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Energy equity under crisis pricing: the vulnerability-responsiveness paradox in Norwegian residential electricity consumption during the European energy crisis

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ABSTRACT

Dynamic electricity pricing is widely advocated for demand-side management, yet its distributional consequences under crisis conditions remain poorly understood. We examine the equity implications of hourly spot pricing during the European energy crisis using metered consumption from 1136 Norwegian households (October 2020–March 2022) linked to socio-demographic surveys. Southern Norwegian wholesale prices nearly tripled (+192%), and mean household electricity costs rose from 484 to 1785 NOK/month. Energy poverty emerged from a zero baseline: no household exceeded the conventional 10% income-burden threshold before the crisis, versus 1.2% during it, and 6.8% exceeded a 6% burden. Impacts were steeply regressive: the mean burden of the lowest-income group reached 7.4%, against 1.9% for the highest — a fourfold gap. SHAP analysis shows that housing characteristics dominate income and price as predictors of consumption, indicating that vulnerability is structural, rooted in the building stock, rather than purely economic. We term this the vulnerability-responsiveness paradox: the households facing the greatest welfare exposure have the least structural capacity to adjust. Counterfactual simulations show that a 1.0 NOK/kWh price cap cuts poverty to 0.3%, and that pairing the cap with targeted retrofits of high-consumption detached homes performs best across cost, poverty, and inequality simultaneously. Crisis pricing policy should combine short-term price caps with structural building-efficiency programmes.

1. Introduction

The European energy crisis of 2021–2022 exposed a fundamental tension at the heart of liberalised electricity markets: the same dynamic pricing mechanisms designed to promote efficient demand response can, under crisis conditions, become engines of distributional injustice. Wholesale price increases of two to ten times pre-crisis levels swept across the continent (Gheorghe, 2022; Wei et al., 2024), prompting emergency interventions in nearly every EU member state (European Commission, 2022). While aggregate impacts have been documented, EU electricity demand fell by approximately 3% in both 2022 and 2023, remaining 6% below the pre-crisis average as late as 2025 (Ember, 2026), the household-level distributional consequences have received far less attention. Understanding these distributional effects is essential, not only for designing effective crisis-response policies but also for ensuring that the ongoing electrification of heating and transport does not create new forms of energy poverty (Jenkins et al., 2016; Sovacool et al., 2019). Norway provides an unusually instructive setting for examining these dynamics. The Norwegian residential sector is among the most electrified in the world, with approximately 84% of household energy demand met by electricity and electric heating predominant even in the coldest regions (IEA, 2022). Critically, most Norwegian households hold spot-price contracts with hourly varying rates, creating direct and immediate transmission of wholesale price movements to household bills (Hofmann and Lindberg, 2024). When wholesale prices in southern Norway nearly tripled between the pre-crisis year and the winter of

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2021–2022, this transmission mechanism meant that households experienced the full force of the price shock without the buffering provided by fixed-rate contracts common elsewhere in Europe.

This paper identifies and empirically documents what we term the vulnerability-responsiveness paradox: the systematic tendency for the households most exposed to the welfare losses of crisis pricing to have the least structural capacity to adjust to it. This paradox, which we demonstrate using a combination of energy poverty metrics, area-level demand comparison, and machine learning based feature importance analysis, has important implications for the design of dynamic pricing and crisis-response mechanisms. Specifically, it challenges the implicit assumption in much demand-response literature that price responsiveness is a uniformly beneficial attribute and demonstrates that policies relying solely on price signals can be regressive even when they successfully reduce aggregate demand (Borenstein, 2012; Boute, 2023).

We develop this argument in five stages. First, drawing on the energy justice framework (Sovacool et al., 2016), we quantify the energy poverty implications of the crisis, documenting the emergence of energy poverty from a zero pre-crisis baseline and a widening of the cost distribution. Second, we examine how demand-price associations vary across income groups, consumer segments, and housing types, documenting a systematic pattern in which lower-income groups exhibit larger demand adjustments, though we are transparent that seasonal confounding between price and weather prevents clean causal identification of pure price effects. Third, we apply SHAP (SHapley Additive exPlanations) values from gradient boosting models to demonstrate that housing characteristics, a proxy for building thermal efficiency, dominate both income and price as predictors of consumption levels, pointing toward structural rather than purely economic solutions. We emphasise that SHAP values measure predictive importance, the contribution of each feature to the model's forecasts, rather than causal primacy. Residence type may capture not only building energy efficiency but also correlated factors such as dwelling size, occupancy pattern and appliance stock. Nevertheless, the dominance of housing-related features over income and price in predictive importance is itself informative for policy targeting. Fourth, we use Gaussian Mixture Model segmentation to identify four distinct consumer classes with markedly different vulnerability profiles. Fifth, we conduct counterfactual policy simulations comparing flat rates, price caps, progressive subsidies, and a hybrid approach combining price caps with building retrofits, finding that the hybrid approach performs best across cost, poverty, and inequality simultaneously, whereas a flat rate at the crisis-average price provides almost no relief because the burden was driven by the price level rather than its volatility.

Our analytical strategy centres on directly observed equity outcomes, energy burdens, poverty rates, and the predictive structure of consumption determinants, rather than on causal estimation of price elasticities. We complement this with an area-level comparison of demand changes across bidding areas with differential price exposure, and with exploratory household-level demand-price associations reported in an appendix. We are transparent throughout about what the data can and cannot identify.

The remainder of this paper is structured as follows. Section 2 develops the theoretical framework. Section 3 reviews the literature. Section 4 describes the data and institutional context. Section 5 presents the methodology. Section 6 reports results. Section 7 discusses implications. Section 8 concludes.

2. Theoretical framework: energy justice and the vulnerability-responsiveness paradox

2.1. The energy justice trilemma

This study is grounded in the energy justice framework, which provides a normative lens for evaluating the equity of energy systems and policies (Sovacool et al., 2016). Following Heffron (2013) and Heffron and McCauley (2017) we engage with all three dimensions of the energy justice trilemma.

Distributional justice concerns the equitable allocation of costs and benefits. In the context of dynamic electricity pricing, distributional justice requires that the costs imposed by price volatility do not fall disproportionately on those least able to bear them. The energy burden ratio, the share of household income devoted to energy costs, serves as the primary quantitative indicator of distributional (in)justice (Boardman, 2013; Bouzarovski and Petrova, 2015). When burdens exceed conventional thresholds (typically 10% of income), households are classified as energy poor, a condition associated with adverse health outcomes, social exclusion, and constrained economic participation (Hills, 2012; Thomson et al., 2017). Pricing itself is increasingly recognised as a core site of energy justice. Boute (2023) analyses the emergency price interventions adopted across the EU during the 2022 crisis through an energy justice lens, arguing that the protection of consumers from unaffordable prices is a distributional-justice requirement that must be reconciled with the preservation of market signals for investment. Our analysis provides household-level empirical evidence for exactly this trade-off: it quantifies who bears the burden of unmitigated crisis pricing and evaluates the instruments available to contain it.

Recognition justice concerns the acknowledgment of diverse needs and vulnerabilities across population groups (Walker and Day, 2012). The standard economic model of demand response assumes a representative consumer who rationally optimises consumption in response to price signals. By identifying distinct consumer segments with fundamentally different consumption profiles, constraints, and capacities for flexibility, we challenge this homogeneity assumption and argue that effective energy policy must accommodate household diversity. This is consistent with the broader call in the energy justice literature to move beyond aggregate metrics toward disaggregated analysis that reveals hidden disparities (Sovacool et al., 2019).

Procedural justice concerns inclusive and fair decision-making. While our data do not directly address procedural dimensions, the widespread adoption of hourly spot-price contracts in Norway, often the default option, raises questions about informed consent to price risk (Jenkins et al., 2016). The crisis revealed that many consumers had limited awareness of their exposure to wholesale price volatility.

2.2. The vulnerability-responsiveness paradox: A conceptual proposition of this paper

The vulnerability-responsiveness paradox is not an established construct in the existing literature; it is introduced in this paper. We present it here, in the theoretical framework, as a conceptual proposition derived from the intersection of distributional and recognition justice; Sections 6.3 and 7.1 then provide the empirical evidence for it and discuss its implications. We are grateful to a reviewer for prompting this clarification.

Standard demand-response theory treats price elasticity as a positive attribute, a measure of consumer engagement with market signals that contributes to system efficiency (Faruqui and Sergici, 2010; Strbac, 2008). From a distributional justice perspective, however, high price elasticity among low-income households may reflect not efficient optimisation but rather involuntary curtailment of essential services driven by budget constraints.

The paradox operates through two reinforcing mechanisms. First, low-income households allocate a larger share of their budget to energy, making them more sensitive to price changes (Borenstein, 2012). Second, these households typically occupy less energy-efficient housing, meaning that even substantial behavioural adjustments yield insufficient savings to offset large price increases (Boardman, 2013). The combination produces a situation in which the households most exposed to welfare losses are also those least able to escape them, a paradox that standard efficiency metrics fail to capture but that energy justice demands we recognise.

We operationalise energy poverty using the 10% energy burden threshold (Boardman, 2013), supplemented by the Gini coefficient of energy costs and sensitivity analysis across thresholds of 6%, 8%, 10%, 12%, and 15% to ensure robustness of our findings to definitional choices.

3. Literature review

3.1. Dynamic pricing and residential demand response

Dynamic electricity pricing encompasses time-of-use tariffs, critical peak pricing, real-time pricing, and day-ahead pricing mechanisms designed to align consumption with grid conditions (Borenstein, 2005; Strbac, 2008). A meta-analysis by Faruqui and Sergici (2010) found average peak demand reductions of 3–6% under time-of-use tariffs and 13–20% under critical peak pricing. Nguyen et al. (2016) documented a 13.8% reduction in consumption during a dynamic pricing experiment in Japan. In Norway, Hofmann and Lindberg (2024) found demand reductions of 2.92% during high-price hours in a field experiment involving 3746 households, with the response persisting over repeated interventions and enhanced when combined with real-time price information.

However, these studies examine planned, moderate price variations rather than crisis-driven extreme shocks. The distinction matters: crisis conditions may produce qualitatively different responses as households exhaust easily available flexibility and confront genuine trade-offs between energy use and other essential expenditures. Furthermore, the behavioural economics literature documents bounded rationality, status quo bias, and heterogeneous time preferences that may become more consequential under crisis stress (Cornago, 2021; Good, 2019). Parrish et al. (2020) found that automated load shifting achieves higher response rates than manual demand response, while Adams et al. (2021) introduced the concept of "social license to automate," emphasising the importance of trust and transparency in automated demand management.

Demand-side management strategies more broadly encompass energy conservation, load scheduling, demand response, distributed generation, and energy storage (Harish & Kumar, 2014; Logenthiran et al., 2012). These strategies aim to reduce peak loads, improve grid stability, and reduce carbon emissions (Howlader et al., 2016; Jensen et al., 2017; Noor et al., 2018). Dynamic pricing has been shown to reduce peak-valley load differences and improve utility revenues (Lu and Zhang, 2022; Wang et al., 2023), but the equity implications of these aggregate gains remain underexplored.

3.2. Energy poverty and distributional impacts of pricing

Energy poverty has received increasing attention in European policy discourse (Bouzarovski and Petrova, 2015; Thomson et al., 2017). Multiple measurement approaches exist, reflecting the concept's multidimensional nature (Boardman, 2013; Hills, 2012). The 10% expenditure threshold, while widely used, has been critiqued as insensitive to household composition and local conditions (Hills, 2012). The Low Income High Costs (LIHC) indicator addresses some limitations but requires modelled energy requirements unavailable for our dataset.

The distributional impacts of dynamic pricing are theoretically ambiguous. Borenstein (2012) showed that time-of-use pricing can be progressive or regressive depending on the correlation between income and peak consumption patterns. Empirical evidence from European contexts suggests that vulnerable households are disproportionately affected by price volatility (Walker and Day, 2012). Fell et al. (2015) raised concerns that demand response programmes may exclude low-income households lacking smart appliances or flexible schedules. Sovacool et al. (2019) documented how energy injustice intersects with other forms of social disadvantage, creating compounding vulnerabilities.

A rapidly growing literature examines the 2021–2022 crisis directly. Guan et al. (2023) combine a global multi-regional input-output model with expenditure data for 116 countries and estimate that the crisis raised total household energy costs by 62.6–112.9%, potentially pushing 78–141 million people into extreme poverty; their analysis also shows that cost burdens are systematically heavier for poorer households. Microsimulation evidence for the EU similarly finds that the 2022 price spike had regressive distributional effects and that the mitigating policies adopted by member states varied widely in their targeting efficiency (IEEP, 2023). From a legal-institutional perspective, Boute (2023) documents the unprecedented wave of price caps, revenue caps, and consumer-protection interventions across Europe and frames affordability during crises as a core energy justice obligation. These studies establish the scale and regressivity of the crisis at the macro and simulation level.

Despite this growing literature, direct empirical evidence on the distributional effects of extreme, crisis-driven price shocks on household energy poverty rates using revealed consumption data remains scarce. Most existing studies rely on simulation, stated preferences, or aggregate data, approaches that may understate the heterogeneity of household impacts (Guan et al., 2023; IEEP, 2023).

3.3. Machine learning for energy policy analysis

The application of machine learning to energy systems has expanded rapidly, offering advantages over traditional econometric models in capturing non-linear relationships and complex variable interactions (Raza and Khosravi, 2015). Consumer segmentation using clustering algorithms, including K-means, Gaussian Mixture Models, and hierarchical approaches, has become standard practice in demand-side management research (Alvarez et al., 2019; Borgohain et al., 2024; Pelekis et al., 2023; Rajabi et al., 2019).

Feature importance and model explainability, particularly through SHAP values (Lundberg and Lee, 2017), have emerged as essential tools for translating complex model outputs into policy-relevant insights. Ensemble methods such as Random Forests and Gradient Boosting Machines have proven effective for energy demand prediction and feature ranking (Belgiu and Drăguţ, 2016; D'Alberto et al., 2024; Sadegh-Zadeh et al., 2023). Recent work has demonstrated the importance of methodological rigour in applying these techniques to limited and heterogeneous datasets, including careful attention to validation strategies and potential data leakage (Sadegh-Zadeh et al., 2024a; Sohrabi et al., 2024). In contexts where sample sizes are constrained, as in our household-level analysis, appropriate regularisation and cross-validation become critical for ensuring reliable inference (Sadegh-Zadeh et al., 2024b).

3.4. The european energy crisis and the Norwegian response

The crisis produced wholesale price increases of two to ten times pre-crisis levels across Europe, prompting price caps, windfall taxes, and direct subsidies in nearly every member state (Boute, 2023). EU electricity demand fell and remained below pre-crisis levels through 2025 (Ember, 2026). Norway's experience was distinctive: near-complete residential electrification, widespread hourly spot pricing, a bidding-area structure creating differential regional price exposure, and significant electric vehicle penetration (IEA, 2022). In December 2021 the government introduced a universal electricity support scheme (strømstøtte) that reimbursed a share of the spot price above a threshold of 0.70 NOK/kWh, 55% in December 2021 and 80% from January 2022, for consumption up to 5000 kWh per month (IEA, 2022). The scheme is price-contingent and universal rather than income-targeted, and it functions economically as a soft price cap. Design questions persist about the targeting and efficiency of such interventions, and about their interaction with the investment signals that market prices are meant to preserve (Boute, 2023).

3.5. Research gap

The specific gap this paper addresses is the absence of empirical evidence, based on revealed consumption during actual crisis conditions, on how the burden of crisis pricing and the capacity to adjust to it vary across household types, and how this heterogeneity relates to energy poverty outcomes. The energy justice literature on pricing remains predominantly conceptual, legal, or simulation-based (Boute, 2023; Guan et al., 2023); quantitative, household-level evidence from metered consumption during an actual crisis is missing. By combining metered data with rich socio-demographic information, we provide a level of analytical resolution that is rare in the existing literature.

4. Data and institutional context

4.1. Norwegian electricity market

Norway's electricity market comprises five bidding areas (NO1–NO5) with hourly prices determined through the Nord Pool day-ahead auction (Fig. 1). Averaged over the pre-crisis study period (October 2020–September 2021), day-ahead prices in the southern areas (NO1, NO2, NO5), which are connected to continental European markets via submarine cables, stood at 0.47 NOK/kWh; during the crisis winter (October 2021–March 2022) they reached 1.38 NOK/kWh, an increase of 192%, and nearly a tripling of the price level. The northern areas (NO3, NO4), with limited interconnection and abundant local hydropower, were essentially unaffected: prices remained at approximately 0.31 NOK/kWh in both periods. This stark differential motivates the descriptive area-level comparison in Section 5.3.

4.2. Dataset

We draw on the publicly available dataset of Hofmann et al. (2023), comprising: hourly metered consumption for 1136 households (October 2020–March 2022) in areas NO1 and NO5; survey responses from 4446 households covering demographics, behavioural responses, and attitudes; hourly day-ahead electricity prices for all five areas (July 2019–July 2022); and aggregated hourly residential demand by area. The data were accessed for research purposes in October 2025. All survey variables were mapped to response codes using the official questionnaire codebook distributed with the dataset, and the data are fully anonymised; at no point did the authors have access to information that could identify individual participants.

We note explicitly that the household-level metered data are available only for areas NO1 and NO5, both high-shock areas. This constrains the household-level analysis to estimating heterogeneous responses within areas experiencing extreme prices, rather than comparing treatment and control households directly. The area-level analysis uses aggregated demand data available for all five areas, but at the cost of individual-level heterogeneity. We return to this limitation in the Discussion.

4.3. Sample characteristics

Table 1 summarises the metered sample. The 1136 households (788 in NO1, 348 in NO5) have a mean respondent age of 54 years (SD = 16), a mean household size of 2.2 persons, and a mean hourly demand of 1.58 kWh (SD = 1.15). Reflecting the urban composition of the sample (greater Oslo and Bergen), apartment blocks are the most common dwelling type (49.5%), followed by detached houses (22.5%), terraced and townhouses (19.5%), semi-detached houses (5.6%), and other dwellings (2.8%). Mean hourly consumption rises steeply with dwelling size, from 0.86 kWh in apartments to 2.88 kWh in detached houses. Electric vehicle ownership is 30.0%. Average monthly electricity costs rose from 484 NOK pre-crisis to 1785 NOK during the crisis (+269%).

Household income is reported in six categorical brackets, from "under 300,000 NOK" to "1,500,000 NOK or more". A further 106 respondents (9.3%) preferred not to state their income and 21 (1.8%) did not know it; these 127 households are excluded from all burden and

Table 1
Characteristics of the metered household sample (N = 1136).

Characteristic	Value
Households (bidding area)	1136 (NO1: 788; NO5: 348)
Respondent age, mean (SD)	54.0 (16.0) years
Household size, mean (SD)	2.2 (1.1) persons
Mean hourly demand, mean (SD)	1.58 (1.15) kWh
Dwelling type	Apartment 49.5%; Detached 22.5%; Terraced/ townhouse 19.5%; Semi-detached 5.6%; Other 2.8%
Mean hourly demand by dwelling type	Detached 2.88; Semi-detached 2.53; Terraced 1.72; Apartment 0.86 kWh
Income bracket (NOK/ year)	<300k: 3.3%; 300–499k: 14.9%; 500–799k: 21.8%; 800–999k: 12.4%; 1000–1,499k: 22.5%; ≥1,500k: 13.9%; prefer not to state: 9.3%; do not know: 1.8%
Analytic sample (valid income)	1009 households
Electric vehicle ownership	30.0%
Mean monthly electricity cost	Pre-crisis 484 NOK; crisis 1785 NOK (+269%)

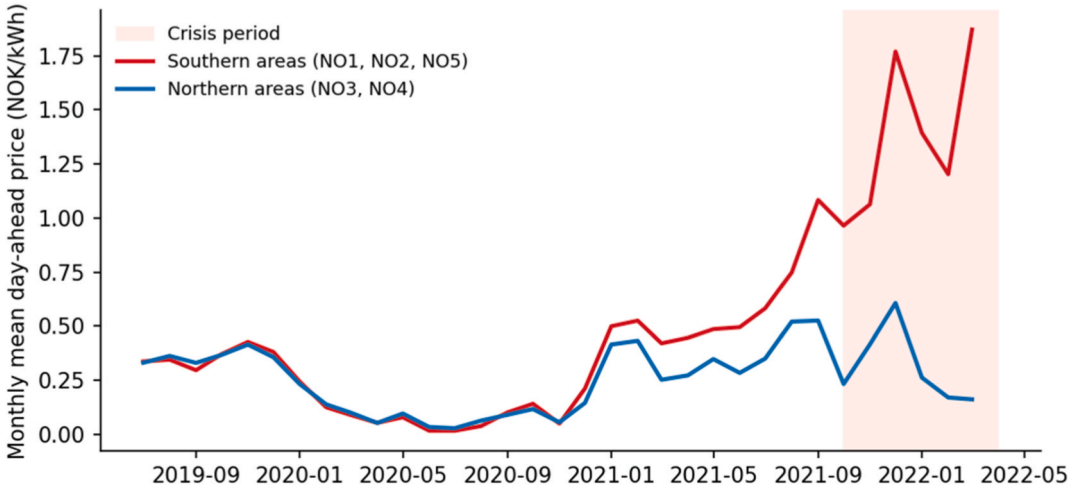

Fig. 1. Monthly mean day-ahead electricity prices by bidding area, July 2019–July 2022. Southern areas (NO1, NO5; solid lines) versus northern areas (NO3, NO4; dashed lines). The shaded band marks the crisis winter (October 2021–March 2022).

poverty calculations, leaving an analytic sample of 1009 households. Burden calculations use bracket midpoints (150,000; 400,000; 650,000; 900,000; 1,250,000 NOK), with the open-ended top bracket assigned 1,750,000 NOK. While this introduces measurement error relative to continuous income data, Section 5.6 shows that all headline results are robust to bootstrap resampling within brackets and to interval-censored bounds.

Table 2 cross-tabulates housing type with income and reveals a pattern that is central to interpreting the results: the share of households in detached houses rises monotonically with income, from 10.8% in the lowest bracket to 41.8% in the highest, while the share in apartments falls from 56.8% to 27.8%. High-consumption dwellings are therefore concentrated among higher-income households, which is why absolute electricity costs rise with income even as relative burdens fall.

5. Methodology

5.1. Energy poverty metrics

This analysis uses the metered consumption data merged with survey responses and area prices, for the analytic sample of 1009 households with valid income. We calculate the energy burden ratio as annual electricity expenditure divided by gross household income. Households exceeding the 10% threshold are classified as energy poor (Boardman, 2013). We supplement this with the Gini coefficient of monthly energy costs and conduct sensitivity analysis across thresholds of 6%, 8%, 10%, 12%, and 15%.

5.2. Consumer segmentation

Segmentation uses the consumption-profile features of all 1136 metered households; no survey variables enter the clustering. We segment consumers using Gaussian Mixture Models (GMM), a probabilistic clustering approach that provides soft assignments and serves as a practical proxy for Latent Class Analysis (McLachlan and Peel, 2000). Six features are used: mean hourly demand, demand variability (standard deviation), peak-to-average ratio, weekend-to-weekday ratio, night-to-day ratio, and monthly coefficient of variation. The Bayesian Information Criterion (BIC) determines the optimal number of components. Features are standardised before estimation.

5.3. Area-level demand comparison

This analysis uses the aggregated hourly residential demand series published for all five bidding areas, together with the corresponding area prices; no household-level data enter this comparison. As descriptive context, we compare aggregated per-meter winter demand across Norway's five bidding areas before and during the crisis. High-shock areas (NO1, NO2, NO5) and low-shock areas (NO3, NO4) experienced dramatically different price trajectories, enabling a descriptive comparison of demand changes. We report this as suggestive evidence rather than a formal causal estimate, since area-level confounders (differential weather patterns, economic conditions, and household composition across regions) cannot be fully controlled.

Our core equity analysis relies entirely on directly observed quantities (consumption × price/income) that do not require estimation of causal price effects. This design choice insulates our central findings from the identification challenges that affect price elasticity estimation in observational energy data.

Table 2
Housing type by income group, row percentages (analytic sample, n = 1009).

Income group (NOK)	Detached	Semi-det.	Terraced	Apartment	Other	n
<300k	10.8	2.7	13.5	56.8	16.2	37
300–499k	6.5	2.4	19.5	68.6	3.0	169
500–799k	13.7	6.5	10.1	64.9	4.8	248
800–999k	22.7	5.0	20.6	49.6	2.1	141
1000–1,499k	30.1	8.2	25.8	34.8	1.2	256
≥1,500k	41.8	7.6	21.5	27.8	1.3	158

5.4. SHAP-based feature importance

This analysis uses the daily household consumption panel (households with valid income, October 2020–March 2022) merged with survey covariates and daily area prices. To identify the relative predictive importance of consumption determinants, we estimate a Gradient Boosting Machine (GBM: 300 trees, depth 5, learning rate 0.05, subsample rate 0.8) with ten predictors: log price, income, residence type, age, household size, month, day of week, consumer cluster, heating degree days, and weekend indicator. The model is evaluated on a held-out 20% test set. SHAP values (Lundberg and Lee, 2017) provide both global importance rankings and individual-level decompositions. We emphasise that SHAP measures predictive contribution, not causal effect: a high SHAP value for residence type indicates that this variable is informative for predicting consumption, but may capture correlated factors (dwelling size, occupancy patterns, appliance stock) beyond building efficiency alone. The consumer-cluster feature is itself derived from consumption profiles; among the exogenous household characteristics, residence type is therefore the relevant benchmark against income and price.

5.5. Counterfactual policy simulation

This analysis uses the analytic sample (n = 1009). We evaluate five pricing scenarios: (A) actual crisis pricing; (B) a flat rate fixed at the crisis-average price in the households' areas (1.38 NOK/kWh), which isolates the effect of removing price volatility while holding the price level constant; (C) a price cap at 1.0 NOK/kWh; (D) a progressive subsidy that halves bills for households with incomes below 500,000 NOK (the two lowest brackets); and (E) a hybrid combining the price cap with building retrofits, modelled as a 20% demand reduction for detached houses with above-median consumption (n = 200). Scenario D is included to represent the income-targeted transfers widely debated as an alternative to the universal, price-contingent design that Norway actually adopted: the strømstøtte scheme described in Section 3.4 is universal and functions as a soft price cap, and critics have asked whether targeting support by income would achieve the same protection at lower fiscal cost. The five scenarios therefore span the three main targeting philosophies in the crisis-response debate: universal price-based instruments (B, C), income-based targeting (D), and structural demand reduction (E).

All scenarios use a conservative constant-consumption assumption: we calculate costs given actual observed consumption under counterfactual prices, without assuming behavioural adjustment. This avoids reliance on estimated elasticities whose identification is complicated by weather confounding (Appendix A). The assumption is conservative in that any demand adjustment under lower prices would further reduce costs. We report the fiscal cost of the cap per household and conduct sensitivity analysis across retrofit assumptions (10–30% reduction).

5.6. Robustness checks

We conduct three formal robustness checks: (1) sensitivity of energy poverty rates to alternative threshold definitions (6–15%); (2) re-estimation after excluding the top and bottom 5% of the consumption distribution; and (3) separate estimation for areas NO1 and NO5 to assess geographic stability. To address income measurement error, we additionally conduct a 500-iteration bootstrap in which each household's income is drawn uniformly within its reported bracket (the open-ended top bracket is bounded at 2,500,000 NOK and the bottom at 100,000 NOK). The bootstrap yields a crisis poverty rate of 1.12% (95%

CI: 0.69–1.59%), bracketing the midpoint estimate of 1.19%. Treating income as interval-censored, and computing burdens at both bracket bounds, yields poverty bounds of [0.4%, 3.5%] during the crisis and [0.0%, 0.1%] pre-crisis. These analyses demonstrate that the central finding, the emergence of a substantial energy-poor population where none existed before the crisis, is robust to reasonable alternative assumptions about income measurement.

6. Results

6.1. Energy poverty dynamics

The crisis produced dramatic shifts in the distribution of energy costs (Fig. 2). Before the crisis, not a single household in the analytic sample exceeded the 10% burden threshold; during the crisis winter, 12 households (1.2%) did. At lower thresholds the deterioration is broader: the share of households devoting more than 6% of income to electricity rose from 0.1% to 6.8%, and the share above 8% rose from 0.1% to 2.8%. For the lowest-income group (below 300,000 NOK), the mean energy burden rose from 2.0% to 7.4%; for the highest-income group (1,500,000 NOK or more) it rose from 0.5% to 1.9%. The proportional cost increase was similar across groups (+268% to +283%), but the welfare consequences were radically different: the poorest households' bills rose from 251 to 923 NOK per month, while the wealthiest paid 745 rising to 2800 NOK. The Gini coefficient of monthly energy costs increased from 0.391 to 0.411.

Sensitivity analysis confirms robustness: using the trimmed sample (excluding the top and bottom 5% of consumers), the 10% poverty rate is 1.0%; the threshold sensitivity, bootstrap, and interval-censored results are reported in Section 5.6.

6.2. Consumer segmentation

The GMM identified four segments (BIC-optimal k = 4, mean assignment probability = 0.872), whose consumption-profile signatures and load curves are shown in Figs. 3 and 4. Cluster 0 (n = 460, 41%): low-to-moderate consumption (mean 0.86 kWh/h), high peak ratio, 29.1% with income below 500,000 NOK. Cluster 1 (n = 333, 29%): high consumption (2.34 kWh/h), the oldest residents (mean 58 years), 31.2% EV ownership. Cluster 2 (n = 199, 18%): the highest consumption (2.79 kWh/h), largest households (3.0 persons), 72.9% EV ownership, and only 3.3% low-income. Cluster 3 (n = 144, 13%): the lowest consumption (0.47 kWh/h), youngest residents, 30.3% low-income. Cluster 2 exhibits a notably flat hourly profile consistent with a high baseload from electric heating and vehicle charging.

6.3. The vulnerability-responsiveness paradox

The paradox is most directly observable in the energy burden data (Fig. 5). During the crisis, the mean burden of the lowest-income group reached 7.4%, approaching the conventional poverty threshold, while the highest-income group remained at 1.9%, a nearly fourfold gap; all 12 households that crossed the 10% threshold are drawn from the lower half of the income distribution. Absolute costs run in the opposite direction: the wealthiest households pay three times more than the poorest (2800 vs 923 NOK/month) because, as Table 2 shows, they disproportionately occupy large detached houses, yet their burdens remain small relative to income. Consumption is driven by housing; vulnerability is driven by the income available to pay for it. It is the combination of the two, structurally elevated consumption needs meeting thin financial buffers, that produces energy poverty under crisis pricing.

Exploratory panel models with household fixed effects suggest that lower-income groups exhibit larger demand-price associations (Appendix A), but a within-week diagnostic exercise confirms substantial weather-driven confounding, and these associations cannot be interpreted as causal price elasticities. Our equity analysis therefore rests entirely on directly observed quantities: consumption, prices, and income. The households bearing the highest cost burdens are those with the least financial capacity to absorb them, regardless of whether their consumption patterns reflect active price response, structural heating needs, or both. This is the vulnerability-responsiveness paradox: vulnerability and exposure to pricing risk are positively correlated across the income distribution, so market-based pricing produces regressive outcomes under crisis conditions.

The segmentation adds a recognition-justice dimension: under identical prices, mean crisis burdens range from 1.1% (Cluster 3) to 3.8% (Cluster 1) across segments, a more-than-threefold spread produced entirely by structural differences in consumption profiles rather than by tariff design.

Area-level evidence provides additional context. Comparing aggregated winter consumption, the high-shock areas (NO1, NO2, NO5), where prices nearly tripled, reduced average per-meter demand by 14.8% between the pre-crisis and crisis winters, while the low-shock areas (NO3, NO4), where prices were essentially flat, reduced demand

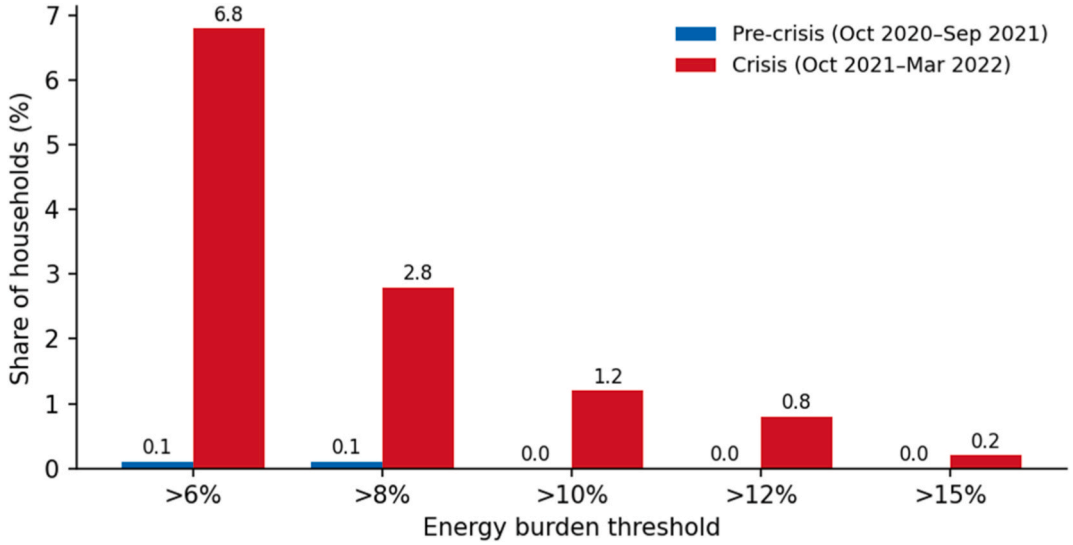

Fig. 2. Mean energy burden by household income group before and during the crisis (analytic sample, n = 1009). The dashed line marks the 10% energy-poverty threshold.

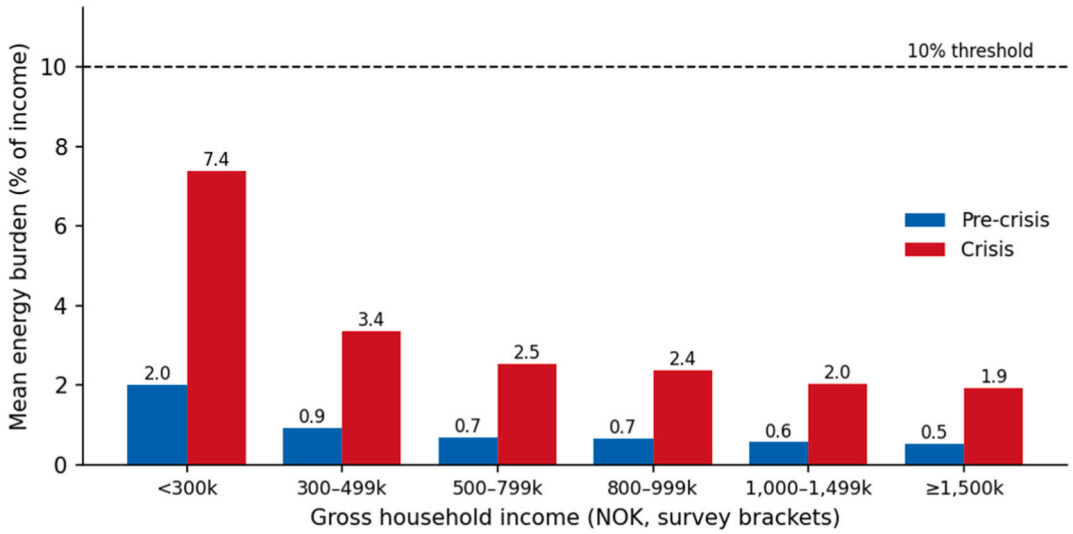

Fig. 3. Consumption-profile signatures of the four GMM segments (features normalised to the 0–1 range across clusters).

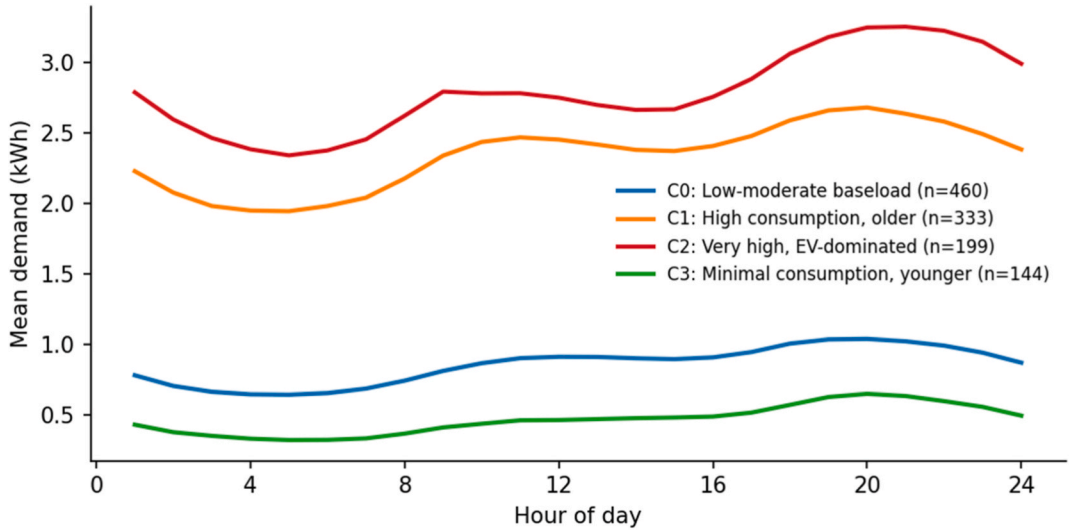

Fig. 4. Mean hourly load curves by consumer segment. The shaded band marks the evening peak (17:00–22:00).

by only 3.8%, a difference of 11.0 percentage points. While this comparison cannot isolate the pure price effect from other factors (including differential weather patterns and composition effects), it provides suggestive evidence that the extreme price shock induced meaningful aggregate demand reductions. The household-level analysis documents how the burden of the crisis, notwithstanding these reductions, was distributed across the income spectrum.

6.4. SHAP-based feature importance

The GBM model generalises well ($R^2 = 0.755$ on the training set and 0.751 on the held-out test set) and reveals that household-structure variables dominate the prediction of daily consumption (Fig. 6). The consumer cluster (mean $|\text{SHAP}| = 0.337$) and residence type (0.332) are jointly dominant, followed by heating degree days (0.223). Because the cluster feature is itself constructed from consumption profiles, residence type is the strongest exogenous household characteristic; it exceeds income (0.045) and price (0.044) by roughly an order of magnitude. Table 2 supplies the socio-economic context for this hierarchy: detached-house living rises steeply with income, so residence type also transmits part of the income-consumption association. The implication for policy is significant: addressing energy poverty through pricing instruments alone addresses a symptom while leaving the structural driver, the thermal quality and size of the dwelling stock, untouched.

6.5. Policy simulation

The counterfactual analysis (Fig. 7) evaluates the five scenarios under the constant-consumption assumption. Scenario B is revealing precisely because it changes almost nothing: a flat rate fixed at the crisis-average price yields a mean cost of 1747 NOK and a poverty rate of 1.2%, statistically indistinguishable from actual crisis pricing (1785 NOK, 1.2%). The burden of the crisis was driven by the level of prices, not their hour-to-hour volatility; removing volatility without lowering the level provides essentially no relief.

The price cap (Scenario C) reduces mean costs to 1233 NOK and poverty to 0.3%, at an estimated fiscal cost of 552 NOK per household per month, while preserving marginal price signals below the cap. The progressive subsidy (Scenario D) matches the cap in poverty reduction (0.3%) at a smaller fiscal outlay concentrated on 206 low-income households, but it leaves mean costs high (1675 NOK) and raises the Gini coefficient of energy costs from 0.411 to 0.447, because relief is

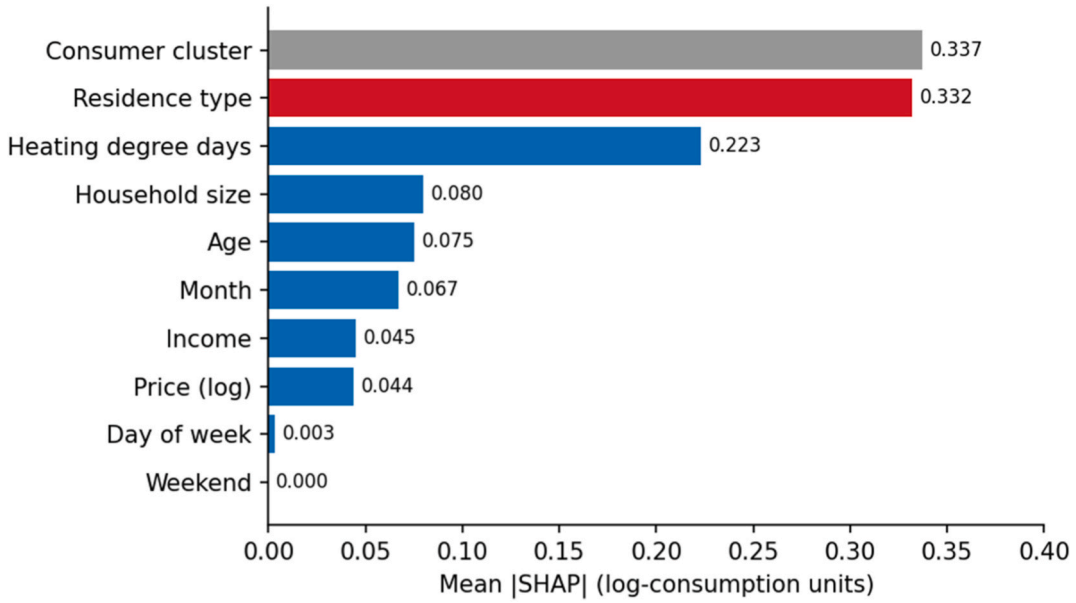

Fig. 5. The vulnerability-responsiveness paradox: mean monthly electricity cost versus mean energy burden by income group during the crisis. Bubble size is proportional to group size (analytic sample, n = 1009).

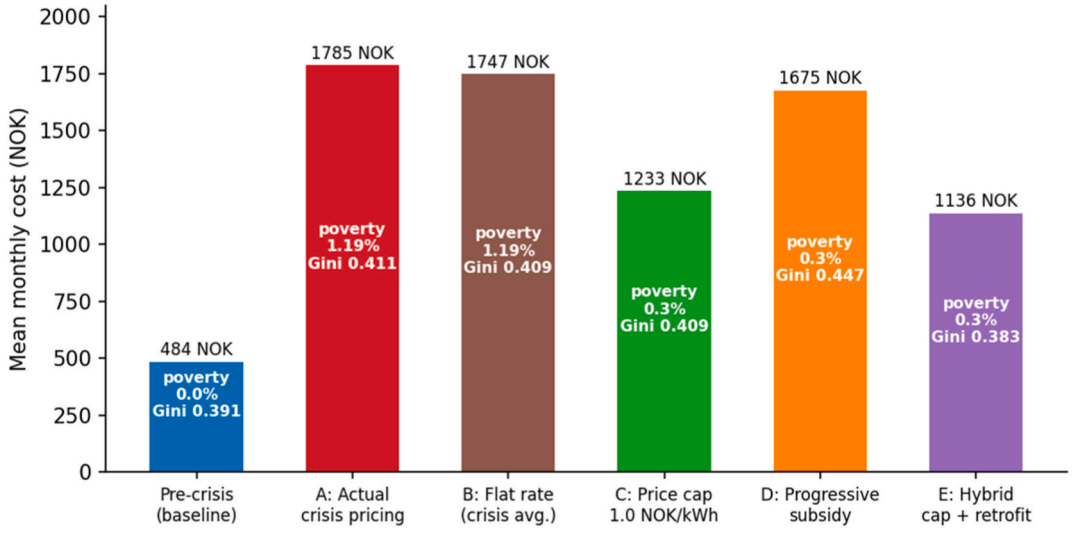

Fig. 6. SHAP feature importance for daily household consumption (Gradient Boosting Machine, 80/20 train-test split).

confined to a narrow group. The hybrid scenario (E) dominates on every other criterion: mean costs fall to 1136 NOK, poverty to 0.3%, and the Gini coefficient to 0.383, below even its pre-crisis level, because retrofitting the 200 high-consumption detached houses compresses the top of the cost distribution while the cap protects the bottom. Only the hybrid scenario permanently reduces baseline consumption, offering protection against future price shocks rather than merely subsidising current ones.

Sensitivity analysis across retrofit assumptions (10–30% consumption reduction) confirms robustness: the poverty rate remains 0.3% throughout, with mean costs of 1,185, 1,136, and 1088 NOK respectively. These simulations do not model behavioural responses, general equilibrium effects, dynamic multi-period adjustments, or administrative implementation costs, and should be interpreted as providing directional guidance about the relative performance of pricing mechanisms rather than precise fiscal forecasts.

7. Discussion

7.1. The vulnerability-responsiveness paradox: contribution to energy justice

The vulnerability-responsiveness paradox describes a systematic pattern documented in these data that has implications for energy justice scholarship. While demand response research typically frames consumer price adjustment as evidence of market efficiency (Faruqui and Sergici, 2010; Strbac, 2008), our findings reveal that the households facing the greatest welfare exposure under crisis pricing are precisely those with the least structural capacity to escape it. The aggregate demand reductions observed in the area-level data (14.8% in high-shock versus 3.8% in low-shock areas) did not prevent the emergence of an energy-poor population where none had existed, because the structural determinants of consumption, primarily housing, constrain the scope for adjustment.

This finding extends the existing literature in three specific ways.

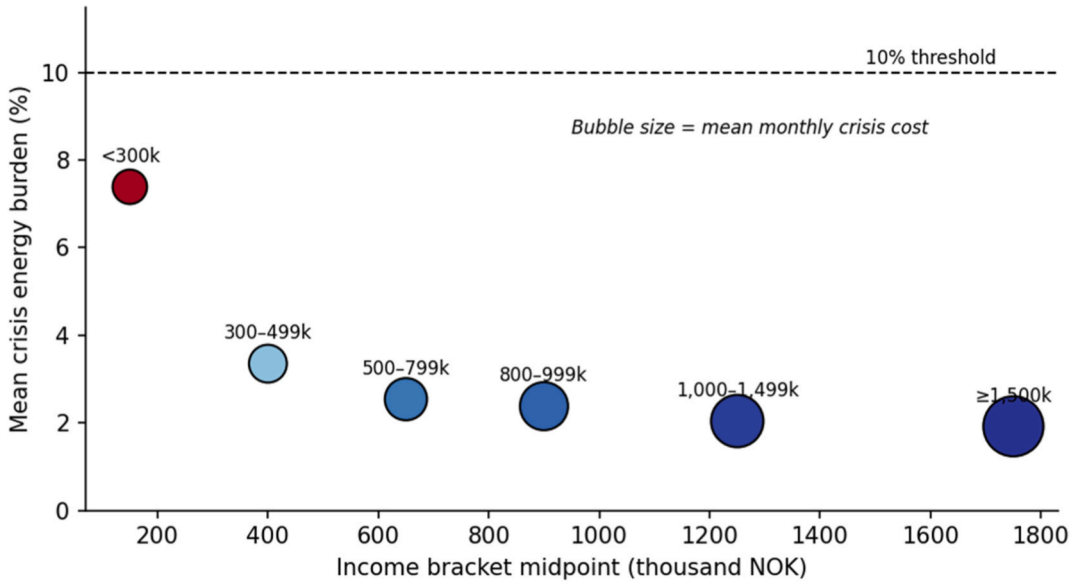

Fig. 7. Counterfactual policy simulation under the constant-consumption assumption (analytic sample, n = 1009): mean monthly cost (bars), energy-poverty rate (diamonds, right axis), and Gini coefficient of monthly costs (lower panel).

First, while Borenstein (2012) demonstrated theoretically that dynamic pricing can be regressive, and crisis-era studies have quantified regressivity through simulation (Guan et al., 2023; IEEP, 2023), the distributional outcome had not been documented with household-level metered consumption during an actual crisis. Our finding that mean burdens diverge fourfold across income groups (7.4% vs 1.9%), and that energy poverty emerged from a zero baseline, provides that evidence. Second, the SHAP analysis identifies the mechanism: housing characteristics, not income per se, drive consumption levels, so the paradox is structural (rooted in the building stock) rather than purely economic (rooted in budget constraints), with fundamentally different policy implications. Third, the explicit mapping of the findings onto the three energy-justice tenets is novel for crisis pricing: the burden and Gini results quantify the distributional dimension; the fourfold spread of burdens across consumer segments under identical tariffs demonstrates the recognition dimension; and the fact that most Norwegian households were defaulted into spot-price exposure they did not actively choose engages the procedural dimension (Jenkins et al., 2016; Boute, 2023).

This finding has theoretical significance beyond the Norwegian context. As electricity markets increasingly adopt dynamic pricing to manage renewable intermittency and peak loads (Müller and Möst, 2018; Noor et al., 2018), the paradox will become more salient. The Norwegian experience, where electrification of heating is already near-complete, provides a preview of conditions that other European countries will face as heat pump adoption accelerates under the EU's Renovation Wave strategy. Our evidence suggests that without deliberate policy intervention, the transition to dynamic pricing may create or deepen energy poverty, particularly among households in thermally inefficient housing.

The finding also resonates with concerns raised by Fell et al. (2015) about the exclusionary potential of demand response programmes. Our evidence goes further: it is not merely that vulnerable households are excluded from the benefits of demand response, but that their exposure to pricing risk is itself a marker of vulnerability. This distinction has implications for programme design: targeting demand response incentives toward the most price-exposed households, as efficiency-oriented programmes would suggest, may inadvertently target the most vulnerable.

7.2. The primacy of housing in energy equity

The SHAP analysis finding that residence type dominates income as a predictor of consumption is perhaps the most policy-actionable result of this study. This echoes Boardman's (2013) argument that energy poverty is fundamentally a problem of building energy performance, not merely of income inadequacy. In the Norwegian context, where electric heating is ubiquitous, the thermal efficiency of the dwelling determines the baseline heating demand over which households have limited short-run control.

Three policy implications follow. First, income-based transfers, while providing necessary immediate relief, do not address the structural driver of energy vulnerability. Second, building retrofit programmes, insulation, heat pump installation, window replacement, offer a permanent reduction in vulnerability by lowering baseline consumption. The cost of such retrofits should be weighed against the recurring costs of income support over many crisis years. Third, consumer segmentation based on housing characteristics may be more useful for targeting crisis-response interventions than segmentation based on income alone. An important nuance follows from Table 2: because detached-house living rises with income, consumption-targeted retrofits channel part of their benefit to better-off households. Retrofit targeting by consumption is therefore not a substitute for protecting low-income households through pricing instruments; the two are complements that operate on different margins, which is precisely why the hybrid scenario performs best.

This finding is consistent with the broader European policy direction toward building renovation as a structural response to energy poverty and provides microeconomic evidence supporting this approach from a household-level analysis of revealed consumption patterns.

7.3. Policy design implications

The simulations yield three concrete lessons for governments seeking to contain price spikes. First, the instrument must lower the price level, not merely its volatility: a flat rate at the crisis-average price delivered essentially no relief (Section 6.5), because the burden was a level phenomenon. Second, a universal price cap is a well-targeted first line of defence under crisis conditions: at 1.0 NOK/kWh it cut poverty from 1.2% to 0.3% at a fiscal cost of roughly 552 NOK per household per month, and Norway's actual strømstøtte, which reimbursed 55–80% of

the spot price above 0.70 NOK/kWh during the study winter, is economically a soft version of the same instrument. This speaks directly to the tension identified by Boute (2023) between consumer protection and the preservation of market signals: a cap set above the threshold retains marginal incentives below it, and our evidence indicates that the affordability gains are concentrated exactly where distributional justice requires them. Third, income-targeted transfers alone are a narrow instrument: the progressive subsidy minimised the poverty headcount but raised measured cost inequality and left mean costs near crisis levels, and it does nothing to the structural driver of vulnerability.

The hybrid design, a cap for immediate protection combined with retrofits of the high-consumption housing stock, dominated every scenario on combined cost, poverty, and inequality criteria and was the only intervention that permanently reduced baseline demand. Structural demand reduction also eases the trade-off that concerns Boute (2023): the less electricity vulnerable households need, the less frequently governments must intervene in prices at all, and the smaller the distortion to investment signals. The choice between instruments thus depends on the policy horizon: caps for immediate crisis relief, retrofit for durable resilience, and the two together for a coherent crisis-preparedness strategy.

These findings contribute to the growing literature on demand-side management design (Chaves-Ávila et al., 2022; Cherukuri et al., 2019; Sheha et al., 2021) by introducing equity as an explicit design criterion alongside the efficiency objectives that have traditionally dominated the field. They also respond to Stawska et al.'s (2021) observation that demand response can serve both congestion management and grid balancing objectives, by adding that it must also serve equity objectives if it is to retain social legitimacy.

7.4. Comparison with existing evidence

The area-level demand comparison shows that high-shock areas reduced consumption by 14.8% compared to 3.8% in low-shock areas, a suggestive difference of 11.0 percentage points. This aggregate response is larger than the 2.92% found by Hofmann and Lindberg (2024) in a controlled Norwegian pricing experiment, likely reflecting the much larger price shock during the crisis (+192% versus experimental variations of 50–100%). Several factors may explain this difference. First, our estimates reflect sustained high prices over an entire winter, not temporary experimental interventions where participants may exert more effort. Second, winter heating demand in Norway is particularly inelastic due to health and comfort constraints. Third, the absence of advance notice or educational components, common in experimental settings, may reduce households' capacity for strategic response. These comparisons suggest that demand response capacity during genuine crises may be substantially lower than controlled experiments predict, a finding with important implications for grid planning that relies on assumed demand flexibility.

7.5. Limitations

Several limitations warrant acknowledgment.

First, the demand-price associations reported in Appendix A are descriptive rather than causal. A within-week identification exercise confirmed that weather confounding is substantial at all temporal frequencies, and cross-season estimates cannot be interpreted as pure price elasticities. However, our core equity findings, energy burdens, poverty rates, and SHAP-based feature importance, are calculated from directly observed quantities and do not depend on elasticity identification.

Second, household-level metered data are available only for areas NO1 and NO5, both of which experienced extreme price shocks. We cannot directly compare household-level behaviour in high-shock and low-shock areas, and the sample may not be representative of all Norwegian households.

Third, income is measured in six categorical brackets rather than continuously, and 127 households without valid income responses are excluded from burden analyses. All survey codes were mapped using the official questionnaire codebook, and the bootstrap and interval-censored analyses in Section 5.6 show that the headline results are robust to the residual measurement error.

Fourth, the analysis covers a single crisis winter (October 2021–March 2022). Longer-term adjustments, including investment in energy efficiency, heat pump adoption, and contractual changes, may differ from the short-run responses captured here.

Fifth, we lack household-level temperature data and data on the Norwegian government's electricity support scheme (strømstøtte) payments. Because the scheme reimbursed 55% (December 2021) and 80% (January–March 2022) of the spot price above 0.70 NOK/kWh for up to 5000 kWh per month, our crisis-period burden estimates are gross-of-support and should be read as upper bounds on the net impact experienced by households; the distributional comparisons across income groups are unaffected because the scheme is universal.

Sixth, the policy simulations use a constant-consumption assumption and do not model general equilibrium effects, dynamic adjustments, or administrative costs. They provide directional guidance rather than precise fiscal forecasts.

Seventh, the Norwegian context, with near-complete residential electrification, widespread hourly spot pricing, and relatively high incomes, is distinctive. Our findings are most directly applicable to other highly electrified economies with market-based pricing. However, the vulnerability-responsiveness paradox is likely to manifest even more severely in countries with greater income inequality and less energy-efficient housing. Norway represents the frontier of residential electrification and provides a predictive glimpse of dynamics that other EU countries will face as heat pump adoption and smart meter rollout accelerate under the Renovation Wave and Clean Energy Package.

Finally, all analysis code is publicly available at https://github.com/salisadegh/Energy-Equity-Under-Crisis-Pricing to support full reproducibility.

8. Conclusion

This study has documented the distributional consequences of dynamic electricity pricing during the European energy crisis using uniquely rich Norwegian household data. The central finding, the vulnerability-responsiveness paradox, reveals that the households most exposed to the welfare losses of crisis pricing are simultaneously those with the least structural capacity to adjust. This paradox challenges the efficiency-focused framing of demand response and argues for the explicit incorporation of equity criteria into the design of dynamic pricing and crisis-response mechanisms.

The emergence of energy poverty from a zero baseline, no household exceeded the 10% burden threshold before the crisis, versus 1.2% during it, with 6.8% above a 6% burden, was driven by the direct transmission of wholesale price shocks to household bills through spot-price contracts, and demonstrates the risks inherent in full market exposure for residential consumers. The dominance of housing characteristics over income in determining consumption points toward building energy efficiency as the most effective structural response to energy vulnerability. The policy simulations identify the combination of a price cap with targeted building retrofits as the preferred mechanism: it was the only intervention that simultaneously lowered costs, reduced poverty, compressed inequality, and permanently reduced baseline demand.

As Europe pursues electrification of heating and transport, the share of household budgets exposed to electricity price volatility will grow. The Norwegian experience during the 2021–2022 crisis provides an early and instructive warning of the distributional challenges this expansion may create. Ensuring that the energy transition is just, not merely efficient, will require pricing mechanisms, safety nets, and building retrofit programmes designed with the vulnerability-responsiveness paradox explicitly in mind.

CRediT authorship contribution statement

Seyed-Ali Sadegh-Zadeh: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Murouj Aljamaeen:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Mohammad Amin Barati:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Lorna Uden:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Delaram Jarchi:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

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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 paper.

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Appendix A. Supplementary material

Supplementary material related to this article can be found in the online version.

Appendix A. Exploratory demand-price associations

Panel regression with household fixed effects

As supplementary analysis, we estimated panel regression models using within-household variation in daily electricity prices over the study period (October 2020–March 2022), for the analytic sample of 1009 households with valid income responses. The model specification is:where D_{it} is daily household demand, P_{it} is average daily price, HDD_t is a heating degree day proxy (base 18°C, from monthly temperature normals), and DOW_t captures day-of-week effects. Household fixed effects are absorbed by demeaning. Standard errors are clustered at the household level.

Cross-season results

The cross-season model yields the following demand-price associations by income group:

Income group (NOK)	Association	SE (clustered)	95% CI	n households
<300,000	−0.030	0.020	[-0.069, +0.009]	37
300,000–499,999	−0.051	0.008	[-0.066, −0.037]	169
500,000–799,999	−0.039	0.007	[-0.052, −0.026]	248
800,000–999,999	−0.036	0.008	[-0.051, −0.021]	141
1,000,000–1,499,999	−0.036	0.006	[-0.047, −0.025]	256
≥1,500,000	−0.025	0.005	[-0.034, −0.016]	158

The aggregate mean association is −0.037 (SE = 0.003, $p < 0.001$). Estimates are geographically stable across NO1 and NO5.

Within-week identification diagnostic

To assess the severity of weather confounding, we estimated a within-week model by demeaning variables at the household-week level. This absorbs weekly-level temperature variation, exploiting only day-to-day price fluctuations within the same week.

The within-week model yields a positive aggregate association of +0.062 (SE = 0.002), with no meaningful heterogeneity across income groups. This reversal in sign confirms that day-to-day price variation within a week is driven primarily by weather (cold days simultaneously increase both demand and wholesale prices), and that substantial weather-driven confounding is present at all temporal frequencies.

Interpretation

The divergence between cross-season (negative) and within-week (positive) estimates means that the cross-season associations cannot be interpreted as causal price elasticities. The core equity analysis in the main text therefore relies entirely on directly observed quantities: consumption, prices, and income. The cross-season associations remain informative as descriptive summaries of how demand-price co-variation differs across income groups; the finding that the lower-income brackets (with the exception of the small under-300k group, n = 37, whose estimate is imprecise) exhibit larger negative associations than the top bracket is consistent across specifications, though it may reflect differential seasonal consumption

patterns rather than differential price responsiveness per se.

Full estimation code is available at https://github.com/salisadegh/Energy-Equity-Under-Crisis-Pricing.

Data availability

All data used in this study are publicly available. The household electricity consumption, survey, and pricing datasets are available from Hofmann, M., Bjarghov, S., & Nessa, S. (2023). Norwegian hourly residential electricity demand data with consumer characteristics during the European energy crisis. Data in Brief, 51, 109687. https://doi.org/10.1016/j.dib.2023.109687. Analysis code and data processing scripts are available at https://github.com/salisadegh/Energy-Equity-Under-Crisis-Pricing.

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