

The value of cabin-based outdoor recreation: Evidence from a natural experiment

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ARTICLE INFO

JEL classification:

JEL
Q21
Q26
Q51
Q56

Keywords:

Outdoor recreation
Nonmarket valuation
Price elasticity
Electricity prices
Strava
Difference-in-difference
Natural experiment
Causal inference

ABSTRACT

Use-values of nonmarket environmental amenities are often elicited by studying the demand for outdoor recreation, and credible value estimates are essential for designing efficient policies affecting the supply of such goods. Yet, rigorous causal identification of outdoor recreation demand remains limited. Our study contributes to the growing literature that applies causal inference techniques and GPS-based observational data to the valuation of nonmarket environmental amenities. We exploit a sharp increase in electricity prices in Norway following Russia's invasion of Ukraine in 2022 as a natural experiment to study the price sensitivity of cabin-based outdoor recreation. Using activity traces from the training app Strava, spatially merged with geolocated cabin sites, we find a 15 % decline in cabin recreation following the price shock. From this response, we infer an average consumer surplus of approximately \$6000 per cabin owner per year, equivalent to about \$204 per use-day, and a price elasticity of -0.24 , indicating inelastic demand. These findings point to considerable welfare benefits from cabin recreation and illustrate the value of combining quasi-experimental designs with high-frequency mobility data for valuation of nonmarket environmental amenities.

1. Introduction

Environmental economists often use structural recreation demand models to estimate the economic value of natural areas under various conditions (English et al., 2018; Lupi et al., 2020; Zandersen and Tol, 2009). Despite recent advances in the causal inference literature, rigorous causal inference remains limited in recreation demand analysis. This research gap is explicitly recognized by best-practice guidance from Lupi et al. (2020), which emphasizes the importance of employing modern identification strategies such as natural experiments to causally elicit economic values of environmental amenities from recreation behavior.

There is a growing body of literature utilizing credible identification strategies in environmental nonmarket valuations. Bradt (2025) shows that standard travel cost models suffer from omitted variable bias due to non-random spatial sorting, undermining the credibility of welfare estimates. He uses an instrumental variable approach to isolate exogenous price variations to elicit welfare losses from the Deepwater Horizon oil spill in a structural demand model. Another application is Earle and Kim (2025) who combine panel data causal inference techniques with a random utility travel cost model, which they call “structural difference-in-differences”, to

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<https://doi.org/10.1016/j.jeem.2025.103243>

Received 28 March 2025; Received in revised form 21 August 2025; Accepted 3 October 2025

Available online 9 October 2025

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estimate the welfare loss from water-quality-induced beach closures. Furthermore Wardle (2025) uses a taxonomic species split as a natural experiment to causally identify the effect of rare species on forest visitation. Wardle (2025) develops a method to elicit welfare estimates from a reduced form approach. The author further highlights the practical advantages of natural experiments in this context, including that they can be estimated using aggregated data, they avoid the incidental parameter problem associated with nonlinear models,¹ and do not require specification of a choice set.

In this paper, we contribute to this literature and use a natural experiment to elicit the value of cabin-based outdoor recreation in a reduced-form design similar to Wardle (2025). We exploit a sharp and geographically confined increase in electricity prices caused by Russia's invasion of Ukraine that substantially raised the cost of cabin-based recreation. While a nationwide government electricity subsidy shielded primary residences from the price increase, cabins—commonly used for recreation in Norway (and elsewhere)—were uniformly excluded. This meant that people could substitute the now costlier recreation at their cabin for relatively cheaper recreation at home. Our identification strategy relies on the discontinuity that occurred at the border between affected and unaffected electricity price zones. This provides an as-if random assignment of recreation sites into a treatment group and a control group. We then compare treated and non-treated areas using a difference-in-differences design.

Another pattern in the literature is that studies often rely on self-reported survey data (e.g., English et al., 2018; Lopes and Whitehead, 2023; Lupi et al., 2020; Whitehead et al., 2010; Xie and Adamowicz, 2023). More recently, the literature has explored novel observational data and public registries, including social media (Keeler et al., 2015; Sinclair et al., 2022), crowdsourced GPS tracks (Dai et al., 2022; Guilfoos et al., 2024; Jayalath et al., 2023; Kolstoe and Cameron, 2017; Wardle, 2025), and reservation records (Lloyd-Smith and Becker, 2020; Gellman et al., 2025; Lloyd-Smith and Zawojka, 2025), to overcome limitations of survey-based methods.

In this paper, we contribute to this literature and rely on novel observational data. To observe changes in recreation behavior across space and time, we use trail-level data from the fitness app Strava. The key advantage of the Strava data is that it captures actual recreation behavior, including geolocation and timing of activities, rather than relying on self-reports. In total, our dataset contains just under 10,000 trails and slightly over 1 million recreation activity observations per year in the period 2019–2022. We combine the Strava trail data with data from the Norwegian cadaster register on building type, weather data, income data, and local data on COVID-19 infections.

We find that the electricity price shock caused the demand for cabin-based outdoor recreation to fall by 15 percent. This finding is significant at the one percent level and robust to controls and specifications. Using a simplifying assumption of linear demand, we use this to calculate that the average cabin-owning household has a consumer surplus (CS) from outdoor recreation through the use of cabins of approximately \$6000 per year. This implies a per day CS of \$204. We furthermore calculate the price elasticity to be -0.24 and show through a Monte Carlo simulation that it is likely that the demand is inelastic. This estimate is more inelastic than what is found in previous studies of travel and recreation demand (Wardle, 2025; Wardman, 2022).

These substantial welfare benefits have direct relevance for ongoing policy debates concerning the building of cabins. Cabin construction in pristine or sparsely developed natural areas can cause significant environmental harm through habitat loss, infrastructure development, and increased human disturbance, particularly in fragile ecosystems (Iversen et al., 2024). In Norway, environmental groups advocate bans on new cabins to prevent such degradation. However, our findings indicate that cabin-based recreation generates substantial welfare benefits, implying that outright bans could lead to large deadweight losses. More efficient policies would weigh environmental costs against these benefits, for example by imposing environmental taxes on developers reflecting the value of lost ecosystem services.

The remainder of the paper is structured as follows: Section 2 provides institutional background on the Norwegian electricity market, cabin culture and the electricity price shock in 2022. Section 3 describes the data and empirical strategy. Section 4 presents results, robustness checks, and placebo tests. In Section 5, we interpret the results and calculate welfare and price elasticity estimates. Section 6 concludes.

2. Background and institutional setting

2.1. The Norwegian electricity system

The Norwegian electricity system is a market-based system divided into five price zones (see Fig. 1). Electricity prices are determined at an electricity exchange separately for each price zone at an hourly basis. The division into price zones accounts for regional variations in power supply and demand, enabling more accurate price signals and efficient resource allocation. If a price zone experiences a demand or supply shock, transmitters will have incentives to move electricity from zones with relatively lower prices to zones with relatively higher prices, evening out prices across zones. Before the price hikes in 2021, the price differences between the zones have been negligible and there has effectively been one electricity price across the country (see Fig. 2).

In Norway, in contrast to many other countries, most households' energy consumption comes from electricity. Electricity is used for heating, cooking and charging of electric vehicles, and substituting away from electricity in the short term, especially during cold winter months, is difficult. Furthermore, most Norwegian households are on spot price based contracts (Statistics Norway, 2024c) which means that changes in the spot price are quickly passed through to consumers.

¹ The incidental parameters problem refers to bias in nonlinear panel models with fixed effects when the time dimension is short, leading to inconsistent estimates (Greene, 2004).



Fig. 1. Electricity price zones in Norway

Notes: The figure illustrates the five price zone in Norway and is retrieved from [Statnett \(2024\)](#).

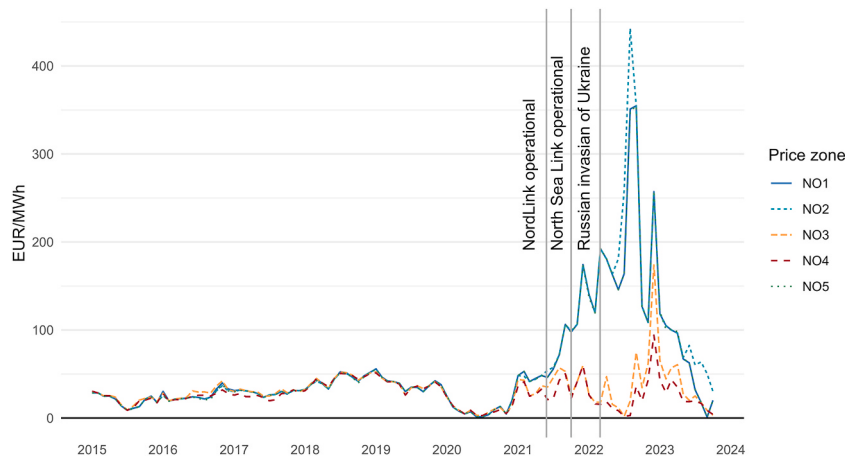


Fig. 2. Monthly (non-weighted) spot price for electricity in the five price zones in Norway between 2015 and 2024

Notes: The prices are aggregated from an hourly time resolution to monthly by simple averaging. See [Table C.1](#) in [Appendix C](#) for the raw monthly prices used to create the figure. The data was retrieved from the ENTSO-E Transparency Platform ([ENTSO-E, 2024](#)).

2.2. A historical price shock

Historically, electricity prices across the five price zones in Norway have effectively been equal. However, in late 2021, there occurred an unprecedented divergence (see [Fig. 2](#)). The three southern zones experienced a large price increase, while the northernmost zones experienced fluctuations within the normal range.

Three key factors explain why the prices diverged: First, the electricity prices at the European continent increased significantly due to a dramatic fall in the gas supply following Russia's invasion of Ukraine and the shut-down of French and German nuclear power plants ([IEA, 2022](#)). This shock did not hit Norway directly as Norway gets most of its electricity from hydropower and wind. Second,

the 17 cross-border transmission lines connecting the Norwegian electricity market to the European continent made the Norwegian market susceptible to spillovers from the European shock. In addition, in 2021 the two largest cross border transmission lines in Norway to date, Nordlink and the North Sea Link, connecting the south of Norway to Germany and the UK, became operational.² Third, limited grid capacity between the southern and the northern price zones created a bottle neck, leaving northern Norway almost unaffected. Therefore, we have an exogenous, large and long-lasting price shock randomly assigned to some price zones and not others. And the extra cost on those affected were substantial. The average price in affected areas in 2022 was three times larger than the prior five year average (Statistics Norway, 2023c).³

2.3. Governmental support scheme

By the end of 2021, the Norwegian government introduced an electricity subsidy intended to shield households from the high prices. The scheme was revised multiple times. Currently, when the price exceeds 7.5 cents (75 øre) per kWh, the subsidy covers 90 % of the spot price above this level (see Table A.1 in Appendix A for information about the evolution of the support scheme). The subsidy only covers households and only primary residences.⁴ Secondary homes not used for residency, including cabins, were not covered by the scheme. The subsidy shielded consumers from some of the extra costs, but even with the subsidy program, the price increases were non-trivial.

In Table 1, we present illustrative calculations of the extra costs for different housing units. The calculations include the annual electricity cost for a household consuming 20,000 kWh per year for their main home and 10,000 kWh per year for their cabin (which are approximately the mean values for homes and cabins, respectively). The consumption is multiplied by the average annual electricity price, including grid fee, VAT, and other taxes and net of the subsidy for homes. An explanation of the stylized calculations is provided in Appendix A. In Table A.2 in Appendix A, we also provide calculations of the annual costs for houses and cabins in the different price areas, which the calculations in Table 1 is based on. We retrieved the data from Statistics Norway (2024a) and Norwegian Consumer Council (2025).

As we can see, a household living in NO1 spending 20,000 kWh a year in their home would have seen an increase in their electricity bill of USD 1833 in 2022 relative to 2020. The cumulative extra cost over the two-year period is USD 3216. If they also own a cabin, the cumulative extra cost is USD 6109. In comparison, the Norwegian median household income in 2022 was USD 82,870 in 2022 (Statistics Norway, 2023a). In other words, this was a very salient shock. It was also a very large shock when we compare treated households to control households. For instance, the cumulative extra cost for a home in NO1 relative to NO3 is USD 2318. Later in the article, we are going to make calculations of welfare effects and the price elasticity of recreation demand. The relevant price change in that calculation is the cost for cabins in NO1 relative to cabins in NO3 in 2022, which is \$1,783, a difference of 353 percent.

2.4. Cabin usage in Norway

In Norway, cabins and cabin usage have long traditions (Vittersø, 2007). They are typically located in wilderness and less densely populated areas with more opportunities for outdoor recreation. Statistics Norway (2018) estimates that almost half of Norwegian households have access to at least one cabin through their family. Cabins are important for outdoor recreation and local economies (Iversen et al., 2024). Currently, Norway has around 488,000 registered cabins and current land use plans facilitate a potential doubling of this number (Blumentrath et al., 2022). To put this in perspective, there are only 2.5 million households in the country. The traditional Norwegian cabin is often on the electricity grid and often energy inefficient. This translates into a relatively higher cost of recreational trips originating from cabins in these areas.

Table 2 shows the total electricity consumption for cabins and households in the five price zones. Two key observations can be made. First, consumption is reduced from 2021 to 2022, with the decline being relatively larger in the price zones that experience the price shock the most (NO1, NO2 and NO5). The fall in the treated areas relative to the fall in the non-treated areas, is approximately –10 %. Second, the decline in electricity consumption is larger for cabins than for households in the affected areas. This finding can be explained by the fact that cabins are not covered by the subsidy scheme which raised prices relatively more, leading to a downward shift in demand.

3. Data and empirical strategy

The general idea in our analysis is to compare counts of activity through the use of the fitness app Strava in areas in electricity price zones that experienced the higher electricity prices to areas in electricity price zones that did not. We further restrict our sample to a belt around the border between the treated and untreated zones (see Fig. 3). In many areas, the border between different price zones can seem somewhat arbitrary, cutting municipalities in half. Drawing inspiration from spatial regression discontinuity designs (e.g., Keele and Titiunik, 2015), the idea is that the closer we are to the border, the more similar we expect treated and untreated units to be.

² If operating at full capacity, the transmission line can transfer 25 TWh per year, which is slightly one fifth of Norway's total annual production.

³ Note, spot contracts were already prevalent before the energy crisis (76.5 % in Q3 2021), rising to 87.4 % in Q4 2022 and 93.2 % in Q4 2023 as many suppliers withdrew fixed-price contracts. Importantly, fixed-price products in treated zones also became more expensive after the shock (Statistics Norway, 2021c, 2023c, 2024b), so treated households could not avoid higher costs by switching.

⁴ Exemption also applied to businesses and the public sector (e.g., universities and schools).

Table 1
Stylized calculations of extra electricity costs for different housing units.

	Homes		Cabins		Homes + Cabins	
	USD	Percent	USD	Percent	USD	Percent
Extra cost in NO1 relative to 2020						
Extra cost in 2022	1833	630 %	750	516 %	2583	592 %
Cumulative extra (2021 + 2022)	3216	553 %	2893	995 %	6109	700 %
Extra cost in NO1 relative to NO3						
Extra cost in 2022	1322	165 %	1783	353 %	3105	238 %
Cumulative extra cost (2021 + 2022)	2318	157 %	2339	277 %	4657	200 %

Notes: Stylized calculations assuming a yearly consumption of 20,000 kWh for a home and 10,000 kWh for a cabin. Calculations are based on the average electricity price in each year, including grid fee, VAT, and other taxes, with support subtracted for homes. Prices are in 2023 USD.

Table 2
Electricity consumption (GWh).

Consumption group	Year	NO1	NO2	NO3	NO4	NO5
Cabins	2021	877	764	409	368	405
	2022	709	555	481	347	323
	2022/2021	81 %	73 %	93 %	94 %	80 %
Households	2021	16,039	9369	6062	5069	3764
	2022	13,854	7867	5759	4881	3294
	2022/2021	86 %	84 %	95 %	96 %	88 %

Notes: Electricity consumption in GWh per year for the consumption groups cabins and households. The data was retrieved from [Elhub \(2024\)](#).

Table 3
Descriptive statistics for activity counts and trail length.

	N	Mean	Median	SD	Min	Max
Monthly activity counts						
Treatment group, NO1 and NO5	58,848	9.6	0	27.3	0	1188
Control group, NO3	53,472	10.9	0	37.9	0	1285
Yearly activity counts						
Treatment group, NO1 and NO5	4904	114.7	50	169.7	0	2328
Control group, NO3	4456	131.0	55	221.7	0	2815
Trail length (kilometers)						
Treatment group, NO1 and NO5	4904	0.8	0.2	1.4	0	16
Control group, NO3	4456	0.8	0.2	1.5	0	19

Notes: The table shows descriptive statistics (number of observations, mean, median, standard deviation, minimum value and maximum value) for activity counts and trail length for trails within 15 km of the border between NO3 and NO1/NO5 in 2020. It shows the statistics for the treatment and the control group and for two temporal aggregation levels: yearly and monthly. The treatment group is defined as trails within 15 km to the south of the southern border of the NO3 price zone border, and hence experienced an electricity price increase in 2021 and onwards. The control group is defined as trails within 15 km to the north of the border, which did not experience the price increase.

The sudden appearance of an arbitrary border creates an as-if random selection into treatment and control. Or to use the difference-in-difference terminology: it is more plausible that the parallel trends assumption holds for units that are close to each other. We have chosen to use 15 km as the bandwidth length and do robustness on increasing it to 20 km and reducing it to 10.

3.1. Strava data

Strava is a popular app for tracking training activities and had more than 120 million registered users worldwide as of January 2024 ([Strava, 2024](#)). To register an activity on Strava, users will open the app, select “Record”, choose the activity type, and press “Start” to track their route, speed, distance, and time. After completing the activity, they press “Stop” and “Save”, optionally adding details before finalizing the activity.

Strava has made aggregated data available for researchers and urban planners on their platform Strava Metro. We accessed monthly data on walking, hiking, running, and biking from January 2019 to December 2022. We have a panel data set and follow the same trails each month. We have obtained activity counts for all trails within 15 km of the electricity price zone border between the zones NO3 and NO1/NO5 ([Fig. 3](#)). Each year, Strava updates their OpenStreetMap basemap, which is used to align and aggregate recreational trips. The OpenStreetMap updates are based on volunteered geographic information where people volunteer to digitize roads, buildings, trails, and more in the map. This means that each year, some new gaps are filled in, e.g., new trails are added. To have a balanced panel data set with full support, we use only trails available at the beginning of our time-period. This accounts for approximately 99 % of the trails. The data comes in the form of activity counts at a given trail segment during a given time interval. If

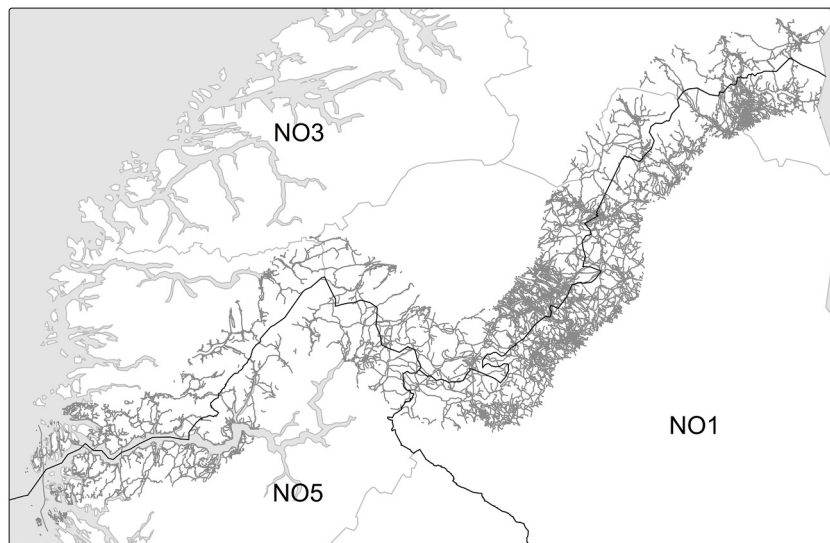


Fig. 3. Strava trails within 15 km of the border between the NO3, and NO1/NO5 electricity price zones

Notes: The figure shows the geographical positions of the 9360 Strava trails we use in the analysis, and the borders between the electricity price zones NO1, NO3 and NO5.

for instance a runner records a run that goes through three trail segments, it is registered as one count for each of the three trail segments the run is comprised of. The median trail segment length is 0.2 km long.

A potential concern with using Strava data to analyze recreational activities is the generalizability of the results to the broader population given who the users are and what activities they engage in. Not everyone registers their activity on Strava, and there is likely a self-selection bias in who downloads the app and records their activities. [Venter et al. \(2023\)](#) examine these biases and the accuracy of crowdsourced recreational activity data from Strava by comparing it to in-situ observations from count stations and questionnaires around Oslo in Norway, which contains 14 % of the total Norwegian population. Their findings suggest that Strava data demonstrated good accuracy in capturing both spatial and temporal variations in recreational activities of the total recreationist population, particularly at the monthly level during the summer. Precision decreased at finer temporal resolutions (e.g. daily, hourly) and during winter. Strava data was further biased in terms of overrepresenting cyclists, males, middle-aged people, and those with higher education and income. However, the demographic biases did not affect the efficacy of Strava data in accurately tracking

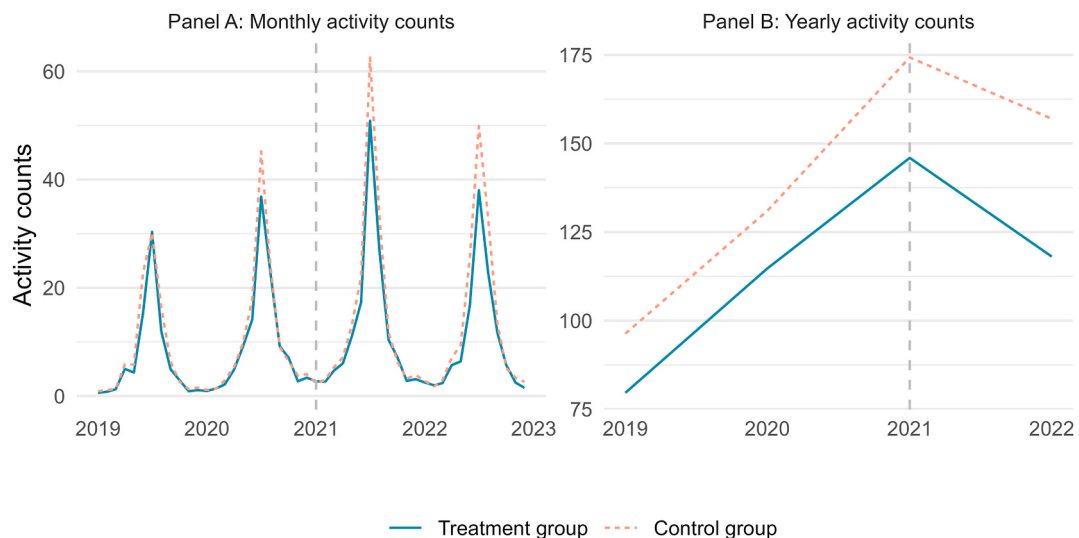


Fig. 4. Outdoor recreation activity counts per month and year.

Notes: Panel A shows the average activity count per trail per month. Panel B shows the average activity count per trail per year. The treatment group is defined as trails within 15 km to the south of the southern border of the NO3 price zone border, and hence experienced an electricity price increase in 2021 and onwards. The control group is defined as trails within 15 km to the north of the border, which did not experience the price increase.

temporal and spatial patterns in total recreation. Therefore, we are of the opinion that this data is valuable and can provide important information on the price elasticity of recreation demand. But we are cautious to generalize our findings to other non-Strava users.

Table 3 shows descriptive statistics for activity counts in 2020 for two different temporal aggregation levels, monthly and yearly. At the monthly level, the mean counts were 9.6 for the treatment group and 10.9 for the control group. The median value is zero, indicating many zeroes, and the high maximum values suggest a long right tail in the count distribution. The yearly aggregation is achieved by summing the counts for each trail over the year. Table 3 also shows descriptive statistics for the length of the trail segments in the treatment and control groups. Most trail segments are small. The smallest segments round to 0 km and are a few meters long, the average length is 0.8 km, the median is 0.2 km, and over 70 % of the trails are under 1 km long. There is, however, a long right tail, and the longest trail segment is 19 km long. As we can see in Table 3, the lengths are fairly equally distributed across treatment and control.

Fig. 4 shows monthly and yearly mean counts of recreation activity for the treatment and control group. The first thing we notice is that there are great seasonal variations, with activity peaking in the summer and dropping in the winter. The pronounced seasonal variations make it challenging to detect any trend shifts in the monthly graph (Panel A in Fig. 4). For the yearly, however, a noticeable change occurs in 2021. First, activity counts go from increasing year-on-year to a sudden decline in both groups in 2022. Second, the decline appears to be greater for the treatment group than the control group.

3.2. Demographics and spatial data

We supplement the Strava tracking data with spatial information on population demographics, cabin presence, prevailing weather, and COVID-19 prevalence. From the Norwegian cadaster register, we have accessed the locations of all buildings in Norway (Kartverket, 2024). The locations of buildings are represented by coordinate points within the buildings' outlines. We then merged all the Strava trail segments with all buildings which are at least one km from the trail and created aggregated counts for different building types near the trail. The two most important building types affecting recreation activities are cabins and housing units. Other important building types for explaining recreation activities are buildings for accommodation such as hotels, motels, rental cabins, and tourist cabins. By merging information on buildings near the trails, we can identify which trails are predominantly in cabin areas and which are in residential or urban areas.

All the spatial calculations we do are done using the nearest point of a trail segment. For instance, to be included in the treatment or control group, the nearest point of a trail segment has to be within 0 km and 15 km of the price border (excluding those who cross the border). Or when we define cabin and residential areas, we require that the nearest point of the segment is within 1 km of at least one cabin/house.

In Fig. 5, we show yearly counts for areas we categorize as cabin areas and areas we categorize as residential areas. Cabin areas are defined as trails with at least one cabin and no housing units or accommodation sites (hotels, camping lots, rental cabins, etc.) within 1 km from the trail. Residential areas are defined as trails with at least one housing unit and no cabins within 1 km from the trail. The graph gives the impression that the treatment and control groups follow each other in the pre-period, and that the treatment group

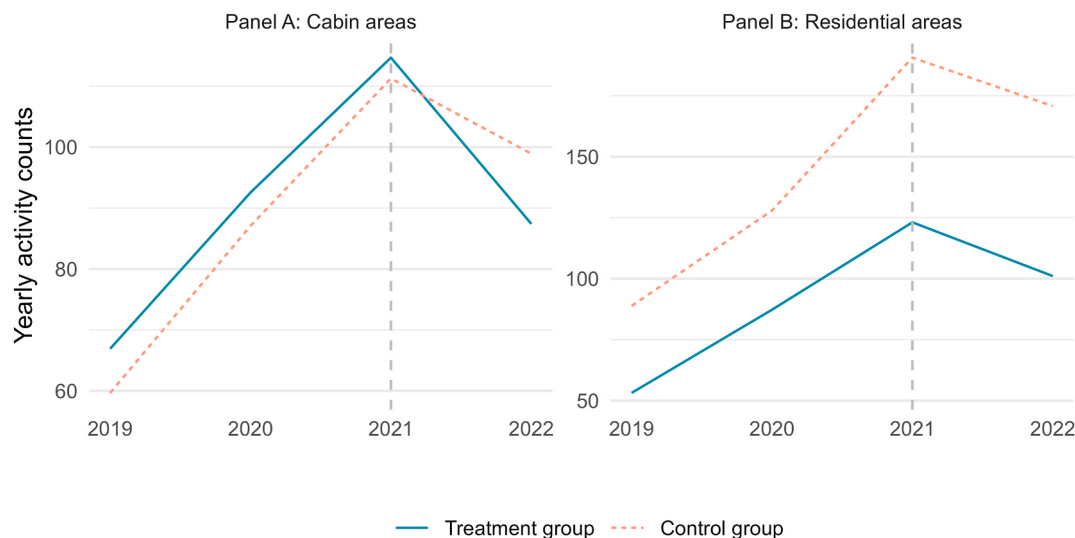


Fig. 5. Yearly outdoor recreation activity counts per cabin areas residential areas

Notes: Panel A shows the average activity count per trail per year in cabin areas. Panel B shows the average activity count per trail per year in residential areas. Cabin areas are defined as trails with at least one cabin and no housing units or accommodation sites (hotels, camping lots, etc.) within 1 km from the trail. Residential areas are defined as trails with at least one housing unit and no cabins within 1 km from the trail. The treatment group is defined as trails within 15 km to the south of the southern border of the NO3 price zone border, and hence experienced an electricity price increase in 2021 and onwards. The control group is defined as trails within 15 km to the north of the border, which did not experience the price increase.

experiences a large excess decline compared to the control group in the cabin areas.

Our identification does not require the treatment and control group to be balanced on covariates, but we still find a balance assessment informative. We have gathered some socio-demographic data for the areas where the trails are located. From [Statistics Norway \(2023b\)](#), we obtain data on mean income per sub-municipality area, which are administrative units within each municipality (on average, each municipality is divided into 4.3 sub areas). This provides us with the most detailed income data publicly available. Additionally, data on household composition have been collected, including the number of single-person households, couples with children, couples with adult children, and couples without children. This is also per sub-municipality area. Weather observations from the nearest weather station have also been merged with the trail count data. The weather data includes temperature and precipitation per hour, which we aggregate to mean values per month. We have also obtained data for the number of covid infections per 1000 inhabitants per municipality per month.

[Table 4](#) reports descriptive statistics on the treatment and control group. The treatment and control group appear to be relatively balanced on the observable covariates. There are a few more housing units and cabins in the treatment group than in the control group. The variables household income and weather (temperature and rain) appear balanced. The weather variables are shown for the summer months (May through September) since these are the months where most of the Strava observations are, but the treatment and control group also seems balanced on yearly averages. Note that the aggregated variables (income, households of different types and covid cases) masks underlying variability since they are based on municipality or sub-municipality area averages. We therefore cautiously conclude that the treatment and control group appear to be balanced, but that the aggregated data adds uncertainty.

3.3. Empirical strategy

To evaluate the causal impact of higher electricity prices on recreation demand, we estimate a two-way fixed effects model. The entity i is a Strava trail segment. For each trail segment, we have activity counts per time interval, t . This is captured by y_{it} . We consider the following model:

$$y_{it} = \sum_{t \neq 2021} \delta_t^* (d_i^* \tau_t) + \alpha_i + \gamma_t + \varepsilon_{it} \quad (1)$$

where α_i captures trail fixed effects and γ_t year fixed effects. d_i is an indicator taking the value 1 if the trail is south of the price border and therefore in the treatment group, and zero otherwise. τ_t is a dummy equal to 1 for time t and zero otherwise, using 2021 as the reference year. The coefficients δ_t are the parameters of interest and gives us the DiD treatment estimate (or placebo) a given year. We estimate separate models of Equation (1) for residential and cabin areas. Additionally, we conduct several robustness checks, involving different estimation techniques and tests of the parallel trend assumption (see [Appendix B](#) and [Section 4.2](#)).

Table 4
Descriptive statistics for covariates in 2020.

	Treatment group	Control group	All trails
Number of trails	4904	4456	9360
Number of municipalities	23	19	37
Yearly income (\$)	39454.1 (2515.9)	39222 (2463.5)	39343.6 (2493.6)
Housing units within 1 km	62.3 (130.9)	50.9 (113.7)	56.9 (123.1)
Cabins within 1 km	22.5 (33.0)	19.8 (41.7)	21.2 (37.5)
Accommodation buildings within 1 km	3.7 (6.7)	3.2 (6.1)	3.5 (6.5)
No buildings within 1 km	0.1 (0.3)	0.1 (0.3)	0.1 (0.3)
Households, couples with kids	111.1 (73.6)	130.1 (76.5)	120.1 (75.6)
Households, couples without kids	181.6 (117.7)	199.5 (89.2)	190.1 (105.5)
Single person households	300.5 (208.6)	316.3 (162.4)	308.1 (188.2)
Rain during summer months (ml)	400.3 (218.6)	422.6 (265.1)	411 (242.1)
Temperature during summer months (° C)	11.1 (1.7)	11 (1.1)	11 (1.5)
Covid cases per capita (1000)	0.7 (0.9)	0.7 (1.2)	0.7 (1)

Notes: The table shows the mean value and standard deviation (in parenthesis) in 2020 for covariates for trails in the treatment group, the control group and the two groups pooled together. The treatment group is defined as trails within 15 km to the south of the southern border of the NO3 price zone border, and hence experienced an electricity price increase in 2021 and onwards. The control group is defined as trails within 15 km to the north of the border, which did not experience the price increase.

4. Results

4.1. Main results

Table 5 shows the DiD estimates. The interaction of the treatment group indicator and a given year identifies the difference in the activity count between the treatment group and control group that particular year relative to the reference year 2021. The group-year interactions before 2021 are placebos and the interaction for 2022 identifies the average treatment effect for the treated that year.

The dependent variable in our model is a count variable which has an excess of zeroes. Even though the real structure of our data is non-linear, we still prefer to estimate a linear OLS model. This is because the model is saturated, and fits the conditional expectation function regardless of the true functional form, and makes no parametric assumptions (Angrist and Pischke, 2009). The table shows the DiD treatment effect estimated through the OLS estimator, as well as the Poisson and Zero-inflated Poisson (ZI Poisson) estimators. For the Poisson and the ZI Poisson, we show the average marginal effects (see Appendix B.1 for the raw coefficient estimates). As we can see, the three estimators produce roughly the same results. Going further, we consider the OLS estimations our main results.

We have estimated the model on two different subpopulations of the trails: cabin areas and residential areas. In cabin areas, the treatment effect is estimated to be -15 counts per year. This effect is statistically significant at a 1 percent level. Implicitly, the activity count in a given trail falls on average with 15 counts throughout the year due to the increased electricity prices. This amounts to a 14.6 % decrease. In residential areas, the treatment effect seems to be positive, but non-significant.

Fig. 6 shows the main results of the regressions in Table 5 (the OLS column) in a graph. Here it becomes clear that there seems to be a shift where cabin owners have moved their recreation away from their cabins. This is in line with the finding in Table 2 where electricity consumption at cabins have fallen more in the price zones NO1, NO2 and NO5 relative to NO3 and NO4 between 2021 and 2022. In the residential areas, we get a positive, but non-significant point estimate after the prices have increased.

4.2. Robustness checks

Appendix B contains a set of robustness checks and sensitivity analyses. Here we test for robustness to different assumptions, regression models and sample restrictions. In the main analysis, standard errors are clustered at the municipality level. We would expect trails within the same municipality to be correlated because they are exposed to the same natural environment, land use policies, and zoning laws, which affects the number and placement of cabins and types of housing, which again affects the supply of recreationists. Furthermore, municipalities differ in how they invest in infrastructure to support outdoor recreation. For example, improving access with trailhead parking and creating and marking new trails. During COVID-19, municipalities had large discretions in deciding which measures to implement to best limit infections. Common restrictions included travel and cabin usage restrictions

Table 5
Effects on yearly recreation activity counts.

	OLS	Poisson	Zero-inflated Poisson
Panel A: Cabin areas			
Treatment group*Year 2019	3.84 (19.67)	8.0 (12.68)	7.65 (15.52)
Treatment group*Year 2020	2.05 (11.81)	2.82 (7.19)	2.54 (7.11)
Treatment group*Year 2022	-14.93^{***} (5.04)	-12.94^{**} (6.36)	-13.54^{**} (5.87)
Number of trails	1915	1915	1915
Panel B: Residential areas			
Treatment group*Year 2019	-11.67 (29.94)	-19.46 (32.43)	-20.25 (20.8)
Treatment group*Year 2020	9.15 (8.04)	8.56 (7.51)	7.49 (8.76)
Treatment group*Year 2022	14.85 (15.33)	13.26 (14.24)	12.05 (13.21)
Number of trails	370	370	370
Additional controls			
Treatment group	✓	✓	✓
Year 2019	✓	✓	✓
Year 2020	✓	✓	✓
Year 2022	✓	✓	✓

Notes: The table shows the results from estimating equation (1) on yearly recreation activity counts. Standard errors are clustered at the municipality level. The treatment group is defined as trails within 15 km to the south of the southern border of the NO3 price zone border, and hence experienced an electricity price increase in late 2021 and onwards. The control group is defined as trails within 15 km to the north of the border, which did not experience the price increase. Panel A shows the results on trails in cabin areas, defined as trails with at least one cabin and no housing units or accommodation sites (hotels, camping lots, etc.) within 1 km from the trail. Panel B shows the results on trails in residential areas, defined as trails with at least one housing unit and no cabins within 1 km from the trail. Column 1 shows the results of an OLS estimation, column 2 the average marginal effects for a Poisson estimation, and column 3 the average marginal effects for a Zero-inflated Poisson estimation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

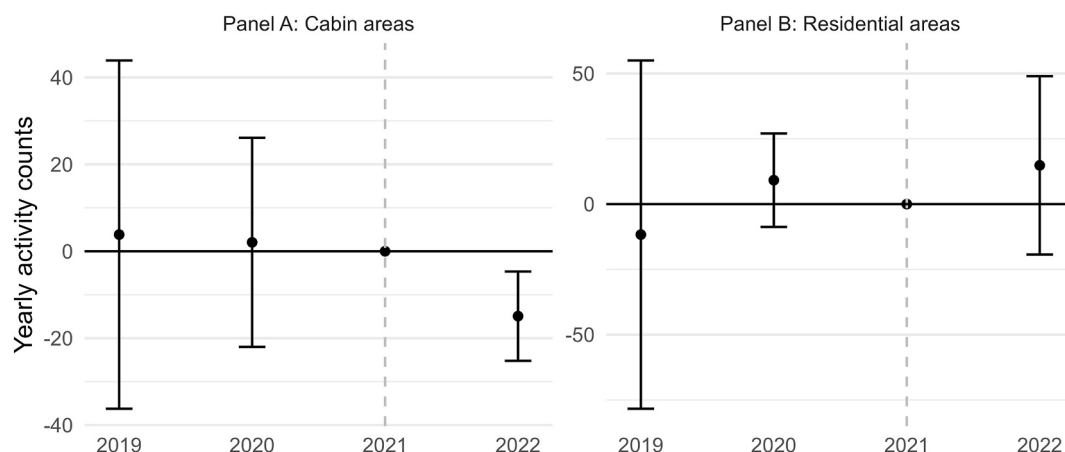


Fig. 6. Effects on yearly activity counts

Notes: The figure shows OLS DiD coefficient estimates and 95 % confidence intervals using the event-study specification in equation (1) on yearly recreation activity counts. Standard errors are clustered at the municipality level. The treatment group is defined as trails within 15 km to the south of the southern border of the NO3 price zone border, and hence experienced an electricity price increase in late 2021 and onwards. The control group is defined as trails within 15 km to the north of the border, which did not experience the price increase. The vertical line represents the time of the treatment. Cabin areas are defined as trails with at least one cabin and no housing units or accommodation sites (hotels, camping lots, etc.) within 1 km from the trail. Residential areas are defined as trails with at least one housing unit and no cabins within 1 km from the trail.

affecting recreation. Given our identification strategy, we only have 37 municipalities in our sample and therefore large sample approximations may perform poorly (Roth et al., 2023).

To check the robustness of our results, we also estimated standard errors clustered at the trail level, see Appendix B2. Clustering at the trail level leads to generally smaller standard errors, but our results remain the same: We get non-significant pre-trends and a significant treatment effect in cabin areas, and no pre-trends or treatment effects in residential areas. In Appendix B.3, we also estimate bootstrapped standard errors. We test simple bootstrapping and block bootstrapping at the level of municipality and trail. Across the board, we get the same results as with analytical standard errors clustered at the municipality.

We have further done a placebo test to test the reliability of our research design by using another electricity price border which did not experience a price divergence. The idea is that if we detect parallel trends between trails close to the border both before and after the price shock in 2021, that indicates that the parallel trends assumption should hold for the price border that did experience the price divergence as well. We use the border between the price zone NO1 and NO5 and use the same specifications as before. The results do indicate that we have parallel trends, particularly in cabin areas. See Appendix B.4.

We have further checked if the results are sensitive to changes in the bandwidth length from the price border in Appendix B.5. In our main analysis, we are using a 15 km bandwidth from the border. The rationale for using a narrow bandwidth is that trails close to the border are expected to be more similar, making the treatment assignment more experimental-like. However, the bandwidth cannot be too small as that significantly reduces the number of observations. We test both a 10 km and a 20 km bandwidth. We find that the results are robust to bandwidth length decisions.

Another uncertainty is whether there are spillover effects for trails right on the border, i.e., that people living or owning cabins on one side of the border use trails on the other side of it. To investigate if this affects our results, we have conducted robustness tests where we have excluded trails within a buffer area close to the border. We test two different buffer lengths: 0.5 km and 2 km and find that the results are robust to these parameters. The results of these analyses are shown in Appendix B.6.

Substitution effects could potentially increase the activity levels in the control sites. This could happen if treated cabin-owners shift their outdoor recreation from areas near their cabins to areas defined as cabin areas in the control zone. The Stable Unit Treatment Value Assumption (SUTVA) would then be violated, and inflate the effect we have found. We are to some extent not too worried about this since we have specifically defined cabin areas with the intent to lower the risk of SUTVA violations. We have defined a trail segment to be in a cabin area if it is within 1 km of at least one cabin, and without houses or accommodation sites (hotels, camping lots, rental cabins, etc.) within 1 km. The logic is that it is implausible that cabin owners would switch their recreation to other cabin areas. There is no good way to formally test if this is a problem, but we can run indicative tests. If we were to detect trend breaks in areas that are likely recipients of a substitution between the control and treatment area, that would be an indication of substitution into the control area and potential SUTVA violations. In Appendix B.7, we test if such areas in the control zone experienced a trend-break with the treatment zone after treatment, and we find no indication of that. Furthermore, the fact that our results are robust when removing trails close to the border (see the previous paragraph and Appendix 6) also points in the direction that this is less of a concern.

Furthermore, we tested the robustness of alternative definitions of cabin areas and residential areas. In our main analysis, we define cabin areas as trails with at least one cabin and no housing units or accommodation sites (hotels, camping lots, etc.) within 1 km from the trail. Residential areas are defined as trails with at least one housing unit and no cabins within 1 km from the trail. The 1-km radius decision is made to capture trails that are in proximity to cabins, while leaving some leeway. The smaller the radius, the more precisely

we capture cabin recreationists, while at the same time reducing our sample. In [Appendix B.8](#) we have tested the robustness of our results of reducing the radius to 0.5 km and increasing it to 1.5 km. The results are robust to this decision in cabin areas. In residential areas, there is a parallel trends violation in the 0.5 km case in 2019.

In [Appendix B.9](#), we show the results of adding control variables to equation (1). We control for rain, temperature and covid cases per month. Adding the control variables increases the R^2 and reduces the standard errors but does not change the overall results. This suggests that the treatment and control group are balanced on these covariates, and we prefer to estimate the saturated model in Equation (1). Furthermore, we follow [Rambachan & Roth \(2023\)](#) and [Rambachan \(2024\)](#) and test the sensitivity of the results to violations of the parallel trends assumption. We find that our results are robust to deviations in the trend between the two groups. The results are reported in [Appendix B.10](#).

Lastly, in the main analysis, we use year as the temporal resolution level for two reasons: First, we experience large seasonal variations (see [Fig. 4](#)), causing difficulty in detecting trends and trend shifts at lower time resolutions. Second and more importantly, we do not expect variations in the electricity price from month to month to affect recreation behavior, but rather the cumulative effect over a longer time period. Instead of going to their cabin three times a year, a household might decide on doing it two times. Or staying for one week instead of two. Lower time interval resolutions would allow us to detect dynamic effects throughout the year, but it would come at the cost of more noisy observations. In [Appendix B.10](#), we run the analysis on lower time resolutions to see if the results hold and to investigate dynamic treatment effects throughout the year. We use both monthly and quarterly resolutions. The first thing we notice is that the results seem noisier and that the standard errors increase. We still do not detect any significant pre-trends, but we also see that the statistical inference of the treatment effects depends on which month or quarter is used as the reference period. This indicates that parallel trends may not hold at lower time resolutions. We note that we have more noisy observations at the lower time resolutions and speculate that this is caused by idiosyncratic shocks at the lower temporal levels which even out throughout the year. We further find that most of the recreation happens during the summer, with August being the most important contributor. We also tested non-calendar year intervals, and find that the results are robust to this (see [Appendix B.11](#)).

5. Interpretation and implications

So far, we found that the electricity price increase led to a 15 % decrease in the demand for cabin-based outdoor recreation. The likely driver is that consumers substitute away from outdoor recreation through the use of cabins because it became relatively more expensive. Our design does not let us rigorously investigate whether consumers shift their recreation to other relatively cheaper areas, like natural areas closer to their homes, or to mountain lodges or resorts, or if they cut back on outdoor recreation overall. We do not find a significant change in recreation in residential areas, which can be interpreted as limited substitution to these areas, but we are careful to draw this conclusion. We have fewer observations here, and it might be that the analysis is just underpowered. The only thing we can say with some degree of certainty is that cabin-owners reduce their consumption of cabin-based outdoor recreation when the cost of consuming that good increases. We use this finding to make welfare calculations and calculate the price elasticity of cabin-based outdoor recreation.

5.1. Welfare effects

Here, we use the estimated demand response and the price increase to calculate welfare effects. We use the statistic-sufficient approach ([Chetty, 2009](#)) and employ the Marshallian elasticity we previously found to calculate the Habsberger welfare loss.

To clarify, let q denote the demand for total outdoor recreation visits linked to cabin usage per year. Let an extra cost of recreation attributable to the extra energy cost be denoted by t . The utilitarian welfare function is given by:

$$w = \sum_{i=1}^N \max_{q_i} [u_i(q_i) - tq_i - cq_i] + t \sum_{i=1}^N q_i \quad (2)$$

The consumer chooses how many units of q to consume taking the cost, c , and the extra cost, t , into account. The extra cost enters the function two times: first as a negative component for the consumers, and second as a positive component for the producers. There is a total of N consumers. The effect on total welfare of the marginal increase in t is found by taking the total derivative of w with respect to t :

$$\frac{dw}{dt} = - \sum_{i=1}^N q_i - t \frac{d \sum_{i=1}^N q_i}{dt} + \sum_{i=1}^N q_i = -t \frac{dq}{dt}, \quad (3)$$

where $q = \sum_{i=1}^N q_i$. The only real effect on total welfare is the deadweight loss. Now let $\tilde{t}$ be the 2022 cost increase. The total welfare loss is given by:

$$w(\tilde{t}) - w(0) = \int_0^{\tilde{t}} -t \frac{dq}{dt} dt. \quad (4)$$

While the functional form of the demand function is unknown, we make a simplifying assumption of linearity and look at the discrete

change in q going from $t = 0$ to $t = \tilde{t}$ as $\Delta q = q(\tilde{t}) - q(0)$. This gives us:

$$w(\tilde{t}) - w(0) = \frac{1}{2}\tilde{t}\Delta q. \quad (5)$$

Assuming that the number of cabin trips per year is proportional to cabin-based recreation, we can calculate the welfare loss as follows: Let $\Delta q = h_0 f_0 \alpha$, where h_0 is the total number of affected cabins before the price increase, f_0 is the average number of trips to the cabin and α is the relative demand change. There were 354,363 affected cabins (Statistics Norway, 2021b) and a typical cabin owner takes 12.4 trips to their cabin each year (Grythe and Lopez-Aparicio, 2021). The 2022 cost increase was \$1783 throughout the year for an average cabin-owner, the cost per trip is $\tilde{t} = \$1,783/12.4 = 143.8$. Given our estimate for $\alpha = 14.6\%$, the estimated total welfare loss for the consumers of the price increase is \$46 million.

Furthermore, we can calculate the total consumer surplus (CS) of outdoor recreation linked to cabin usage under the assumption of linear demand. The linear demand function is given by:

$$q(t) = q_0 - \frac{\Delta q}{\tilde{t}}t, \quad (6)$$

where $q_0 = f_0 h_0$. Let $\tilde{t}$ be the choke cost where demand hits 0, i.e., $q(\tilde{t}) = 0$. Solving for $\tilde{t}$ gives:

$$\tilde{t} = \frac{q_0 \tilde{t}}{\Delta q} = \frac{q_0 \tilde{t}}{q_0 \alpha} = \frac{\tilde{t}}{\alpha} = \$985.8. \quad (7)$$

Assuming linearity, we can find the total CS for a cabin trip with outdoor recreation as $w(\tilde{t}) - w(0) = \frac{1}{2}\tilde{t}q_0 = \frac{1}{2}\tilde{t}h_0f_0 = \2.3 billion, where h_0 is now the total number of cabins in Norway, which is 473,235 (Statistics Norway, 2021b). Furthermore, we can calculate the yearly value per cabin owner as $\frac{1}{2}\tilde{t}f_0 \approx \$6,112$ and per cabin trip as $\frac{1}{2}\tilde{t} \approx \493 . According to Grythe and Lopez-Aparicio (2021), an average cabin trip lasts for about 2.4 days. This amounts to a value of \$204 per use-day. Table 6 summarizes the welfare estimates.

The linearity assumption is very strong, so these are uncertain estimates. It is worth noting that if the demand function is convex, we will overstate the values in the interpolation between 0 and $\tilde{t}$, and understate it in the extrapolation between $\tilde{t}$ and $\bar{t}$.

5.2. The price elasticity of cabin-based outdoor recreation

We calculate the arc elasticity of cabin-based outdoor recreation with respect to the price of electricity according to $e_{arc} = \frac{q_1 - q_0}{\frac{1}{2}(q_1 + q_0)} / \frac{p_{e1} - p_{e0}}{\frac{1}{2}(p_{e1} + p_{e0})}$ (Amiran and Hagen, 2010), where q is demand and p_e is the price of electricity. The observed demand was 87 counts per trail in 2022, and the counterfactual demand was estimated to 102 counts per trail. The electricity price was 4.6 U.S. cents/kWh in unaffected areas and 21.1 U.S. cents/kWh in affected areas. The elasticity is therefore calculated to -0.12 .

A more interesting statistic than the elasticity of cabin-based recreation with respect to electricity prices, is the general price elasticity of cabin-based recreation, no matter which cost component experiences the price increase. The marginal cost of recreation through cabin usage is comprised of elements such as the travel cost, the cost of wear and tear of the cabin, and equipment and clothing used for outdoor recreation, as well as the cost of electricity consumption. Let the price of cabin-based outdoor recreation in period 0 be comprised of electricity costs in period zero, p_{e0} and all other relevant costs in period zero, p_{a0} , i.e.: $p_0 = p_{e0} + p_{a0}$. To find the general price elasticity, we therefore need to calculate:

$$e_{arc} = \frac{q_1 - q_0}{\frac{1}{2}(q_1 + q_0)} / \frac{p_{e1} - p_{e0}}{\frac{1}{2}(p_{e1} + p_{e0} + 2p_{a0})} \quad (8)$$

Where the denominator is found by plugging in for p_0 and p_1 :

$$\frac{p_1 - p_0}{\frac{1}{2}(p_1 + p_0)} = \frac{(p_{e1} + p_{a0}) - (p_{e0} + p_{a0})}{\frac{1}{2}((p_{e1} + p_{a0}) + (p_{e0} + p_{a0}))} = \frac{p_{e1} - p_{e0}}{\frac{1}{2}(p_{e1} + p_{e0} + 2p_{a0})} \quad (9)$$

Ideally, we would observe each person's travel cost, electricity cost and their value of wear and tear of the cabin and equipment. That, we do not, and must instead rely on mean values at the population level. This approach lets us calculate the value of the elasticity for an average person. We do this calculation in Table 7, where we have found the electricity bill in the absence of the price shock to on

Table 6
Estimates of consumer surplus from cabin-based outdoor recreation.

Consumer surplus from cabin-linked recreation in Norway per year	\$2.3 billion
Consumer surplus from recreation per year per cabin owner	\$6112
Consumer surplus from recreation per cabin trip	\$493
Consumer surplus from recreation per use-day	\$204

Notes: Welfare calculations based on the assumption of linear demand.

average constitute 35 % of the total marginal cost of recreation. Data on electricity consumption was retrieved from Ballo (2019) and Statistics Norway (2025d) and data on the different cost components was retrieved from Statistics Norway (2021a), Statistics Norway (2025c), Farstad et al. (2008), Kaggle (2025), Statens vegvesen (2021), Statistics Norway (2025a) and Statistics Norway (2025b). In Appendix D.1, we explain how we retrieved the data. Using $p_{a0} = \$48 + \$15 = \$63$, $p_{e0} = \$34.4$ and $p_{e1} = \$158$, we can calculate the elasticity according to Equation (8), which gives an elasticity of -0.2 . To put this number into perspective, we compare it to previous research. Wardman (2022) conducts a meta-analysis of price elasticity of travel demand in the UK, and find the long-run elasticity for leisure travelling to be -0.59 when travelling with car, i.e. more elastic. Similarly, Wardle (2025) find more elastic arc price elasticities of forest travel demand for bird watchers, varying between -1.13 and -2.26 .

We can furthermore learn about the uncertainty by running a Monte Carlo simulation where we make random draws of uncertain parameters according to their distributions and calculate the elasticity for each. This lets us calculate the standard deviation and confidence interval. In Appendix D.1 we explain how we retrieved the data and found their distributions, and in Appendix D.2 we explain how we conducted the Monte Carlo simulation. The results are presented in Table 8 and Fig. 7.

Table 8 shows summary statistics of the results of the Monte Carlo simulation. We get that the elasticity has an expected value of -0.26 with a 95 % confidence interval of $[-0.75, -0.06]$. Fig. 7 shows the distributions as well as expected values and 95 % confidence intervals for the two variables. We see that the distribution is left-skewed.

6. Conclusion

In this paper, we utilize a natural experiment and investigate the effect of an economic shock from extraordinarily high electricity prices on the demand for cabin-based outdoor recreation using observational data. We find that the electricity price shock caused the demand for outdoor recreation to fall by 15 percent in cabin areas. This is significant at a one percent level and robust to estimator and model specifications. While we do observe an increase in outdoor recreation in residential areas, suggesting a substitution from relatively more expensive cabin-based outdoor recreation to relatively cheaper local outdoor recreation, this effect is insignificant.

We find that the response is relatively small compared to how large the price increase was. As a result, back-of-the-envelope calculations of the consumer surplus cabin-owners obtain from using their cabins to do outdoor recreation, suggest high values. Under the assumption of a linear demand function, we have calculated the value to on average be over \$6000 per household with access to a cabin per year, equivalent to a CS of \$204 per use-day. While the welfare calculations are uncertain, we still find it likely that the consumer surplus is large. The ever-rising cabin prices (Statistics Norway, 2025a), the higher income and wealth among cabin owners, and the modest demand response to a substantial price shock all support the notion that the CS from cabin-based recreation is high.

Furthermore, our calculations of the price elasticity suggest a highly inelastic demand function. Using a Monte Carlo simulation, we calculated the expected value of the elasticity to be -0.24 and a 95 % probability that it is between -0.73 and -0.05 . While there clearly is uncertainty associated with Monte Carlo simulations, we are so far away from elastic demand that we are confident to claim that it is inelastic.

The policy implication from this finding is that there is a potential to raise more revenue from cabin owners to restore and protect natural areas and ecosystem services to offset the degradations they cause. This is of particular interest to rural municipalities with a high concentration of cabins who have local economies which relies on cabin visitors. They can increase fees and taxes on cabin ownership and usage without seeing the demand fall too much. From an environmental standpoint, it is worth noting that cabins generate large welfare effects. Policies aimed at regulating the development of new cabins should balance the environmental cost against the welfare benefits.

Lastly, another avenue we could explore is potential health effects. If the overall outdoor recreation falls, we would expect to see worse health outcomes. We are, however, reluctant to make strong claims here because we do not have a design that lets us observe substitution patterns. Although some outdoor activity may have shifted from cabin areas to residential areas or indoor exercise as these have become relatively cheaper, we did not find a statistically significant increase in recreation in residential areas in our study. This may indicate an overall decrease in outdoor recreation because of the electricity price increase. If so, this reduction could have public health implications, potentially diminishing both mental and physical well-being. For Strava users, however, it is reasonable to assume that reduced outdoor activity has been offset to a greater extent by indoor exercise, thus minimizing the impact on physical health. Nonetheless, there may still be a negative effect on mental health if time spent outdoors in natural settings decreased, as a vast research literature shows that mental health correlates positively with nature experiences (see for instance Thomsen et al., 2018).

Notably, our analysis is restricted to Strava users, which may limit the generalizability of our results. Strava users are typically male, richer, and more active compared to the general population (Venter et al., 2023). Therefore, we must be careful drawing too general conclusions from the research. We speculate that because cabin-owning Strava users are in general wealthier, they are also less price sensitive, especially if there are important income effects driving the results. It is reasonable to speculate that for the greater public, the elasticity is greater and the CS is smaller than what we have found here. Future research should confirm this finding in the broader population. An extension to the current work is to leverage improved access to rich individual-level data. Linking observational data like we have here with registry data would enable us to directly estimate price and income elasticities without needing to rely on aggregate data and assumptions on people's marginal cost of outdoor recreation.

CRedit authorship contribution statement

Andreas Skulstad: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Project

Table 7

Calculations of the total marginal cost of recreation through the use of cabins per trip.

Cost component	Assumptions	Cost	Share
Travel cost	Distance: 275 km Gas price per liter: \$1.5 Liter per km: 0.1 Toll fees per km: \$0.03	\$48	49 %
Wear and tear of cabin, clothes and equipment when used	kWh = 748 Wear and tear per kwh: \$0.02	\$15	16 %
Electricity bill for two weeks	kWh = 748 Contrafactual el. Price/kwh = \$0.046	\$34	35 %
Total expenditures		\$98	100 %

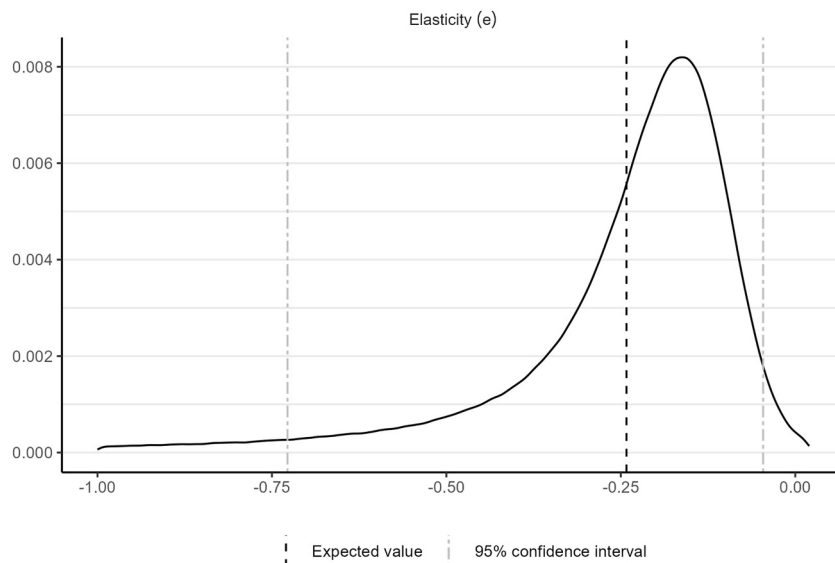
Notes: The calculations show the share of different cost components of the marginal cost of outdoor recreation for a cabin owner using their expected values.

Table 8

Monte Carlo simulation results.

	Mean	Median	Standard deviation	95 % confidence interval
Price elasticity	-0,24	-0,20	0,16	[-0.73, -0.05]

Notes: The table shows descriptive statistics for 1,000,000 Monte Carlo simulations of the price elasticity of outdoor recreation.

**Fig. 7.** Distribution of the price elasticity of cabin-based outdoor recreation

Notes: The figure shows the distribution, expected value and 95 % confidence interval of 1,000,000 calculations of the electricity cost's share of total marginal cost of cabin-based outdoor recreation and cabin-based outdoor recreation's price elasticity. Uncertain parameters are randomly drawn from their distributions according to [Table D.1](#).

administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Erlend Dancke Sandorf:** Writing – review & editing, Writing – original draft, Conceptualization. **Zander Venter:** Writing – review & editing, Data curation. **Anders Dugstad:** Writing – review & editing, Writing – original draft, Conceptualization.

Financial statement

This research was funded by the Research Council of Norway through the project LandValUse (#319917).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

Acknowledgements

This research was funded by the Research Council of Norway through the project LandValUse (#319917). We thank Ståle Navrud, Stainar Strøm, Peter Hull, participants at NAERE 2024, ECS575 at NHH in 2024, Statistics Norway's research seminar and AERE 2025 for valuable comments and feedback. We also thank the handling editor and two anonymous reviewers for providing valuable comments and suggestions, which contributed to improve the manuscript. This article includes aggregated and de-identified data from Strava Metro.

Appendix A. Supplementary material

Supplementary material to this article can be found online at <https://doi.org/10.1016/j.jeem.2025.103243>.

Data availability

The authors do not have permission to share data.

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