occurring in Norway between 1993 and 2023. Natural disasters are defined as those municipality events where insurance payouts to local labor income exceed 5%. Municipalities in red experienced at least one natural disaster during the 1993–2023 period. Darker red shading indicates that the municipality experienced multiple natural disasters.

a light red means a disaster occurred, while a darker red shows that a municipality has experienced multiple 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.

Summary statistics for affected and non-affected municipalities are reported in Appendix A.4. Affected municipalities are on average smaller and less urban, and they exhibit lower levels of wealth and debt than municipalities that have not experienced a natural disaster. Labor income and consumption, and demographic characteristics such as age and education are broadly similar across the two groups. Insurance payouts are comparable when excluding the disaster years, suggesting that the events identified are large relative to both the size of the local economy and the historical distribution of insurance claims.

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 may be 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.[5] Dismatching at the county level allows us to account for impacts that may spill over municipal boundaries within the same county.

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, 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

[5] 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.

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.

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 2 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 about one quarter have children. Most households are not self-employed, tend to have low education levels (below secondary level) and tend their average age is 60. Financially, the average household has a disposable income of approximately 42,000

Table 2: T-tests Treated vs Control

	Treated (N=7,646)	Control (N=165,281)	Difference	t-statistic	p-value
Homeowner	0.766	0.777	-0.010	-1.845	0.065
Has kids	0.247	0.246	0.001	0.132	0.895
Self employed	0.062	0.057	0.005	1.425	0.154
Maximum HH education	1.747	1.750	-0.002	-0.204	0.839
Age of head of HH	59.921	59.979	-0.058	-0.292	0.770
Income after tax	42,129	41,467	662	3.189	0.001
Total consumption	30,891	30,141	750	2.907	0.004
Housing wealth	126,257	122,620	3,637	2.747	0.006
Debt	49,231	48,563	667	0.821	0.411
Liquid wealth	44,814	43,786	1,028	1.553	0.120
Move to new municipality	0.007	0.006	0.001	0.621	0.534
Move to same municipality	0.017	0.019	-0.002	-1.301	0.193

Note: This table contains the mean values for several variables for the households that were affected by a natural disaster ("Treated") and households that never lived in a municipality hit by a natural disaster ("Control"). Differences in the mean, t-statistics, and p-values are contained in the last three columns. All variables are measured on the year prior to the disaster.

USD, with total consumption around 31,500 USD. Housing wealth is around 125,000 USD, while debt levels average approximately 49,000 USD. Additionally, liquid wealth (deposits and securities) are sliglthly lower than the amount of debt.

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.

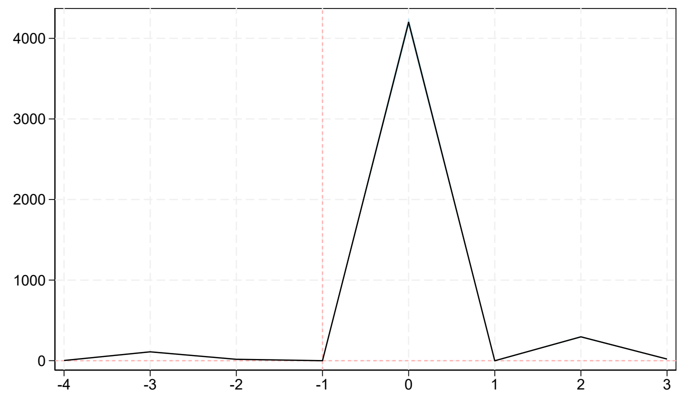
4 Results

We now present our estimation results. In Section 4.1, we estimate the direct economic damages from the natural disasters, and we demonstrate that coverage is near-comprehensive. In Section 4.2, we demonstrate the credibility of our research design by confirming that treated households increase payments of insurance deductibles in the year of the event. Finally, Section 4.3 shows our main results.

4.1 Direct damages

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 in the control group. 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 $\$4,200$ in the year of the disaster. The Norwegian insurance scheme provides full coverage of damages related to natural disasters, except for a deductible which was equal to 8,000 NOK (slightly below $1,000) throughout our sample period. Adding the deductible increases our estimate of the average damages due to the disaster by $100, which implies that households have to cover a minimal part (2.3%) of the direct damages caused by the events. Hence, the estimates in Figure 5 provide a good approximation of the average direct economic effects of the events in our dataset, and the results confirm that households cover only a minimal share of the direct damages.

Figure 5: Direct damages per household.

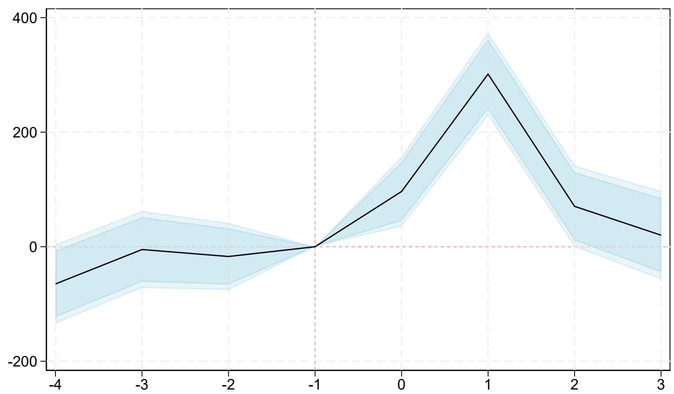


Note: This figure shows the estimated coefficients β_k ($k = -4, \ldots, 3$) from Equation 1. The dependent variable is the average insurance payout per household in the municipality. The sample consists of households living in municipalities hit by a natural disaster ("Treated") and a matched sample of households that were never affected by natural disasters ("Control"). The horizontal axis represents the number of years relative to the natural disaster occurirng in year 0. Treatment effects are calculated relative to the year immediately before the disaster ($t = -1$), as indicated by the orange vertical line. Amounts are expressed in real 2018 USD. Shaded areas in light blue show 90% and 95% confidence intervals for the point estimate.

4.2 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: Treatment validation: Transfers from insurance companies.



Note: The black line in this figure shows the estimated coefficients β_k ($k = -4, \ldots, 3$) from Equation 1. The dependent variable corresponds to the annual transfers from insurance companies to each household. The sample consists of households living in municipalities hit by a natural disaster ("Treated") and a matched sample of households that were never affected by natural disasters ("Control"). The horizontal axis represents the number of years relative to the natural disaster occurirng in year 0. Treatment effects are calculated relative to the year immediately before the disaster ($t = -1$), as indicated by the orange vertical line. Amounts are expressed in real 2018 USD. Shaded areas in light blue show 90% and 95% confidence intervals for the point estimate.

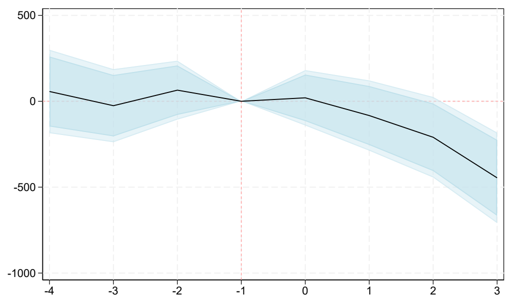
Most households affected by natural disasters allow the insurance company to manage the entire reconstruction or repair process, including contractor payments. While households may opt to receive a direct payout instead, this option is typically chosen only for small damages, such as losses to movable 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.

4.3 Main results

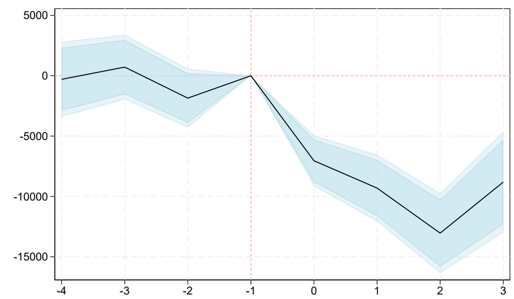
Figure 7 shows the dynamic effect of natural disasters on household post-tax income, wealth and consumption. Each subgraph shows the results for a separate dependent variable. As before, period 0 along the horizontal axis corresponds to the event year. The figure shows that the difference between treated – 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.

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

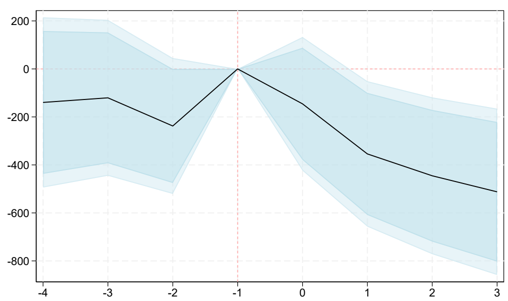
Figure 7: Effect of natural disasters on income, net wealth and consumption.



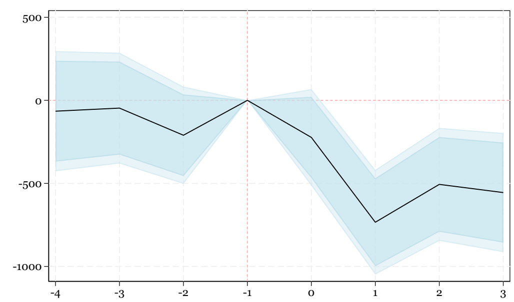
(a) Income After Tax



(b) Net Wealth



(c) Consumption, unadjusted



(d) Consumption, adj. for insurance transfers

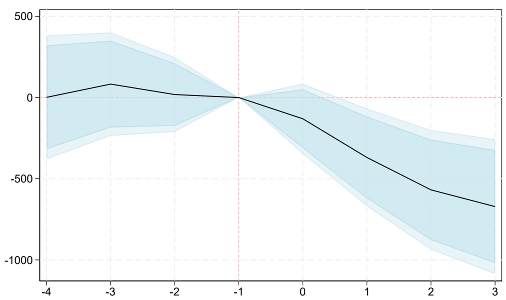
Note: This figure shows the estimated coefficients β_k ($k = -4, \ldots, 3$) from Equation 1. The dependent variable in Panel (a) is income after taxes; net wealth in Panel (b); unadjusted consumption in Panel (c), and consumption net of insurance transfers in Panel (d). In all panels, the sample consists of households living in municipalities hit by a natural disaster ("Treated") and a matched sample of households that were never affected by natural disasters ("Control"). The horizontal axis represents the number of years relative to the natural disaster occurring in year 0. Treatment effects are calculated relative to the year immediately before the disaster ($t = -1$), as indicated by the orange vertical line. Amounts are expressed in real 2018 USD. Shaded areas in light blue show 90% and 95% confidence intervals for the point estimate.

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.

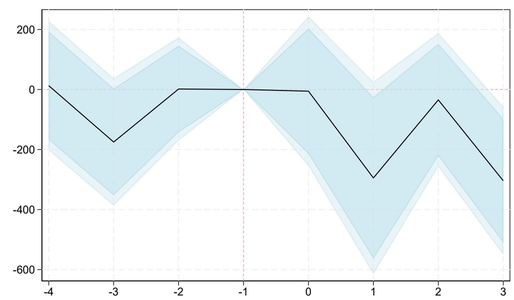
To understand how large the estimated indirect effects of natural disasters on income and consumption are, we can compare them to the direct economic damages measured by the insurance payouts related to natural disasters, shown in Figure 5. The cumulative effect on income over the four post-event years 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 when looking at average post-period effects, although some year-specific effects are present for firm-related events, see Appendix A3.

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



(a) Labor Income



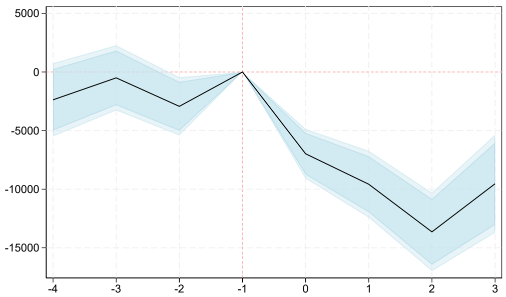
(b) Capital Income

Note: This figure shows the estimated coefficients β_k ($k = -4, \ldots, 3$) from Equation 1. The dependent variable in Panel (a) is labor income; in Panel (b) it is capital income. In both panels, the sample consists of households living in municipalities hit by a natural disaster ("Treated") and a matched sample of households that were never affected by natural disasters ("Control"). The horizontal axis represents the number of years relative to the natural disaster occurring in year 0. Treatment effects are calculated relative to the year immediately before the disaster ($t = -1$), as indicated by the orange vertical line. Amounts are expressed in real 2018 USD. Shaded areas in light blue show 90% and 95% confidence intervals for the point estimate.

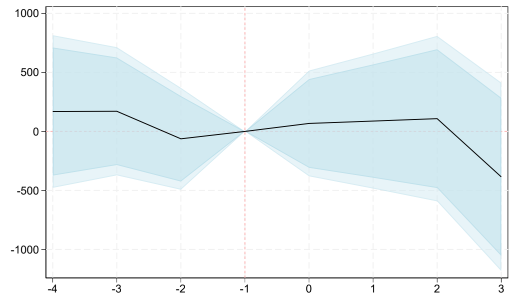
In Figure 9 we show the response of the components of net wealth: housing wealth (a) and gross financial wealth (b) –which together constitute total gross wealth (c)– and debt (d). We find no significant effect on financial wealth, mirroring the result for financial income. Instead, all of the steep 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.[6] 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.

[6]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.5, 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.

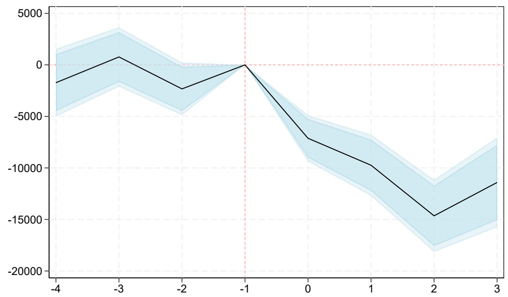
Figure 9: Effect of natural disasters on components of household wealth.



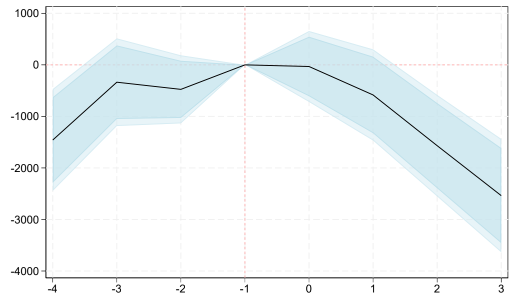
(a) Housing Wealth



(b) Financial Wealth



(c) Total Gross Wealth

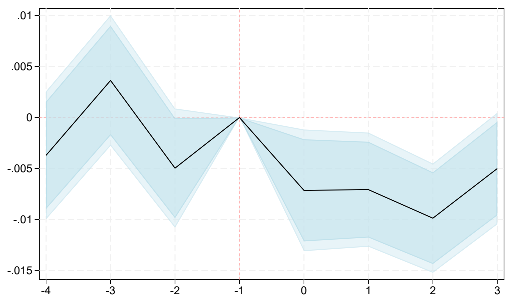


(d) Debt

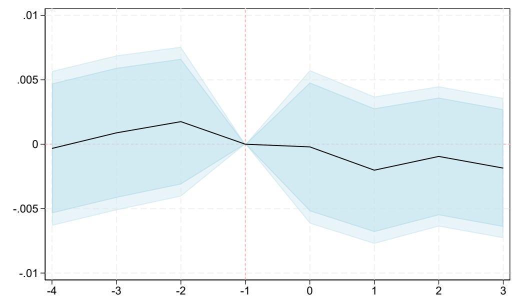
Note: This figure shows the estimated coefficients β_k ($k = -4, \ldots, 3$) from Equation 1. The dependent variable in Panel (a) is housing wealth; financial wealth in Panel (b); total gross wealth in Panel (c), and debt in Panel (d). In all panels, the sample consists of households living in municipalities hit by a natural disaster ("Treated") and a matched sample of households that were never affected by natural disasters ("Control"). The horizontal axis represents the number of years relative to the natural disaster occurring in year 0. Treatment effects are calculated relative to the year immediately before the disaster ($t = -1$), as indicated by the orange vertical line. Amounts are expressed in real 2018 USD. Shaded areas in light blue show 90% and 95% confidence intervals for the point estimate.

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,

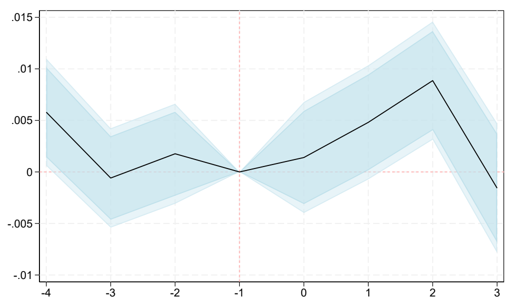
Figure 10: Effect of disasters on housing transactions and relocations.



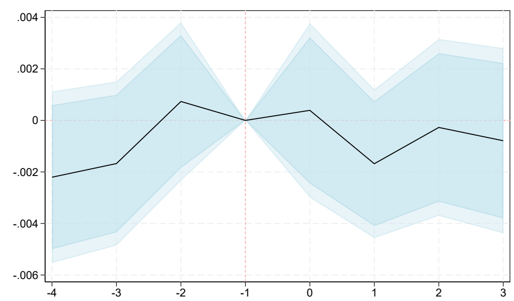
(a) Housing Transactions: Purchases



(b) Housing Transactions: Sales



(c) Moves Within Municipality



(d) Moves to New Municipality

Note: This figure shows the estimated coefficients β_k ($k = -4, \ldots, 3$) from Equation 1. The dependent variable in Panel (a) is a dummy variable taking the value one if the household purchased a house; in Panel (b) it is a dummy variable taking the value one if the household sold a house; in Panel (c) it is a dummy variable taking the value one if the household moved to a different address within the municipality, and in Panel (d) it is a dummy variable if the household moved to another municipality. In all panels, the sample consists of households living in municipalities hit by a natural disaster ("Treated") and a matched sample of households that were never affected by natural disasters ("Control"). The horizontal axis represents the number of years relative to the natural disaster occurring in year 0. Treatment effects are calculated relative to the year immediately before the disaster ($t = -1$), as indicated by the orange vertical line. Amounts are expressed in real 2018 USD prices. Shaded areas in light blue show 90% and 95% confidence intervals for the point estimate.

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 3 shows estimates of the

Table 3: 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)

Note: This table contains estimates for the average treatment effect over years 0 to 3, where year 0 is the year of the disaster. Each row corresponds to a different outcome variable, as indicated in the leftmost column. Estimates in column (1) correspond to the average treatment effect for the full sample of treated and control households. In columns 2 and 3, the average treatment effect is calculated separately for natural disasters that have a large effect on local firms or on households, respectively. In columns 4 and 5, the average treatment effect is estimated separately for households owning a house and for renters, respectively. All amounts correspond to real USD in 2018 prices. Standard errors are in parentheses ($^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$).

average treatment effects 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.

Panel (d) of Figure 9 shows a significant negative effect on debt held by treated households.[7] 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.

4.3.1 Decomposing the consumption response

We now attempt to understand what drives the large consumption response to natural disasters. To that end, we ask whether the consumption response is consistent with the responses of income and wealth under standard marginal propensities to consume. In the empirical literature, estimated marginal propensities to consume (MPC) out of unexpected, temporary income shocks are typically in the range of $30 - 50\%$. [8] Using variation due to the onset of unemployment for Norwegian workers, Fagereng et al. (2024) estimate an MPC of 40%, while Bilbiie et al. (2025) find an average MPC of 38% using the same consumption data as in this paper.

[7]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.

[8]See e.g. Andersen et al. (2023); Patterson (2023), who estimate the MPC out of unemployment shocks. Parker et al. (2013); Jappelli and Pistaferri (2014); Parker (2017); Aguiar et al. (2020); Fagereng et al. (2021); Gelman (2022); Boehm et al. (2023); Hamilton et al. (2023); Borusyak et al. (2024); Orchard et al. (2024) find similar magnitudes for the MPC out of windfall income gains.

Assuming an MPC of 40%, 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 account for the rest of the consumption effect, our estimates imply an MPC out of housing wealth changes of around 3%.[9] This number is in line with the literature on consumption responses to exogenous movements in house prices, which typically finds MPCs between 3% and 5%. For instance, the benchmark estimate by Guren et al. (2021) is 3.3 cents on the dollar, while Aastveit et al. (2025) find an MPC of 3.6% in Norway using the same consumption data as in this paper. Hence, our estimated consumption response is consistent with the responses of income and wealth, and they demonstrate the important role for housing wealth in transmitting the effect of natural disasters to household spending. Further underlining the importance of housing wealth for the consumption response, Table 3 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.

4.4 Firm and household events

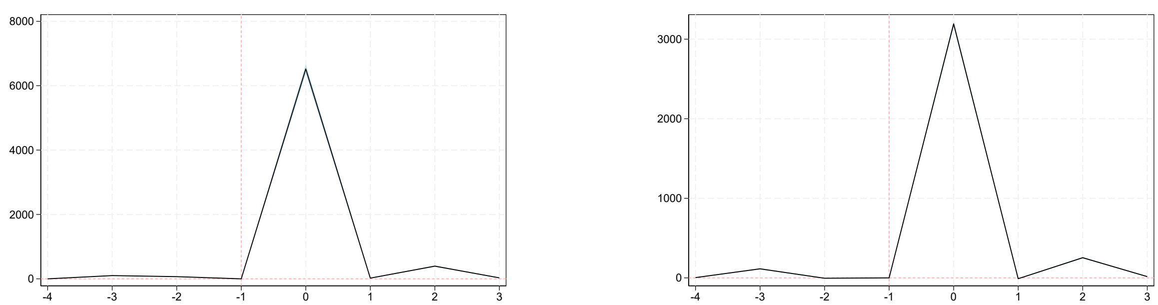
We now split the events by type to explore the economic mechanisms driving our results. Specifically, we divide the sample into events that mostly affected the property of firms and those that mainly affected the property of households, based on the type of insurance policy covering the damage – either 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 3 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

[9]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).

– for events classified as firm events.[10] 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.

Figure 11: Insurance payouts per household. Firm and household events.



(a) Firm events **(b)** Household events

Note: This figure shows the estimated coefficients β_k ($k = -4, \ldots, 3$) from Equation 1. Estimates are calculated separately for events having the largest impact on firms (Panel a) or on households (Panel b). The dependent variable in both panels is the average insurance payout per household in the municipality. The sample consists of households living in municipalities hit by a natural disaster ("Treated") and a matched sample of households that were never affected by natural disasters ("Control"). The horizontal axis represents the number of years relative to the natural disaster occurirng in year 0. Treatment effects are calculated relative to the year immediately before the disaster ($t = -1$), as indicated by the orange vertical line. Amounts are expressed in real 2018 USD. Shaded areas in light blue show 90% and 95% confidence intervals for the point estimate.

4.5 Essential vs non-essential consumption

The credit card transaction data contains information on several consumption categories, based on a classification of the establishments at the point of sale. Figure A4 in the Appendix contains a summary of the main differences in consumption for treated vs control households across the reported consumption categories.[11] On average, af-

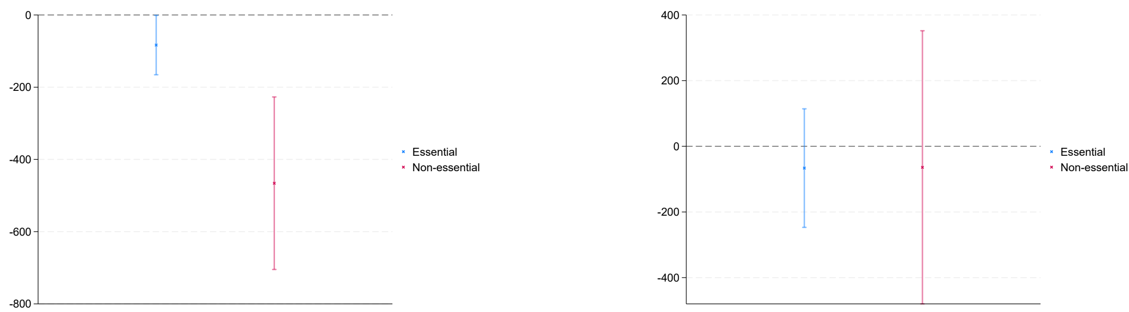
[10]The insurance payments to households are smaller for firm events than for household events.

[11]We exclude all transfers to and from financial institutions from the consumption categories.

fected households did not make large adjustments to the allocation of consumption in the majority of categories. However, some exceptions stand out: affected households reduced their average expenditures on food and non-alcoholic beverages (i.e. grocery store spending), on communications and especially on purchases of vehicles. At the same time, they increased their expenses in the operation of transportation equipment (e.g. fuel costs and expenses for rental of cars and trucks) and personal care. These findings suggest that affected households had some increased spending due to e.g. clean-up costs, but had to forego some expenditures on both essential items and especially on non-essential items such as vehicles.

We aggregate the consumption categories into essential items (food, clothing, health, communication and personal care) vs non-essential items (the remaining categories) to analyze whether the differences in average consumption between homeowners and renters observed previously mask some heterogeneity on the margins of this adjustment across these two broad categories. Panel (a) in Figure 12 displays the average change in these two categories for treated homeowners relative to non-affected homeowners, while panel (b) focuses on renters. Results show that the adjustments in both essential and nonessential consumption are driven by affected homeowners, who spend on average about \$85 less on essential items and $-$\$470 less on non-essential items. By contrast, renters do not significantly reduce their consumption on either of these categories.

Figure 12: Effect of disasters on consumption categories. Owners vs renters.



(a) Homeowners

(b) Renters

Note: This figure shows the point estimate and 95% confidence intervals for the average difference in consumption of essential items (food, health, communication and personal care, in blue) and non-essential items (the rest of the categories, in red) between treated and control households during years 0 to 3, where year 0 corresponds to the year of the natural disaster. The sample consists of households living in municipalities hit by a natural disaster ("Treated") and a matched sample of households that were never affected by natural disasters ("Control"). Differences are estimated separately for homeowners in panel (a), and for renters in panel (b). Amounts are expressed in real 2018 USD.

5 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.

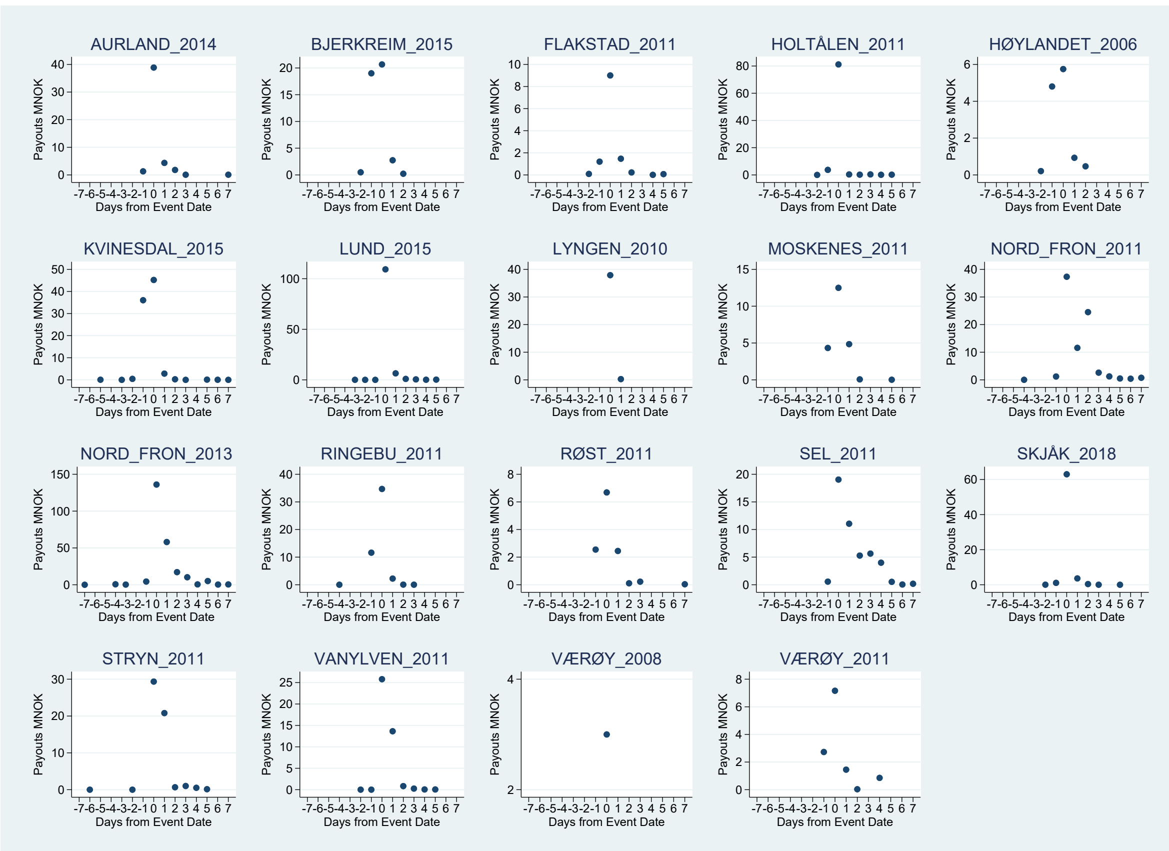
Table A2: Natural Disasters by Largest Impact: Firm vs. Household Events.

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 Summary statistics for municipalities

Table A3: 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	29224.23	29072.22	2973.83	25315.19	36857.61
Total Gross Wealth	133857.33	136041.99	17514.90	98957.33	168319.02
Debt	46447.17	44386.16	8744.45	36839.93	70591.05
Total Consumption	22467.27	22033.36	3521.06	18827.93	34385.33
Total Payouts incl. Events	347.36	288.60	147.59	160.30	654.60
Total Payouts excl. Events	38.02	35.40	26.41	10.68	124.79

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	30579.08	29952.37	4443.74	22443.32	48349.65
Total Gross Wealth	150083.36	141284.36	43603.51	86504.60	386650.83
Debt	56592.05	54631.96	15480.58	24306.11	102876.72
Total Consumption	21720.30	21595.17	2316.55	15848.26	30853.15
Total Payouts	68.10	60.05	39.62	14.67	254.42

Notes: Total number of observations is 356 (municipal level).
An affected municipality is a municipality that has experienced a natural disaster
in one of the years in the sample period. All monetary values are in real USD (2018 prices), per capita.
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.

Table A3 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 ≈ 2,040), whereas not affected municipalities average around 11,600 residents (median ≈ 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.

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, while labor income and consumption is quite comparable, affected municipalities report notably lower total gross wealth, and debt compared to their not affected counterparts.

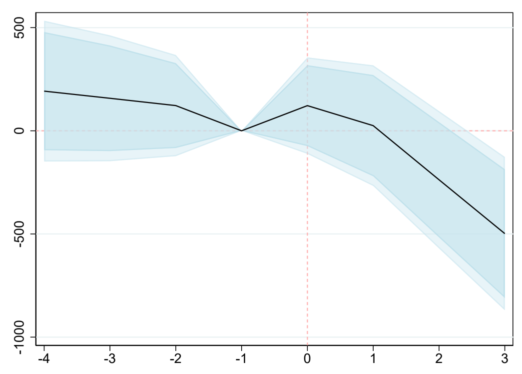
When it comes to insurance payouts, we see from Table A3 that the two groups are comparable when excluding the years in which the natural disaster occurred (see Total Payouts including and excluding the events), and there is no indication that affected municipalities generally receive higher insurance 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.

A.5 Adjustment of housing wealth with municipal weights

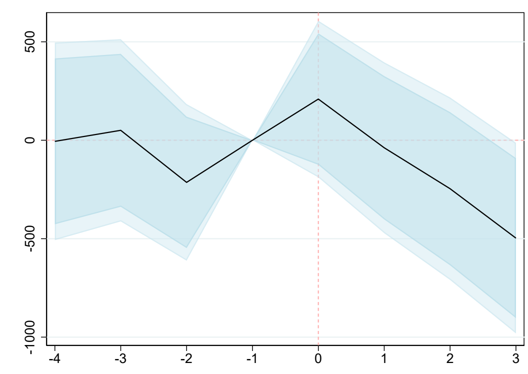
To correct for the systematic undervaluation of housing wealth in the tax data, we apply adjustment factors that link the tax-assessed values to estimated market values from the machine learning model in Fagereng et al. (2020). For each year and municipality, the ratio of the estimated market value to 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.6 Additional Figures

Figure A2: Subset of treated households with insurance transfers.



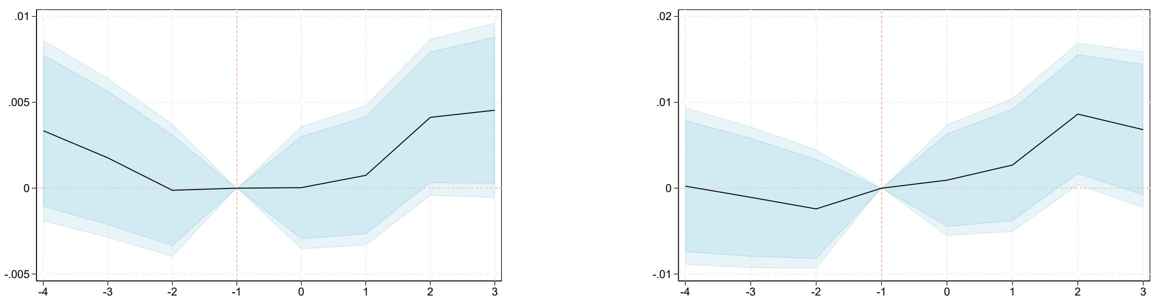
(a) Income after tax



(b) Consumption

Note: This figure shows the estimated coefficients β_k ($k = -4, \ldots, 3$) from Equation 1. The dependent variable in Panel (a) is income after tax; in Panel (b) it is consumption. In both panels, the sample consists of the subset of treated households who receive positive transfers from insurance companies in year 0 or 1 and their corresponding control households. The horizontal axis represents the number of years relative to the natural disaster occurring in year 0. Treatment effects are calculated relative to the year immediately before the disaster ($t = -1$), as indicated by the orange vertical line. Amounts are expressed in real 2018 USD. Shaded areas in light blue show 90% and 95% confidence intervals for the point estimate.

Figure A3: Self-Employment.



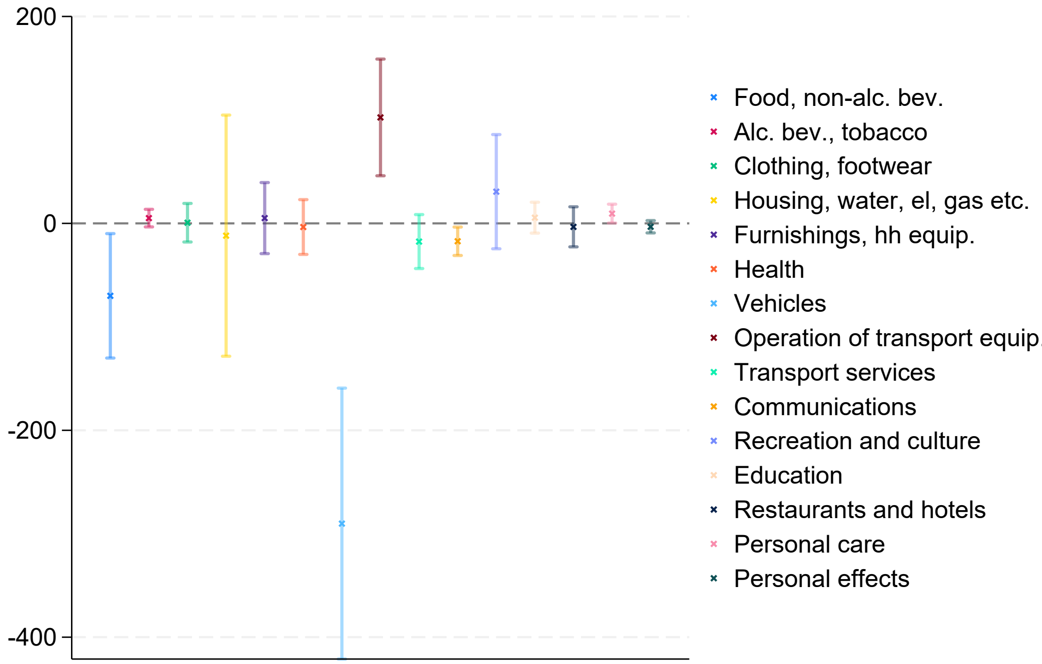
(a) Self-Employment

(b) Self-Employment in Firm-Events

Note: This figure shows the estimated coefficients β_k ($k = -4, \ldots, 3$) from Equation 1. The dependent variable is an indicator taking the value one if the household is self-employed. The sample in Panel (a) corresponds to all households living in municipalities affected by a natural disaster and a matched sample of control households. In Panel (b) the sample is restricted to natural disasters where effects to firms is large. The horizontal axis represents the number of years relative to the natural disaster occurring in year 0. Treatment effects are calculated relative to the year immediately before the disaster ($t = -1$), as indicated by the orange vertical line. Amounts are expressed in real 2018 USD. Shaded areas in light blue show 90% and 95% confidence intervals for the point estimate.

A.7 Consumption categories

Figure A4: Consumption categories.



Note: This figure shows the point estimate and 95% confidence intervals for the average difference consumption between treated and control households during years 0 to 3, where year 0 corresponds to the year of the natural disaster. Estimates are calculated separately across the different consumption categories indicated in the right-hand side of the figure. The sample consists of households living in municipalities hit by a natural disaster ("Treated") and a matched sample of households that were never affected by natural disasters ("Control"). Amounts are expressed in real 2018 USD.