Household-Level Responses to the European Energy Crisis

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Abstract

This paper studies household responses to a sharp energy price increase. Using Finnish household-level microdata from the 2022 European Energy Crisis, we exploit quasi-random contract expiration dates to identify adjustments across key margins: energy use, earnings, financial distress, and residual consumption. High- and middle-income households primarily reduce electricity use and modestly increase earnings, whereas low-income groups lack these adjustment channels, facing rising defaults and cutbacks in other spending. Households with an anticipation period adjust electricity use in advance, softening the impacts of the price shock. We apply these results to quantify the incidence of a hypothetical carbon price.

Keywords: energy, inequality, energy poverty, energy crisis

JEL codes: H23, Q41, Q54

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1 Introduction

High energy prices—driven by supply disruptions, renewable energy intermittency and climate policies—have motivated policymakers to introduce initiatives aimed at mitigating the financial burden on households.[1] High prices by themselves need not be a problem if households can adapt through a range of margins, such as reducing energy consumption, adjusting earnings, or making other financial choices. This paper is the first to offer a comprehensive examination of household adjustments across main response channels.

We provide causal evidence on heterogeneous household-level responses to a sharp and unexpected energy price increase, leveraging a natural experiment from the 2022 European Energy Crisis. We exploit quasi-random expiration dates of fixed-term electricity contracts in Finland to identify the causal effects of higher prices. Households whose contracts expired during the crisis faced an immediate and steep increase in electricity prices—up to eightfold overnight—while those with ongoing contracts remained temporarily shielded. This setting allows us to apply a stacked difference-in-differences design, distinguishing between direct responses to the price increase and forward-looking adjustments in anticipation of contract expiration.

Our study captures all major household adjustment margins using rich administrative microdata. First, we analyze changes in energy consumption using real-time metered electricity data. Second, we study labor market responses, analyzing changes in earnings and benefits from monthly tax records. Third, we assess financial distress, measured by court-reported payment defaults on utility bills and other financial obligations. Finally, we use the detailed data to construct a household-level measure of residual consumption, reflecting broader spending and savings adjustments beyond direct energy expenditures.

We find that, on average, households respond to a doubling of electricity prices by reducing electricity use by 18.4% (indicating an elasticity of -0.18) and increasing labor earnings by 1.4%. As for the adverse effects of the price shock, households experience a 0.4 percentage-point increase in the probability of default (around 4% increase relative to the mean) and reduce their residual consumption by 4.5% when the electricity price doubles. Yet, these average treatment effects mask substantial heterogeneity. Households in the highest income quintile have more elastic electricity use, with only a modest reduction in residual consumption and no statistically significant effect on defaults. In stark contrast, those in the lowest income quintile have the lowest demand elasticity and limited capacity to adjust earnings and, consequently, experience a substantial decline in residual consumption alongside a significant rise in defaults. Between these two extremes, we

[1] To name a few, the EU Energy Efficiency Directive (EU/2023/1791) aims to reduce energy poverty across Europe; the U.S. Low Income Home Energy Assistance Program (LIHEAP) provides financial support for low-income households' energy needs; and the UK Fuel Poverty Strategy (UK Government, 2021) seeks to ensure energy affordability for low-income citizens.

find a statistically significant earnings response for middle-income households and, somewhat surprisingly, also an increase in payment defaults.

Beyond the direct effects, our setting allows us to study anticipation effects. Households whose contracts end later in the crisis have time to adjust their behavior before experiencing the price shock. By observing behavior in the months leading up to contract expiration, we find that households are forward-looking and begin reducing electricity consumption several months before their contracts expire. We do not find similar effects for households whose electricity retailer abruptly goes bankrupt during the crisis. Similar anticipation effects are not observed for earnings. A longer anticipation period softens the financial impact and mitigates negative effects on residual consumption but does not significantly affect defaults.

Regulations influence energy prices; notably, carbon pricing aimed at reducing greenhouse gas emissions raises electricity costs for consumers. We use the estimated behavioral effects to simulate household-level responses to a hypothetical €100/tCO_2 carbon price. Our results identify three channels through which low-income households are hit by carbon pricing: (i) they spend a larger share of disposable income on electricity, (ii) they have lower demand elasticity, and (iii) they are less able to increase earnings. These response channels help medium- and high-income households to reduce their cost burden by around one half, but low-income households only by less than one fourth. As a result, the poor face a higher risk of default, and they are forced to reduce their already low residual consumption further. Last, our setting allows a data-driven approach to identify vulnerable groups—those with most pronounced adverse effects—based on their socio-economic characteristics.

Literature Our results provide a detailed breakdown of household-level responses to energy price shocks, informing both economic theory and policy design. The distributional impacts of energy price shocks can only be fully understood when all household adjustment channels are considered. Existing studies that assess policy-induced costs often rely on static incidence measures, estimating how price increases affect households based solely on income and expenditure shares (Grainger and Kolstad, 2010; Fischer and Pizer, 2019; Cronin et al., 2019; Pizer and Sexton, 2019; Douenne, 2020; Levinson and Silva, 2022; Fetzer et al., 2024). However, such approaches overlook the fact that households actively respond—by adjusting energy consumption, labor supply, and financial decisions—and that their ability to do so varies. Our contribution is to provide empirical evidence on these broad behavioral responses, showing that policy-induced inequality is not only driven by initial exposure to price increases but also by differences in adjustment capacity.[2] Households

[2]Relatedly, there is an extensive literature on defining and identifying vulnerable or energy-poor households (e.g., Boardman, 1991; Legendre and Ricci, 2015; Romero et al., 2018; Charlier and Legendre, 2021; Numminen et al., 2024). Existing studies propose different risk factors—such as low income, high energy use, rural residence, or age—but lack consensus on a definitive measure of vulnerability. Our approach allows us to identify the subgroups

with limited flexibility face greater financial strain, making distributional effects fundamentally a question of both exposure and adaptation.

Our study also contributes to the literature that uses quasi-experimental methods to study demand-response to higher energy prices (e.g., Ito, 2014; Deryugina et al., 2020). To move beyond aggregate responses, several studies use household-level microdata on energy use, allowing for the analysis of heterogeneous demand elasticities across households (Sahari, 2019; Burger et al., 2020; Alberini et al., 2020; Cahana et al., 2022; Gravert, 2024; Rubin and Auffhammer, 2024; van Soest, 2025). Our contribution to this literature stems from the linked administrative data, which allows us to capture all major household adjustment margins simultaneously. This enables a more complete assessment of how households respond to price shocks.

Last, this paper connects to the emerging theoretical literature on the interaction between inequality, taxation, and regulation (Pai and Strack, 2022; Douenne et al., 2023; Bierbrauer, 2023; Doligalski et al., 2025), see also Drupp et al. (2024) for a review. In this literature, the optimal information-constrained policies involve equity-efficiency trade-offs and, as a result, the optimal policies typically deviate from the first-best level. Ahlvik et al. (2024) show that income-dependent behavioral responses are key sufficient statistics in determining optimal policies. We estimate these responses empirically and find that low-income households are less responsive across all behavioral margins. Intuitively, this implies that a relief programs subsidizing energy use of low-income households would result in small efficiency distortions while yielding potentially large equity gains.

2 Background, data and empirical strategy

2.1 Background

On February 24, 2022, Russia invaded Ukraine. As a major supplier of approximately 40 percent of the European Union's gas, Russia weaponized energy exports, disrupting gas supplies to Europe. This triggered the 2022 European Energy Crisis, during which prices peaked at record-breaking levels in the fall of 2022. Figure 1a shows consumer electricity price development in Finland for variable prices and 2-year fixed-term prices.[3] Two-year fixed-term contract prices peaked in September 2022, and the variable-price contract prices peaked in December. Both fixed-term and variable prices started to decrease in spring 2023.

for whom high energy prices translate into arrears on utility bills, a widely recognized indicator of financial distress.

[3]The retail market in Finland is completely deregulated and households have full freedom to choose their electricity contracts. Pre-crisis, 54% of the households had a fixed-price and fixed-term contract, 9% a real-time price contract tied to the hourly day-ahead spot rates, and the remaining 37% an open-ended variable tariff contract, where the price follows mean spot price levels (e.g., 1 month or 3 months), but does not vary by the hour (Finnish Energy Authority, 2021).

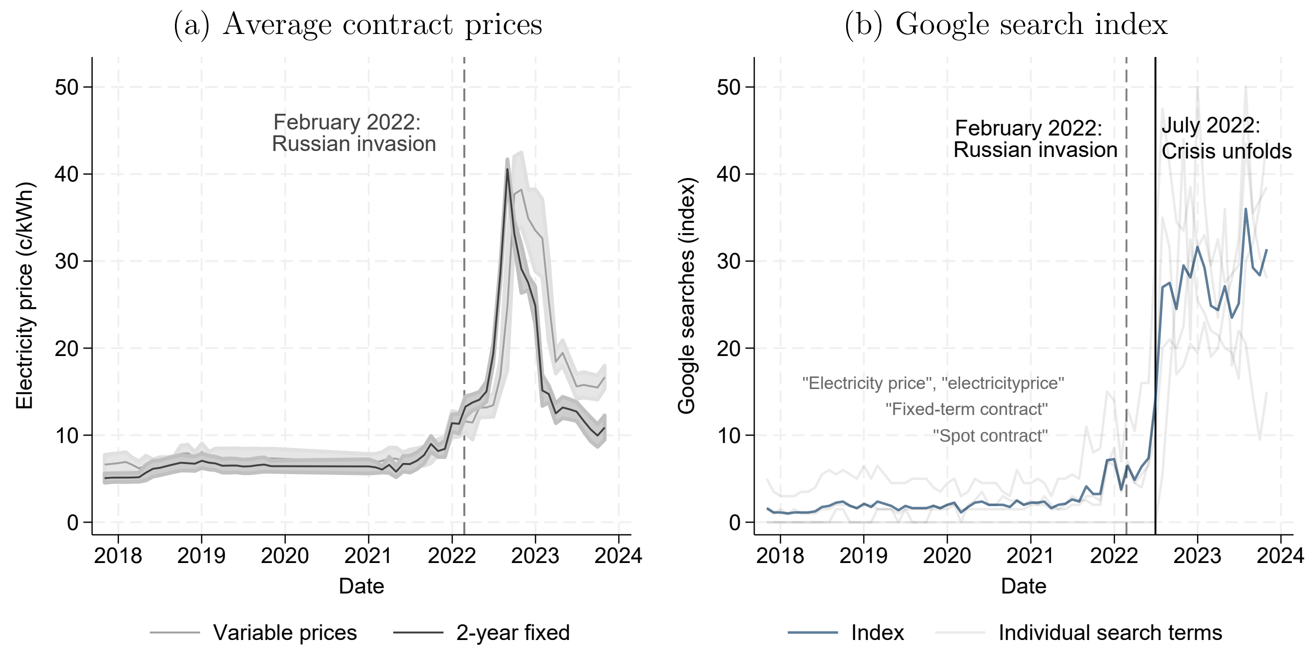


Figure 1: Development of energy crisis in Finland

Notes: Figure (a) shows the development of average contract prices for variable-price contracts (gray line) and two-year fixed-term contracts (black line), with shaded areas indicating the entire average price across all household types. Data is from the Finnish Energy Authority. Figure (b) gray lines show Google trends search results for selected keywords: (i) electricity price (*sähkönhinta*, *sähkön hinta*), (ii) fixed-term contract (*määräaikainen sähkösopimus*) and (iii) spot contract (*pörssisähkö*). The blue line is the simple average over these individual keywords.

To understand our identification, consider two households, one that signed a two-year fixed-price contract in October 2020 and another that did so in July 2021. Two years later, in October 2022, the first household's contract expired, requiring them to enter a new fixed- or variable-price contract amid the crisis, creating within-household variation in prices. In contrast, the second household's contract maintained a low electricity price (below 10 c/kWh) throughout the crisis. We classify all households whose contract ends in the middle of the crisis (between August 2022 and January 2023) as treated. Households whose contracts extended beyond our study period (June 2023) serve as controls.

The crisis was unexpected, and electricity prices, including futures contracts, gave no advance warning. Figure 1b shows Google searches related to individual electricity-related keywords (gray lines) and a combined index (blue line). The effect of the Russian invasion on electricity prices began to draw media and public attention in July, as is evident from the sharp increase in the index in July 2022. We treat July as the point when the crisis unfolded and became widely salient.

2.2 Data

Our initial dataset comprises monthly data covering all households in Finland for the period from March 2022 to June 2023. It is natural to think about the margins through which households can respond using the following household budget constraint:

$$\underbrace{\text{Electricity use}}_{(a)} \times \text{Price} - \underbrace{\text{Income}}_{(b)} - \underbrace{\text{Defaults}}_{(c)} + \underbrace{\text{Consumption} + \text{Savings}}_{(d)} = 0$$

Each term represents a separate dependent variable in our analysis: (a) household-level electricity use from the transmission system operator Fingrid, (b) monthly gross income from the tax authority, including labor earnings, pensions, and government-paid benefits, and (c) defaults from the legal register center. By observing other sources of income, we can then mechanically derive the residual term (d) as income net of costs, defaults, and taxes, which captures response through all other channels such as reduced consumption or savings. For the heterogeneity analysis, we use pre-crisis household-level background information. These datasets are explained below.[4]

Household-level background data Individual-level background data is obtained from Statistics Finland's pre-population statistics as well as basic and income data modules. The dataset provides annual individual-level information on employment status, disposable income, total debt and family statistics for 2021, one year prior to the crisis. We use monthly preliminary population statistics to aggregate the background data at the household level, pooling individuals living in the same dwelling and connected to the same electricity meter each month. If a household moves, they are dropped from the analysis.

Electricity consumption and contracts The electricity consumption and contract data are obtained from Fingrid Datahub, which is a regulated centralized information exchange system for the Finnish electricity retail market. This dataset includes monthly electricity use, a binary contract type (fixed or variable price), contract start and end dates, identifiers such as electricity meter numbers, the social security numbers of customers in contracts, and electricity retailer's identifier. We link household-level information to electricity contracts by identifying the individual to whom the bill is assigned. Our data does not contain contract-level price information. Instead, we use monthly average electricity prices by contract type (variable-price, one-year, and two-year fixed-price) and user type (e.g., apartment type and fuse size) from the Finnish Energy Authority, which include both electricity and transmission fees.

Earnings, pensions and benefits We obtain income and benefit data from the Finnish Tax Authority and use it to calculate household-level monthly labor earnings, pensions, and other benefits by summing across all household members. to mitigate the effects of the electricity

[4] A more detailed description of how the final dataset is found in the Supplemental Appendix, including summary statistics in Appendix Table A.1, and pure data plots of all dependent variables in Appendix Figures B.1-B.6.

crisis, the Finnish government implemented support schemes. Our analysis incorporates the most important ones: a temporary reduction in the electricity VAT rate (reflected in prices) and an electricity bill compensation (HE 324/2022), which applied to four winter months (November 2022–February 2023) and was based on past electricity use.[5] It covered 50% of monthly electricity expenses exceeding €90, with a cap of €700 per month. Eligibility was restricted to individuals paying an electricity price above 10c/kWh. Compensation was paid automatically as reductions on electricity bills starting in March 2023. We calculate compensation amounts using consumption data and the estimated prices.

Defaults Data on payment defaults are obtained from the Finnish Legal Register Center. The dataset includes individual-level defaults enforced by district courts, which we link to households. The default data also include the subject matter of the default, the principal, interest, fees, penalties, collection expenses, the summons date, and the court decision date. We define the month of the summons date as the default time, which typically occurs one or two months after a missed payment. Our analysis includes defaults for all purposes (e.g., services, goods, debt), because we anticipate that a higher utility bill may lead to other types of defaults, for instance, via payday loans. We calculate the total amount of accumulated defaults for each household and construct an indicator variable that equals one if a household has had at least one default in the register before a given month, and zero otherwise.

Residual consumption Households may respond to the higher prices by switching to a more affordable consumption basket, using their savings, borrowing from relatives, and so on.[6] These channels are unobservable to us. However, we can indirectly observe their combined effect at the household level as the "residual" term, which is defined as: after-tax earnings (labor and pension) + after-tax benefits (including electricity support) - electricity bill + defaults. We calculate monthly residual consumption for each household and treat it as a dependent variable in the analysis.

2.3 Empirical strategy

To identify causal effects, we use a difference-in-differences design comparing treated households whose contracts end during the crisis (from August 2022 to January 2023) to a control group of households whose contracts end after our study period (after June 2023). The main sample

[5]The other support programs, an income tax deduction for electricity expenses (HE 204/2022) and a subsidy through social insurance institution (HE 234/2022) were small in size and underutilized; they totalled to only €3 million compared to €440 million through the VAT reduction and electricity support (YLE, 2023). We consider these other programs to be minor and exclude them from the analysis.

[6]For instance, Steen et al. (2021) use household-level transaction data from a large Norwegian grocery chain to show that households shift to cheaper stores, bulk products, and sales in response to a regional income shock.

includes only households with a two-year fixed-price contract at the beginning of our study period (March 2022). The energy crisis was unforeseen when these contracts were signed in 2020-2021, and therefore the expiration date of long-term contracts during the crisis can be considered plausibly exogenous. However, the group of households that sign their contracts in a given month may not be random. For example, students tend to move during certain months, or seasonal advertisement campaigns may target households in specific areas. To address this, we use a matched difference-in-differences design, matching each household with its nearest neighbor based on heating technology, electricity usage, default indicators, benefits, and earnings in the five months preceding the crisis unfolds (for period March–July 2022).[7] The final matched dataset includes 270,054 households.

Households whose contracts end later in the crisis know their exact expiration dates and may react in advance to the anticipated price hike. For example, forward-looking households may install energy-saving investments or earn a financial buffer in anticipation of their contract ending soon. Such anticipation could bias estimation if not accounted for (Malani and Reif, 2015). Our setting, in which household's contract expiration months vary, allows us to explore these anticipation effects directly. Based on the effects shown in Figure 1b, we conclude that the crisis became salient in July 2022. This lets us study both price effects after the contract ends and anticipation effects that occur after the crisis unfolds (August 2022 or later) but before the contract ends.

Using the final dataset of treated households and their matched control group, we estimate separate event study models for each treatment month (contract expiration month), which we refer to as cohort h:[8]

$$Y_{iht} = \sum_{t=1, t\neq 5}^{16} \beta_{ht} I_{iht} + \alpha_{hi} + \gamma_{ht} + \epsilon_{iht} \quad \text{for each } h \tag{1}$$

where Y_{iht} is the logarithmic transformation of the dependent variable in month t (electricity use, earnings, defaults, and residual consumption) for household i whose contract ends in cohort h. Variable I_{iht} is an indicator equalling one at month t for treated households. We omit the month before the crisis unfolds, meaning that the results are shown relative to that month (July 2022, $t = 5$). All regressions control for cohort-household fixed effects α_{hi} and cohort-month fixed effects γ_{ht}.[9]

[7] This approach follows Goldschmidt and Schmieder (2017) and Adams-Prassl et al. (2024). In the Supplemental Appendix Appendix Figure B.8 we use a fuzzier matching approach, where matching is done using only the first month of our data (March 2022) based on electricity use, default indicator, an indicator for electricity heating, benefits and earnings. We show that pre-trends remain parallel and that the effects are similar in size.

[8] In our setting, we have two treatments: an anticipation effect that takes place in calendar time (July) and a direct effect that takes place in event time (month when contract ends). Because of this, the length of the anticipation period differs between contracts ending in different months, and we cannot show all results in a single event study figure. Supplemental Appendix Figures B.1-B.6 show event studies for all cohorts separately.

[9] In some months, the same households may serve as controls for different treated households. By including fixed effects α_{hi}, these households can be considered independent across months.

To aggregate the results from all cohorts during the crisis ($h = 1, ..., 6$), we run the following stacked OLS regression model:

$$Y_{iht} = \beta ContractEnds_{iht} + \beta_A Anticipation_{it} + \alpha_{hi} + \gamma_{ht} + \epsilon_{iht} \tag{2}$$

Here $ContractEnds_{iht}$ is an indicator turning one in the month when the fixed-term contract ends, and $Anticipation_{iht}$ is an indicator turning one after the crisis unfolds (August 2022 or later), but before the contract ending month. This specification compares treated households only to never-treated households as in Cengiz et al. (2019), thereby avoiding the potential bias identified in the recent literature (Goodman-Bacon, 2021; Roth et al., 2023).

In addition to studying the reduced-form effects of contract expiration on behavior, we are interested in quantifying the responses as price elasticities. Our setup includes two types of variation in prices that consumers face: one stemming from the plausibly exogenous contract ending dates, and another stemming from the endogenous choice between fixed- and variable-price contracts after the contract ends. To use only the exogenous variation from the contract ending times, we instrument the electricity price with contract ending in a two-stage least squares estimation (2SLS):

$$Y_{iht} = \beta_p Price_{iht} + \beta_A Anticipation_{it} + \alpha_{hi} + \gamma_{ht} + \epsilon_{iht} \tag{3}$$

$$Price_{iht} = \alpha ContractEnds_{iht} + \alpha_A Anticipation_{it} + \alpha'_{hi} + \gamma'_{ht} + \epsilon'_{iht} \tag{4}$$

where $Price_{iht}$ is the logarithmic transformation of electricity price paid by household i in cohort h at month t.[10] Equations (3) and (4) respectively represent the second-stage and the first-stage, and they effectively scale the estimated effect of contract ending from equation (2) with the effect of contract ending on the electricity price, such that $\beta_p = \beta/\alpha$.

3 Results

3.1 Timing of the effect

Figure 2 presents the event study coefficients from equation (1) for four outcome variables of interest: (a) electricity use, (b) labor earnings, (c) defaults and (d) residual consumption. The figure shows graphical evidence supporting common trends prior to the energy crisis (left of the vertical black line). For clarity, we present results for two cohorts: households whose contract ends in August and therefore have no time to anticipate the shock (blue line), and households whose

[10]Note that mechanically, anticipation has no effect on electricity price, so $\alpha_A = 0$.

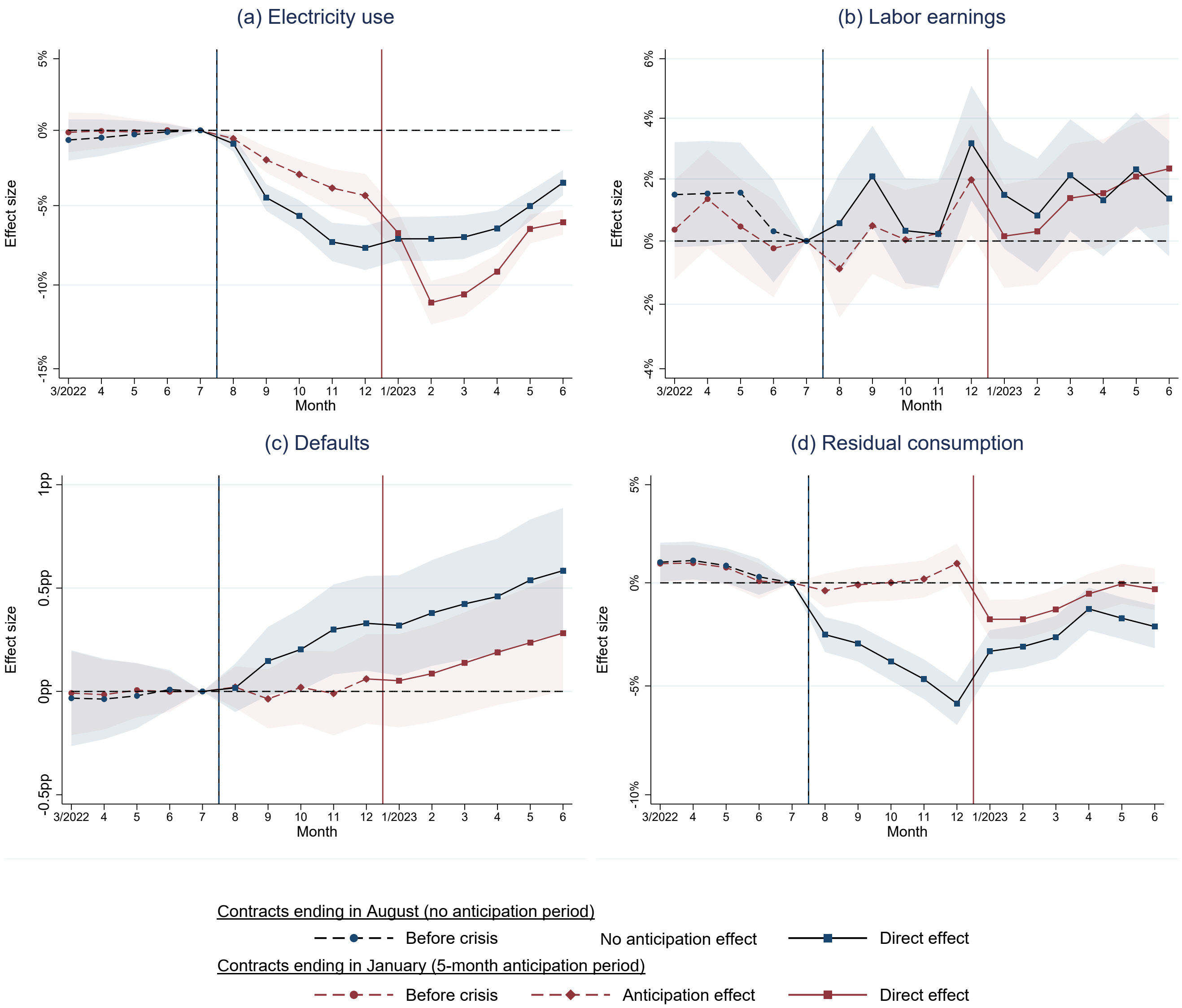


Figure 2: Timing of the treatment effects

Notes: The figure reports coefficients per calendar month as in equation (1) for the four main variables of interest, (a) the logarithm of electricity use, (b) the logarithm of labor earnings, (c) an an indicator for defaults and (d) the logarithm of residual consumption. Blue line shows effects for contracts ending in August (marked by the vertical black line) and the red line for contracts ending in January (vertical red line). Shaded areas show the 95% confidence intervals. Standard errors are clustered at the household level.

contract ends in January and have a five-month anticipation period (red line).[11]

Figure 2a shows the effect on electricity use. We find a clear effect for households whose contracts end in August (blue line), where electricity use decreases by around 5-8 percent after the contract ends. The effect fades toward the summer for two reasons: prices in variable-price contracts decrease over time and elasticity is lower during summer months.[12] For households

[11]Separate event study graphs for all treated stacks (contract ending months) are shown in the Supplemental Appendix Figures B.1-B.6, also for pensions and government benefits.

[12]In the Supplemental Appendix we show results separately for households switching to variable-price and fixed-price contracts. Households that switch to fixed-price contracts experience a small decrease in elasticity (in absolute value) toward the summer, indicating seasonal elasticity as in Rubin and Auffhammer (2024).

whose contracts end later (red line), we find an anticipation effect *after* the crisis unfolds but *before* their contract ends. These anticipation effects grow over time, reducing electricity use by an additional 2–4%, or about one-third of the total effect.[13] We expect these effects to arise because forward-looking households start making energy-saving investments before their contracts end.

Figure 2b shows the effects on labor market earnings. These effects are noisy and not large, but the aggregate direct effect across all cohorts turns out to be positive and statistically significant indicating around a one percent increase in labor earnings in response to a doubling of the price (see Table 1). We find no evidence of anticipation effects in income before the contract ends.

Figure 2c presents results for cumulative probability of defaults. For households whose contracts end in August (blue line), we find an effect that kicks in after one month, likely due to the delay from billing to the recording of the default, and gradually increases after that. We find a similar trend for households whose contracts end later and have an anticipation period (red line). The anticipation period gives households time to make the needed investments and plan accordingly but, nevertheless, it does not eliminate their risk of payment defaults.

Figure 2d shows the impact on residual consumption, which captures all other margins through which households can respond. The effect appears after the contract expires, and it is alleviated in early 2023 when the government distributes electricity support payments (from January to April). The effect is somewhat smaller for households with longer anticipation, which is explained by their greater reduction in electricity use and somewhat smaller price increase.

3.2 Heterogeneous responses: contract expiration

Figure 3 shows the heterogeneous responses to contract expiration by income and initial electricity use. The figure aggregates all six treatment cohorts (contract expiration months) as in equation (2), but runs separate regressions for different subgroups. The sample is divided into ten equal-sized groups based on five pre-crisis income quintiles and above- or below-median electricity use within each quintile.

Figure 3a shows heterogeneous responses in electricity use. We find greater elasticity among high-usage households, likely because such households are more likely to use electric heating and can reduce energy consumption by adjusting indoor temperatures.[14] We also find that high-income households are more price elastic than low-income households, especially among those that use little electricity. Low-income households may be closer to their subsistence level of electricity use,

[13] In the Supplemental Appendix we provide more evidence that the anticipation effect is robust by running the analysis for households whose contracts end unexpectedly due to the bankruptcy of their service provider. We find no 'placebo anticipation effect' for these households in Appendix Figure B.10.

[14] For reference, lowering the room temperature by one degree can save up to 5% of electricity consumption on average (Motiva, 2015).

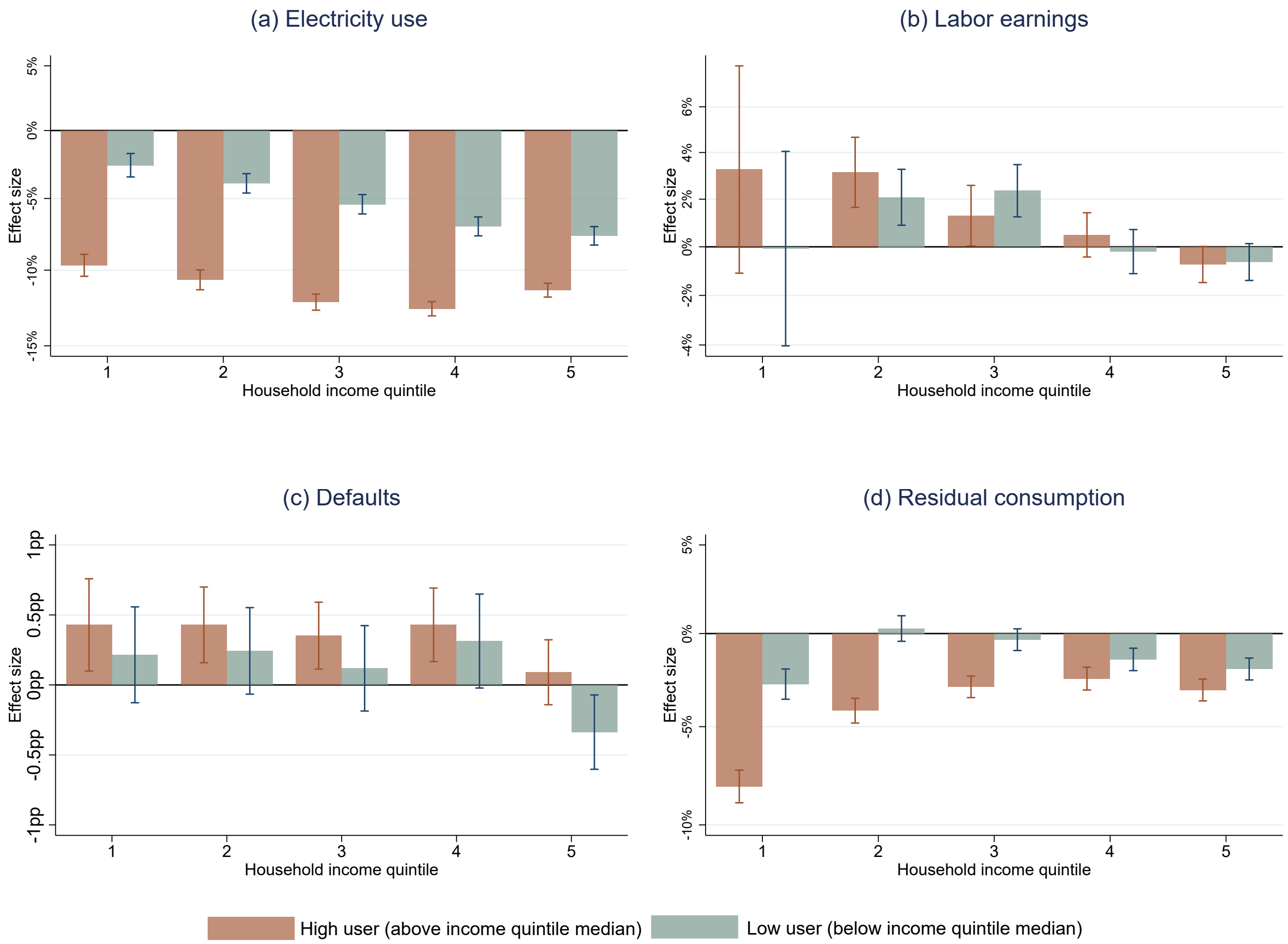


Figure 3: Heterogeneous responses to contract expiration

Notes: The figure reports coefficients from the stacked regression equation (2) for the treatment group with contracts expiring between August 2022 and January 2023. Each bar represents results for a different subset of the data: red bars indicate effects for households whose pre-crisis electricity use exceeds the median within their income quintile (high users), while blue bars are all the other households (low users). Whiskers indicate 95% confidence intervals. Standard errors are clustered at the household level.

making it more difficult for them to reduce consumption further.

Figure 3b unpacks the positive labor earnings response. The response is most robust among the middle-income households. For low-income households, the point estimate is large, but the estimate is noisy because many in this group have no labor income and they are dropped from our analysis due to the log-transformation. In contrast, we do not find similar effects for the highest income quintile.

Figure 3c shows the effect on household payment defaults. As expected, we find larger and statistically significant effects for households with above-median electricity use, who are consequently more exposed to price increases. To our surprise, the increase in defaults is observed among both low- and middle-income households. One possible explanation is that middle-income households may hold mortgages or other debt, leaving them with limited liquidity despite relatively high incomes. Supporting this mechanism, Section 3.3 shows a pronounced effect on households with a high debt-to-disposable income ratio. We find no corresponding increase in defaults for the highest income quintile.

Figure 3d depicts the negative effects on residual consumption. The effect is larger among households with high electricity consumption and particularly large for the lowest-income groups, who already had lower baseline consumption levels. This finding can be explained by three factors. First, low-income households spend, on average, a larger fraction of their income on electricity. Second, the government's electricity support had a threshold of €90 per month—a significant amount for low-income households—which directed support primarily to high-income households. Third, low-income households had fewer adjustment margins, as their electricity use was less elastic and their earnings did not respond.

3.3 Heterogeneous responses: price elasticities

Table 1 presents the main results as price elasticities. These results are based on the estimation of equations (3)-(4) using 2SLS, where the coefficients on the logarithm of $Price$ represent the change in key outcome variables in response to a percentage change in electricity price. All results control for the Anticipation-indicator to ensure that potential anticipation effects do not bias our estimates. We also examine heterogeneity in the results through three interaction terms (i) by household disposable income (in €10,000 per year), (ii) by electricity use (below or above the income quintile median), and (iii) by lag, representing the length of the anticipation period (months between the crisis unfolding and contract expiration).[15]

For electricity use (column 1), we find an own-price elasticity of -0.184, indicating that doubling the electricity price reduces electricity use by 18.4%. This confirms that residential electricity use is relatively inelastic in the short term, and our estimated elasticity is somewhat higher but within the range of previous results (Ito, 2014; Burke and Abayasekara, 2018; Deryugina et al., 2020). Notably, the energy crisis was highly salient, which may explain the somewhat higher elasticities (Alberini et al., 2020). We find that a one-month longer anticipation period changes elasticity by -0.049, suggesting that long-run demand is more price-elastic than short-run demand. We also find that demand elasticity varies across households: For each €10,000/year increase in household income, the elasticity changes by -0.0011, and for above-median users, the elasticity is 0.097 larger in absolute value.

We find a positive response in labor earnings (column 2), but no effect on pensions (column 3). For labor earnings, doubling the electricity price increases labor income by 1.4% with no evidence of anticipation effects. This effect decreases with income, such that for every €10,000 increase in

[15] All interaction terms are demeaned by subtracting the sample mean from each observation, so that they do not interact with the mean electricity price. All results, including ones without the interaction terms, are shown in Appendix Table A.2.

Table 1: Effects of electricity prices

	Electricity use	Labor earnings	Pensions	Benefits	Defaults	Residual consumption
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Full sample						
Price	-0.184***	0.0139**	0.0004	0.143***	0.0039***	-0.0451***
	(0.0026)	(0.0043)	(0.0020)	(0.0127)	(0.0009)	(0.0024)
...x income	-0.0011***	-0.0010***	0.0003***	-0.0013***	-0.0001***	0.0039***
	(0.0001)	(0.0014)	(0.0011)	(0.0031)	(0.0000)	(0.0008)
...x use	-0.0969***	0.0074	-0.0062*	0.402***	0.0046**	-0.0535***
	(0.0043)	(0.0065)	(0.0030)	(0.0209)	(0.0016)	(0.0038)
...x lag	-0.0488***	0.0036	-0.0002	-0.0013	0.0002	0.0021
	(0.0014)	(0.0024)	(0.0010)	(0.0071)	(0.0006)	(0.0013)
Anticipation	-0.0266***	-0.0005	0.0006	-0.0277***	0.0005	-0.0045***
	(0.0011)	(0.0021)	(0.0007)	(0.0049)	(0.0004)	(0.0012)
N	4,228,556	2,404,502	1,885,189	1,876,091	4,230,893	4,110,374
Panel B: Rural area						
Price	-0.229***	0.0136	0.0070	0.275***	0.0050**	-0.0627***
	(0.0048)	(0.0084)	(0.0022)	(0.0282)	(0.0018)	(0.0043)
Anticipation	-0.0323***	0.0039	0.0007	-0.0297*	0.0006	-0.0029
	(0.0022)	(0.0043)	(0.0011)	(0.0118)	(0.0007)	(0.0021)
N	1,156,444	592,389	615,640	478,765	1,157,284	1,114,960
Panel C: Over 70 years old						
Price	-0.144***	0.0140	-0.0015	1.201***	0.0023**	-0.0615***
	(0.0047)	(0.0200)	(0.0014)	(0.0553)	(0.0009)	(0.0022)
Anticipation	-0.0218***	-0.0132	-0.0006	0.0274	0.0007*	-0.0018
	(0.0021)	(0.0113)	(0.0004)	(0.0201)	(0.0003)	(0.0009)
N	1,218,253	122,779	1,214,102	301,973	1,219,162	1,204,420
Panel D: Indebted households						
Price	-0.243***	0.0181**	0.0129	0.0226	0.0077***	-0.0317***
	(0.0050)	(0.0061)	(0.0092)	(0.0159)	(0.0020)	(0.0052)
Anticipation	-0.0336***	0.0043	0.0049	-0.0343***	0.0013*	-0.0049*
	(0.0020)	(0.0028)	(0.0027)	(0.0070)	(0.0064)	(0.0023)
N	1,251,569	1,066,939	175,882	694,278	1,251,997	1,213,022

Notes: This table reports regression coefficients from 24 separate regressions (six columns × four panels). The dependent variables are the natural logarithm of electricity consumption (column 1), labor earnings (column 2), pension payments (column 3), government-paid benefits including the electricity support (columns 4), the level of the defaults indicator (column 5) and the natural logarithm of residual consumption (column 6). The table estimates price elasticities following eqs. (3)-(4), where Price is the logarithm of contract price. Panel A uses the full sample, Panel B includes only households in rural area, Panel C includes only households where the bill payer is over 70 years old, and Panel D Panel D includes only households whose debt-to-annual-income ratio exceeds 100%. All panels include interactions (differences from the sample mean) with income (in 10,000 euros), electricity use (an indicator for high use, taking value one if electricity consumption is above median for a given income quintile), and lag defined as the difference between contract ending month and August 2022. All columns control for household-stack (ih), stack-month (ht) and match-id fixed effects. All results also control for post- and treatment- interactions (for example, post-earnings and treatment-earnings). Standard errors, clustered by households, are shown in parentheses. * p<.05, ** for p<.01, and *** for p<.001.

income, the effect is 0.1 percentage points lower. Although we find no significant average effect of electricity prices on pension payments, there is some weak evidence of an effect for higher-income households. This effect arises from voluntary supplementary pensions, which are more popular among those with higher-income. Doubling the electricity price increases received benefits by 14% (column 4). These effects are largely driven by the electricity bill compensation, which was tied to past consumption. The effect is 40 percentage points larger for high users, and it decreases with income, such that for every €10,000 of income, the effect is 0.1 percentage point lower.

We find that doubling the electricity price increases the probability of household default by 0.4 percentage points, with no anticipation effect (column 5). In total, 270,000 Finnish households—nearly one in ten—experienced at least one payment default on their bills over the past five years, suggesting that the price shock increased the default indicator by roughly 4% across the board. This effect is smaller for high-income households, with a €10,000/year increase in income decreasing the effect by 0.01 percentage points. Those with above-median electricity consumption have a 0.4 percentage point higher probability of default, which is approximately twice the average effect. We find no evidence that a longer anticipation period leads to fewer defaults. Last, we find that doubling the electricity price decreases residual consumption by around 4.5%, with a small anticipation effect (column 6). This effect is pronounced for those with low income (0.4 pp per additional €10,000/year), high energy use (5.3 pp for above-income consumption), but we find no statistically significant effect for the length of the anticipation period.

To explore the heterogeneity further, we present results for three vulnerable groups of households: Those living in rural areas (Panel B), those where the bill payer was over 70 years old during the crisis (Panel C) and indebted households whose debt-to-annual disposable income ratio exceeds 100% (Panel D).[16] Households in rural areas experience a slightly larger default effect (0.50 pp vs. 0.39pp in the full sample), and a larger decrease in residual consumption (-6.3% vs. -4.5% in the full sample) compared to the total population. The elderly have a *lower* default effect (0.23 pp), but they experience a larger overall reduction in residual consumption (-6.2%) than the average population. Indebted households face a much higher risk of defaults (0.77 pp), but exhibit a smaller reduction in residual consumption (-3.2%).

3.4 Illustration: impacts and household responses to carbon pricing

To illustrate our results, we perform a stylized calculation to study the effects of a hypothetical carbon price. To this end, we make the following assumptions in this illustration:

- We use our estimated treatment effects from Table 1 (in %) and multiply them by the household-level variables to obtain the total effect size (in Euros). We use the estimated interactions to allow the effect to vary with income, electricity use, and the anticipation

[16] In addition, Appendix Table A.2 explores heterogeneity across the following proxies for vulnerable households: those with electric heating, those receiving social assistance, tenants, and language minorities. The three groups shown in Table 1 are the ones that show pronounced negative effects of electricity prices (defaults and residual consumption).

period which we assume to be three months.

- We assume a carbon price of €100/tCO_2 and a full pass-through to consumer prices (Fabra and Reguant, 2014), leading to a price increase of 10c/kWh.[17] All households are assumed to have a variable-price contract, so they all face the price increase.

- Although some estimated effects are not statistically significant at conventional levels, we use the point estimate rather than zero as the "best guess". In order to avoid outlier responses, we restrict the response to be between 0% and 100% of the carbon cost.

The results are shown in Figure 4a for the full population. The total bar height represents the static cost burden of the hypothetical carbon price without behavioral responses. It is calculated as initial electricity use multiplied by the price increase, divided by household disposable income.[18] The static burden is found to be highest for low-income households, consistent with previous findings.[19] For middle-and high-income households the static cost incidence is relatively flat.

The total cost burden changes when household-level responses are taken into account. Households adjust by reducing their electricity use (gray bar). This effect represents a smaller share of the total incidence for low-income households, as high-income households have greater demand elasticity. Households may also increase their labor earnings (orange bar) or claim supplementary pensions (blue bar). However, these effects are minimal for low-income households, because they do not actively participate in the labor market and cannot influence pension payouts. Taken together, these response margins reduce the static cost incidence by half for the middle- and high-income households, but by only less than one-fourth for those with the lowest income. As a result, low-income households are more likely to default on their bills (red bar) and experience a larger impact on their residual consumption (black bar). This heterogeneity in response behavior is a novel driver of climate policy-induced inequalities.

Figures 4b-4d show results for subsamples that resemble vulnerable groups: people living in rural areas (Panel b), those over 70 years old (Panel c), and indebted households (Panel d). We find that households living in rural areas face significantly higher costs than the average household, particularly among households with the lowest incomes. In contrast, the effects on the low-income elderly and indebted households are less drastic. For the elderly, the main reaction

[17] We assume that marginal producer has coal's emission intensity (335g/kWh) with plant efficiency of 0.33. Alternatively, we could assume that gas is the marginal producer (200g/kWh with 0.5 efficiency) and a carbon price of €250/tCO_2. For reference, the average EU Emissions Trading System (ETS) allowance price was around €70/tCO_2 during 2024. Note that subsidies paid on renewable energy lower the electricity price and have opposite impacts (Liski and Vehviläinen, 2020).

[18] Note that annual disposable income is a commonly-used metric, but not a perfect measure as it varies over lifetime and with stochastic life events such as unemployment and family conditions; see Cronin et al. (2019) for discussion. Ideally, we would use permanent income or wealth, but those data are not available to us.

[19] This pattern also follows the predictions of the Stone-Geary utility function, where households have certain sufficiency level of consumption of necessities (Geary, 1950; Stone, 1954).

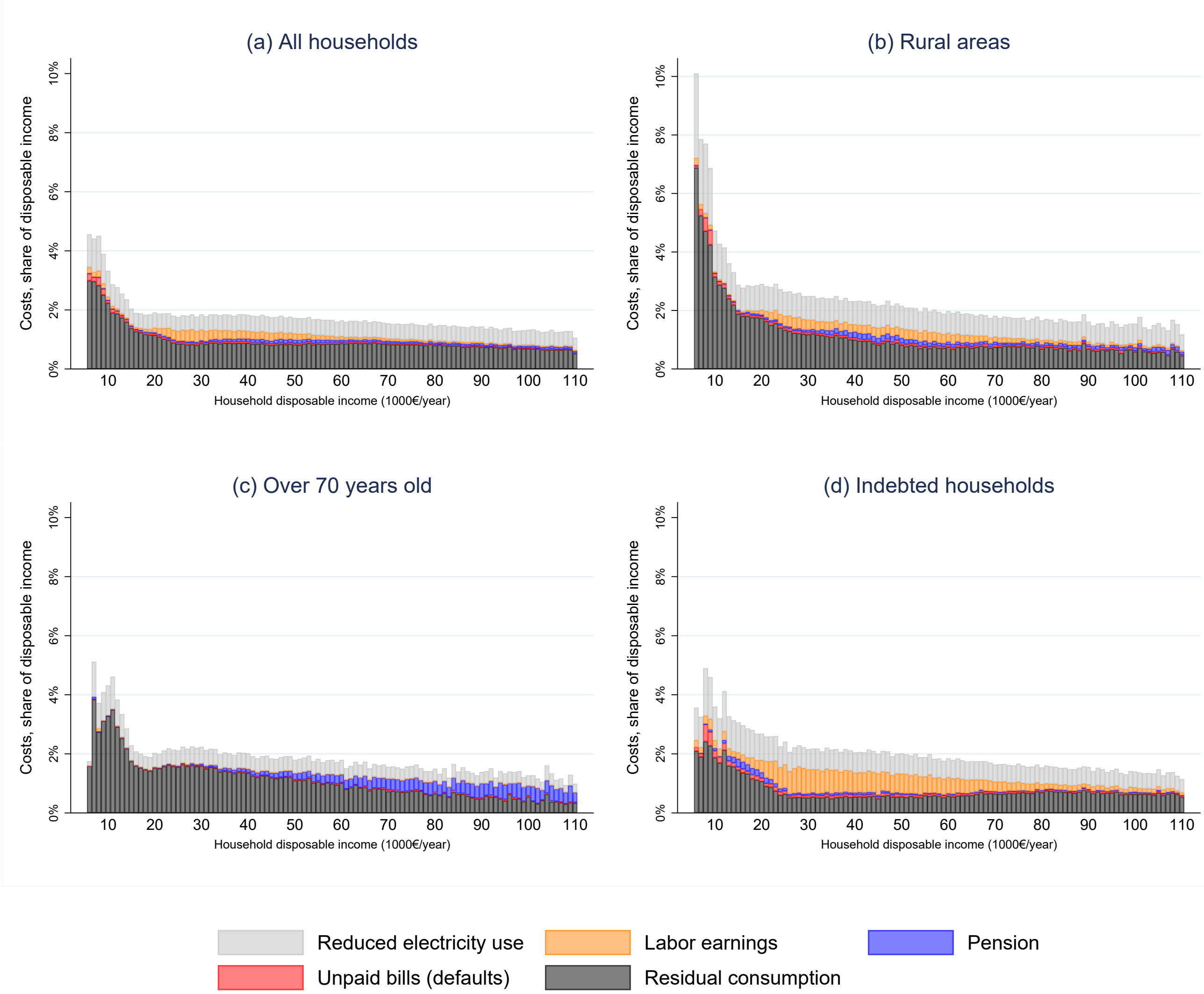


Figure 4: Illustration, the cost burden of a hypothetical €100/tCO_2 carbon price

Notes: The figure reports cost burden of a hypothetical €100/tCO_2 carbon price that is assumed to increase electricity prices by 10 c/kWh. The total bar height is the static incidence (initial consumption times the price increase). Gray bar denotes the cost savings of the reduced use, orange bar is the additional labor earnings, blue are is the additional pension earnings, red area denotes the defaulted amount (probability of default times the total bill), and black area is the effect on residual consumption (total incidence minus all response channels). Figure (a) uses the full sample and estimated coefficients from panel A of Table 1; (b) uses only households living in rural area (classifications M4-M7) and estimated coefficients from panel B of Table 1 and interactions from Appendix Table A.2; (c) uses only households where the person who pays the bill is born in 1952 or earlier and uses coefficiens from panel C of Table 1 and interactions from Appendix Table A.2; (d) uses only households whose debt-to-disposable annual income is over 100%, with coefficients from panel D of Table 1 and interactions from Appendix Table A.2. All figures assume an anticipation period of three months.

channel is pension, as older cohorts are more likely to have adjustable voluntary supplementary pensions, especially among those with high incomes. Indebted households have a pronounced risk of defaulting on their bills (see Table 1, Panel D) but they are more likely to be active in the labor market and can therefore adjust their labor earnings more easily.

4 Conclusions

Climate policies or volatility in fossil fuel markets can drive up energy prices. Policymakers are concerned that high energy prices harm '*vulnerable*' or '*energy poor*' households, who currently spend a high share of income on fossil fuels. Yet, standard economic reasoning emphasizes that this expenditure alone does not reflect the true impact, but it also depends on the behavioral response across all relevant response margins. We leverage the 2022 European Energy Crisis and the quasi-random expiration of long-term contracts amid the crisis to provide the first detailed breakdown of household-level responses to energy price shocks.

Our main result is that the energy price hike does not affect all households equally; heterogeneous adjustment channels become a driver of price-induced inequalities. High- and middle-income households can more easily adapt by reducing electricity use or increasing earnings, while low-income families often lack these options, forcing them to reduce their remaining consumption more sharply and making them more likely to default on their bills. These results provide empirical grounding for discussions on the distributional effects of energy policy.

References

Adams-Prassl, A., K. Huttunen, E. Nix, and N. Zhang (2024). Violence against women at work. *The Quarterly Journal of Economics 139*(2), 937–991.

Ahlvik, L., S. Alhola, T. Blauberg, H. Laasonen, M. Liski, O. Malinen, M. Mattila, O. Nokso-Koivisto, A. Sahari, M. Seppä, et al. (2023). Sähkön hinnannousun ja sähkötukien arvioidut vaikutukset kotitalouksiin.

Ahlvik, L., M. Liski, and M. Mäkimattila (2024). Pigovian income taxation. *CESifo Working Paper* (11174).

Alberini, A., O. Khymych, and M. Ščasnỳ (2020). Responsiveness to energy price changes when salience is high: Residential natural gas demand in ukraine. *Energy Policy 144*, 111534.

Bierbrauer, F. (2023, August). Is a market-based approach to climate policy desirable? Working Paper 2023, University of Cologne.

Boardman, B. (1991). Fuel poverty: from cold homes to affordable warmth.

Burger, S. P., C. R. Knittel, I. J. Pérez-Arriaga, I. Schneider, and F. Vom Scheidt (2020). The efficiency and distributional effects of alternative residential electricity rate designs. *The Energy Journal 41*(1), 199–240.

Burke, P. J. and A. Abayasekara (2018). The price elasticity of electricity demand in the united states: A three-dimensional analysis. *The Energy Journal 39*(2), 123–146.

Cahana, M., N. Fabra, M. Reguant, and J. Wang (2022). The distributional impacts of real-time pricing.

Cengiz, D., A. Dube, A. Lindner, and B. Zipperer (2019). The effect of minimum wages on low-wage jobs. *The Quarterly Journal of Economics 134*(3), 1405–1454.

Charlier, D. and B. Legendre (2021). Fuel poverty in industrialized countries: Definition, measures and policy implications a review. *Energy 236*, 121557.

Cronin, J. A., D. Fullerton, and S. Sexton (2019). Vertical and horizontal redistributions from a carbon tax and rebate. *Journal of the Association of Environmental and Resource Economists 6*(S1), S169–S208.

Deryugina, T., A. MacKay, and J. Reif (2020). The long-run dynamics of electricity demand: Evidence from municipal aggregation. *American Economic Journal: Applied Economics 12*(1), 86–114.

Doligalski, P., G. P. Dworczak, M. Akbarpourr, and G. S. D. Kominers (2025). Optimal redistribution via income taxation and market design.

Douenne, T. (2020). The vertical and horizontal distributive effects of energy taxes: A case study of a french policy. *The Energy Journal 41*(3), 231–254.

Douenne, T., A. J. Hummel, and M. Pedroni (2023). Optimal fiscal policy in a climate-economy model with heterogeneous households. *Available at SSRN 4018468*.

Drupp, M. A., U. Kornek, J. Meya, and L. Sager (2024). The economics of inequality and the environment.

Fabra, N. and M. Reguant (2014). Pass-through of emissions costs in electricity markets. *American Economic Review 104*(9), 2872–2899.

Fetzer, T., L. Gazze, and M. Bishop (2024). Distributional and climate implications of policy responses to energy price shocks. *Economic Policy 39*(120), 711–756.

Finnish Energy Authority (2021). National report on the state electricity and gas markets in Finland to the agency for the cooperation of energy regulators and to the european commission.

Fischer, C. and W. A. Pizer (2019). Horizontal equity effects in energy regulation. *Journal of the Association of Environmental and Resource Economists 6*(S1), S209–S237.

Geary, R. C. (1950). A note on "a constant-utility index of the cost of living". *The Review of Economic Studies 18*(1), 65–66.

Goldschmidt, D. and J. F. Schmieder (2017). The rise of domestic outsourcing and the evolution of the german wage structure. *The Quarterly Journal of Economics 132*(3), 1165–1217.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of econometrics 225*(2), 254–277.

Grainger, C. A. and C. D. Kolstad (2010). Who pays a price on carbon? *Environmental and Resource Economics 46*, 359–376.

Gravert, C. (2024). From intent to inertia: Experimental evidence from the retail electricity market. Technical report, CEBI Working Paper Series.

Ito, K. (2014). Do consumers respond to marginal or average price? evidence from nonlinear electricity pricing. *American Economic Review 104*(2), 537–563.

Ito, K., T. Ida, and M. Tanaka (2023). Selection on welfare gains: Experimental evidence from electricity plan choice. *American Economic Review 113*(11), 2937–2973.

Legendre, B. and O. Ricci (2015). Measuring fuel poverty in france: Which households are the most fuel vulnerable? *Energy Economics 49*, 620–628.

Levinson, A. and E. Silva (2022). The electric gini: Income redistribution through energy prices. *American Economic Journal: Economic Policy 14*(2), 341–365.

Liski, M. and I. Vehviläinen (2020). Gone with the wind? an empirical analysis of the equilibrium impact of renewable energy. *Journal of the Association of Environmental and Resource Economists 7*(5), 873–900.

Luotonen, N., V. Puttonen, and E. Rantapuska (2022). Maksuhäiriöt Suomessa 2015-2020. *Kansantaloudellinen aikakauskirja 118*(2), 194–216.

Malani, A. and J. Reif (2015). Interpreting pre-trends as anticipation: Impact on estimated treatment effects from tort reform. *Journal of Public Economics 124*, 1–17.

Motiva (2015). Sähkölämmityksen tehostamisohjelma elvari. Website. Available at https://www.motiva.fi/koti_ja_asuminen/energiatehokas_pientalo/energiatehokas_sahkolammitys/sahkolammityksen_tehostamisohjelma_elvari.

Numminen, S., T. Kajoskoski, Y. Kaltampanidis, and M. Jalas (2024). Energy vulnerability of detached home owners in Finland: An explorative study. *Energy and Buildings 310*, 114082.

Pai, M. and P. Strack (2022). Taxing externalities without hurting the poor. *Available at SSRN 4180522*.

Pizer, W. A. and S. Sexton (2019). The distributional impacts of energy taxes. *Review of Environmental Economics and Policy*.

Romero, J. C., P. Linares, and X. López (2018). The policy implications of energy poverty indicators. *Energy policy 115*, 98–108.

Roth, J. and P. H. Sant'Anna (2023). When is parallel trends sensitive to functional form? *Econometrica 91*(2), 737–747.

Roth, J., P. H. Sant'Anna, A. Bilinski, and J. Poe (2023). What's trending in difference-in-differences? a synthesis of the recent econometrics literature. *Journal of Econometrics 235*(2), 2218–2244.

Rubin, E. and M. Auffhammer (2024). Quantifying heterogeneity in the price elasticity of residential natural gas. *Journal of the Association of Environmental and Resource Economists 11*(2), 319–357.

Sahari, A. (2019). Electricity prices and consumers' long-term technology choices: Evidence from heating investments. *European Economic Review 114*, 19–53.

Steen, F., S. A. Ulsaker, and T. A. Aursland (2021). Unemployment shocks, cyclical prices and shopping behavior. NHH Dept. of Economics Discussion Paper 03/2021.

Stone, R. (1954). Linear expenditure systems and demand analysis: an application to the pattern of british demand. *The Economic Journal 64*(255), 511–527.

van Soest, D. (2025). The price elasticity of energy demand and implications for climate policy. Working paper

Vesterberg, M. (2018). The effect of price on electricity contract choice. *Energy Economics 69*, 59–70.

SUPPLEMENTAL APPENDIX

A Data appendix

This section provides a detailed description of the datasets, variables, and the matching process. The data is proprietary and accessible through Statistics Finland. All identifiers (such as social security number, meter number or firm identifier) are pseudonymized. The main outcome variables are measured at the monthly level for the period from March 2022 to June 2023. To examine heterogeneity, we use a more comprehensive cross-sectional background dataset from 2021, one year prior to the crisis. Figure A.1 illustrates how the final dataset is constructed.

First, we construct households by using preliminary population statistics, then link each individual's background, earnings, benefits, and default data to a specific household using a pseudonymized social security number. Electricity data is linked to other datasets through the social security number of the individual who signed the electricity contract. Once the electricity data is integrated, we aggregate other data to the household level. The aggregation process involves the following steps:

- **Summable variables:** Variables such as earnings, pensions and benefits are summed across all members of the household to produce household-level totals.
- **Indicator variables:** For binary variables, such as default status, the household is assigned a value of 1 if any household member meets the condition. For example, if at least one household member has a recorded default, the household-level default variable is set to 1.
- **Categorical variables:** These are determined based on the person making the electricity contract. The characteristics of this individual, such as the year of birth, are used as household representatives.

In total, 2.5 million households in Finland have an electricity contract (excluding the autonomous region of Åland, 0.5% of the total population). Our identification strategy is based on the expira-

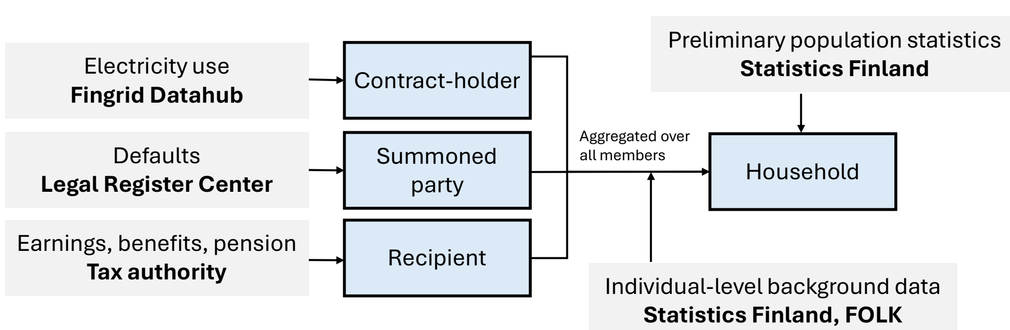


Figure A.1: Illustration of the datasets tion of fixed-price contracts, and the main sample consists of households with a two-year fixed-price contract at the start of the study period (March 2022). Approximately one-third of households have such contracts, reducing the sample size to 926,000. Treated households are those whose contracts expire during the crisis period (August 2022–January 2023), resulting in 138,756 unique treated households. We identify a nearest neighbor match for each treated household, bringing the total sample—including both treated and control households—to 270,054.

Household-level background datasets The analysis is conducted at the household-dwelling level (or 'households' for short). A household-dwelling unit consists of the permanent occupants that consistently use a given electricity meter. If the electricity meter changes, for instance, if a household moves, they are dropped from our sample. Households are constructed at the monthly level using preliminary population statistics, which provide monthly information on all individuals residing in Finland, including their place of residence and pseudonymized building, dwelling, and social security numbers.

We use Statistics Finland FOLK (income and basic dataset modules) for 2021 (a year before the crisis) for the background information. The FOLK module for basic data contains annual individual-level data from the statistics on the structure of the population, employment statistics, and some data from the family statistics, as well as the statistics on the educational structure of the population. The FOLK income module contains annual data on persons' disposable income, current transfers received, wealth, and outstanding debts. From the FOLK datasets, we use the following variables in our analysis: birth year, urban-rural classification, disposable income, and total debts. Disposable income in 2021 (comprising labor and capital earnings as well as benefits, net of taxes) is used to construct income quintiles for the sample.

Electricity consumption and contract data The data is obtained from Fingrid Datahub, a centralized information exchange system for the electricity retail market. Datahub is owned by Fingrid Oyj, Finland's transmission system operator (TSO). For a more detailed description of the dataset, see Ahlvik et al. (2023). The dataset includes monthly electricity consumption and contract details at the electricity meter level. The analysis utilizes the following variables: the pseudonymized electricity meter number, the pseudonymized social security number of the contract holder, contract type (fixed-term or temporary), consumer type (e.g., apartment block, detached house, farm), and whether the dwelling relies on electricity for heating.

Contract-level electricity prices are not available from Datahub. Instead, we use monthly average electricity prices from the Finnish Energy Authority, categorized by contract type (variable price, 1-year, and 2-year fixed price) and user type (e.g., apartment type and fuse size). Electricity distribution companies and retailers are required to report existing prices to the Finnish Energy

Authority, which then publishes monthly electricity price statistics by contract type (fixed-term, variable price, and other temporary contracts) and consumer type. For fixed-term contracts, we use the electricity price from the month the contract was signed for its entire duration (one or two years). The contract type variable in the Datahub dataset does not differentiate between variable price and other temporary contracts; therefore, we use the average price of these two contract types by user type. The user types included in this study are (i) K1: Apartment, no electric sauna stove, main fuse 1x25 A, (ii) K2 – Detached house, electric sauna stove, no electric heating, electricity consumption 5,000 kWh/year, (iii) L1 – Detached house, room-specific electric heating, main fuse 3x25 A, and (iv) L2 – Detached house, partially storage-based electric heating, main fuse 3x25 A. The price we use also includes the average transmission fee by user type.

Income and benefits registers We obtain monthly earnings, pensions, and other benefits data from the Finnish Tax Authority's Income and Benefits Register, which serves as the source for the dependent variables in our analysis. The Incomes Register is an electronic database that records monthly reports on paid wages, pensions, and benefits. The dataset does not include sensitive information, such as social assistance payments. Furthermore, the reporting obligation does not cover most capital income or a self-employed person's earnings if they are insured under the Self-Employed Persons' Pensions Act or the Farmers' Pensions Act. Note that these limitations apply only to the monthly data and not to FOLK disposable income (for 2021), which we use as a background variable.

The Income Register includes various income types (e.g., total wages, overtime, evening work compensation, and performance bonuses), as well as the pseudonymized social security number and employer business identity code. Employers must report income at either the mandatory minimum level, which includes total wages, or at a more detailed complementary level, which provides additional breakdowns. We aggregate labor earnings at the monthly and household levels. The Benefits Register contains information on paid benefits and pensions, which we separate in the econometric analysis. Benefits are reported similarly to income data, except that each benefit must be classified under a specific income type. We aggregate all benefit income types to calculate total household benefits.

Court-reported defaults Data on defaults are obtained from the Finnish Legal Register Center. The dataset includes individual-level and firm-level payment defaults enforced by district courts in Finland from 2016 to 2023. Each default entry contains pseudonymized register and social security numbers, along with details such as the subject matter of the default, the principal, interest, fees, penalties, and collection expenses. We link defaults to households based on the defaulter's social security number and include only individual-level enforced defaults in our analy-

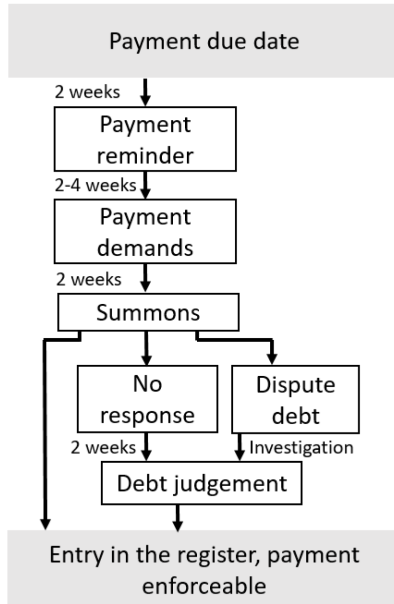


Figure A.2: The default process: from unpaid bills to enforceable payments

Notes: The figure, based on Luotonen et al. (2022), illustrates the progression of a payment default in Finland, beginning with the payment due date and progressing through reminders, demands, and court-issued summons. The process diverges depending on whether the debtor responds or disputes the debt. Time intervals between steps highlight the typical delays in the default resolution timeline.

sis. The dataset also records the summons date, court decision date, and default status (annulled or enforced). We define the month of the summons date as the time of default, which typically occurs 1–2 months after a missed payment. We use the summons date instead of the decision date due to the relatively short time window of our data and the potentially lengthy interval between summons and decision.

Figure A.2 illustrates the default process from an unpaid bill to an enforced default. We cannot separately identify utility bill defaults in the dataset, but there is a broader category for services that includes utility bills. However, financial distress may lead households to default on other types of bills—for instance, they may rely on payday loans to cover expenses. Therefore we include defaults for all purposes and calculate each individual's total accumulated defaults (including interest, penalties, and other fees) starting from March 2022. We construct an indicator variable equal to one if an individual—or any individual in a household—has a default in the register after March 2022 and zero otherwise. Additionally, we define a background variable indicating whether an individual had at least one default in the five years preceding March 2022.

B Additional results and robustness analyses

We present the following robustness checks, organized in the order they appear in the text.

Summary Statistics Table A.1 presents the means and standard deviations of the outcome variables (in both log and level forms) and background demographic variables for the treated group, matched control group, unmatched control group, and full population. As expected, the matched control group is, on average, the most similar to the treated group. The unmatched control group consists of all households with fixed-term contracts expiring after the end of the study period (June 2023). On average, this group exhibits higher electricity use, earnings, pensions, social assistance, benefits, and residual consumption than the treated group. Difference-in-differences identification strategy only relies on parallel trends and differences in levels are not a threat to our identification as such. However, with differences in levels, the parallel trends become sensitive to the functional form of the dependent variable (Roth and Sant'Anna, 2023), potentially leading to distinguishable pre-trends given the large number of power in this setting.

Raw data and all event studies We present the results of all event studies: electricity use in Figure B.1, earnings in Figure B.2, pensions in Figure B.3, benefits (including electricity support) in Figure B.4, defaults in Figure B.5, and residual consumption in Figure B.6. These figures display both the raw data (logarithmically transformed) and event study estimates based on equation (1). We show all results for contract that are expiring during the first six months (August 2022 to January 2023), as these are the treated households in our analysis.

Matching: additional results Figure B.7 presents the matched data for the treatment and control groups before the crisis unfolds (first five months) as a binscatter plot. The matching performs well for electricity use, benefits, and defaults but is slightly less effective in matching high-income treated households to high-income control households.

One concern with the matching techniques is the potential overfitting between the treatment and control group. To address this, we perform a simplified matching procedure using only the first month of our data (March 2022). Matching is based on household heating technology, electricity use, default indicator, benefits, and earnings. Figure B.8 displays the outcome variables for households whose electricity contracts terminate in August 2022 and January 2023.

The simplified matching approach yields results that are similar to our main findings for all outcome variables. The anticipation effects for households whose contracts terminated in December remain comparable to those in the main analysis. Pre-trends remain centered around zero and are in line with those observed in our primary results, albeit somewhat weaker for labor earnings and defaults. Among all groups (results for other months not shown), contracts ending in September and October 2022 exhibited the weakest pre-trends under simplified matching. Results for other months closely align with those of the December group, with all groups showing evidence of anticipation effects in electricity use.

Full result tables Table A.2 extends the main results from Table 1 and presents estimates for all variables. First, we report results with (odd-numbered columns) and without (even-numbered columns) interactions and show that the main effects are not sensitive to the introduction of the interaction terms. We also provide results for different subsets of the data:

- Panel A: Full sample
- Panel B: Households where the bill payer is over 70 years old
- Panel C: Households living in in rural areas
- Panel D: Households whose heating depends on electricity (according to Fingrid Datahub)
- Panel E: Households with a pre-crisis debt-to-annual income ratio exceeding one
- Panel F: Households that received social assistance one year prior to the crisis
- Panel G: Households that rent their homes
- Panel H: Households where the bill payer's mother tongue is neither Finnish nor Swedish, indicating a minority status

We find particularly large effects on defaults for indebted households. The negative effect on residual consumption is pronounced among households where the bill payer is over 70 years old and those living in rural areas. We examine these subgroups in more detail in the main text.

Heterogeneity: contract type In Figure B.9, we split the results by contract choice (between variable-price and fixed-price) after the contract ends. This choice is endogenous and correlates with household-level characteristics and past behavior (Vesterberg, 2018). While this is not causal evidence, we can make three observations. First, households with lower demand elasticity are more likely to choose variable-price contracts, which benefit them (as in Ito et al., 2023). Second, even for fixed-term contracts, the effect fades toward the summer months, indicating seasonality in electricity demand (as in Rubin and Auffhammer, 2024). Third, aside from elasticity, the results are largely similar across the two groups.

Placebo for anticipation effects: Bankruptcy analysis To further assess the plausibility of the anticipation effect, we compare households whose electricity retailer unexpectedly went bankrupt in September 2022, resulting in the sudden termination of their electricity contracts, with households that knew in advance that their contracts would terminate in September (as in the main analysis).

Figure B.10 presents two event study plots comparing the anticipation effects on electricity consumption for these groups. Figure B.10a shows results for households whose electricity retailers went bankrupt, leading to unexpected contract terminations. These households did not reduce their electricity consumption before the termination date, even as the crisis unfolded, as they had no reason to expect that high prices would affect them. In contrast, Figure B.10b illustrates results for households whose contracts were scheduled to terminate in September 2022. These households began reducing their electricity consumption in advance of the termination date. These results are in line that households reduce consumption as anticipation to the future energy price hike, likely by installing energy-saving equipment.

Table A.1: Summary Statistics

	Treated		Matched Control		Unmatched Control		Full population	
	Levels	Log	Levels	Log	Levels	Log	Levels	Log
Panel A: Outcome variables								
Electricity use	560.65	5.80	556.90	5.81	586.49	5.83	542.56	5.74
	(612.29)	(1.08)	(582.11)	(1.06)	(637.65)	(1.13)	(614.629)	(1.23)
Earnings and pensions	4,394.96	8.17	4,346.61	8.19	4,702.70	8.24	4,446.79	8.19
	(7,679.26)	(0.84)	(4,055.38)	(0.78)	(6318.23)	(0.86)	(7379.22)	(0.86)
Social assistance and benefits	277.16	5.71	243.30	5.64	306.45	5.79	304.94	5.78
	(613.93)	(2.16)	(537.84)	(2.16)	(651.83)	(1.99)	646.96	2.00
Residual consumption	3,240.55	7.82	3,200.60	7.84	3,454.78	7.88	3,303.15	7.83
	(5,429.17)	(0.84)	(2,631.00)	(0.79)	(4,673.46)	(0.85)	(5424.38)	(0.85)
Defaults	0.0101	-	0.0098	-	0.0107	-	0.0117	-
	(0.0999)	-	(0.0985)	-	(0.1029)	-	(0.1076)	-
Panel B: Demographic and background variables								
Electric heating	0.591	-	0.592	-	0.578	-	0.550	-
	(0.492)		(0.492)		(0.494)		(0.497)	
Share of rural households	0.653	-	0.646	-	0.631	-	0.619	-
	(0.476)		(0.478)		(0.483)		(0.486)	
Share of over 70 years old	0.283	-	0.288	-	0.214	-	0.242	-
	(0.451)		(0.453)		(0.410)		(0.428)	
Share of indebted households	0.298	-	0.303	-	0.332	-	0.313	-
	(0.457)		(0.460)		(0.471)		(0.464)	
Share of pensioners	0.417	-	0.424	-	0.352	-	0.365	-
	(0.493)		(0.494)		(0.478)		(0.482)	
Share of students	0.017	-	0.017	-	0.026	-	0.026	-
	(0.127)		(0.130)		(0.160)		(0.158)	
Unemployment	0.048	-	0.040	-	0.048	-	0.051	-
	(0.214)		(0.197)		(0.214)		(0.220)	
Past defaults	0.0805	-	0.0689	-	0.0780	-	0.0874	-
	(0.272)		(0.253)		(0.268)		(0.282)	
Age	59.03	-	58.96	-	56.01	-	56.32	-
	(17.27)		(17.36)		(17.74)		(17.96)	
Households with children	0.258	-	0.256	-	0.285	-	0.269	-
	(0.437)		(0.436)		(0.452)		(0.444)	
Household size	2.013	-	2.015	-	2.108	-	2.045	-
	(1.205)		(1.192)		(1.262)		(1.233)	
N	1,391,445		1,309,080		1,660,797		6,597,024	

The table compares treated and control groups, with an additional column for an unmatched control group. The outcome variables show averages from the five months before the electricity crisis became salient (March 2022 to July 2022). Earnings, social assistance, and residual consumption are in euros per month. Electricity consumption is in kWh per month, earnings and pensions, social assistance and benefits and residual consumption are euros per month. Past default shows the share of households who defaulted in the past five years before the analysis. Indebted households are defined as households whose debt-to-disposable annual income share is over 100%. Standard errors are shown in parentheses.

Table A.2: Price elasticity, full data and various subsamples

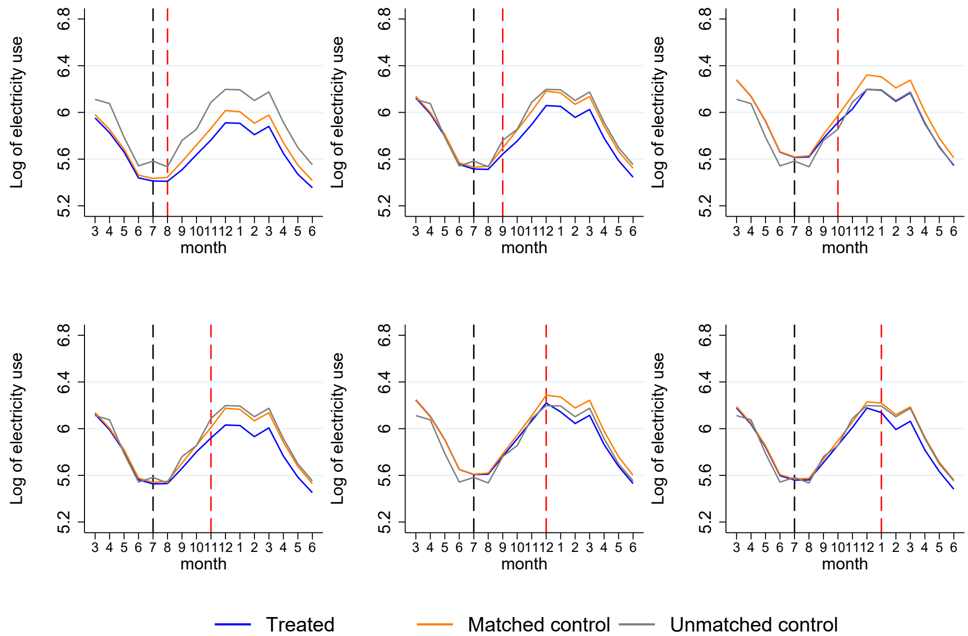
	Electricity use		Labor earnings		Pensions		Benefits		Defaults		Residual consumption	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Full sample												
Price	-0.150***	-0.184***	0.0115***	0.0139**	0.0008	0.0005	0.137***	0.143***	0.0039***	0.0038***	-0.0466***	-0.0451***
	(0.0022)	(0.0026)	(0.0034)	(0.0043)	(0.0016)	(0.0020)	(0.0101)	(0.0127)	(0.0009)	(0.0010)	(0.0020)	(0.0024)
...x income		-0.0011***		-0.0010***		0.0003***		-0.0013***		-0.0001***		0.0004***
		(0.0001)		(0.0001)		(0.0001)		(0.0003)		(0.0000)		(0.0001)
...x use		-0.0969***		0.0074		-0.0062*		0.402***		0.0046**		-0.0535***
		(0.0043)		(0.0065)		(0.0030)		(0.0209)		(0.0016)		(0.0038)
...x lag		-0.0488***		0.0036		-0.0002		-0.0013		0.0002		0.0021
		(0.0014)		(0.0024)		(0.0010)		(0.0071)		(0.0006)		(0.0013)
Anticipation	-0.0118***	-0.0266***	-0.0014	-0.0005	0.0006	0.0006	-0.0272***	-0.0277***	0.0005	0.0005	-0.005***	-0.0045***
	(0.0010)	(0.0011)	(0.0019)	(0.0021)	(0.0006)	(0.0007)	(0.0045)	(0.0049)	(0.0003)	(0.0004)	(0.0011)	(0.0012)
N	4,252,520	4,228,556	2,418,560	2,404,502	1,855,601	1,843,997	1,885,189	1,876,091	4,254,870	4,230,893	4,133,722	4,110,374
Panel B: Over 70 years old												
Price	-0.118***	-0.144***	0.00888	0.0140	-0.000973	-0.00152	0.995***	1.201***	0.00190**	0.00228**	-0.0644***	-0.0615***
	(0.0041)	(0.0047)	(0.0161)	(0.02)	(0.0012)	(0.0014)	(0.0435)	(0.0553)	(0.0007)	(0.0009)	(0.0019)	(0.0022)
...x income		-0.000592**		-0.000176		0.000186**		0.00759***		0.0000645		0.000860***
		(0.0002)		(0.0008)		(0.0001)		(0.0022)		(0.00004)		(0.0001)
...x use		-0.0900***		-0.0285		-0.00382		1.517***		-0.000349		-0.0806***
		(0.0084)		(0.0319)		(0.0022)		(0.0920)		(0.00137)		(0.0036)
...x lag		-0.0369***		0.000222		-0.000722		0.206***		0.00054		0.00366**
		(0.0026)		(0.0109)		(0.0007)		(0.0297)		(0.00048)		(0.0012)
Anticipation	-0.00976***	-0.0218***	-0.0125	-0.0132	-0.000338	-0.000583	-0.0405*	0.0272	0.000577*	0.000754*	-0.00285***	-0.00184*
	(0.0020)	(0.0021)	(0.0105)	(0.0113)	(0.0004)	(0.0005)	(0.0202)	(0.0201)	(0.0003)	(0.0004)	(0.0009)	(0.0009)
N	1,225,272	1,218,253	123,704	122,779	1,221,113	1,214,102	303,053	301,973	1,226,183	1,219,162	1,211,399	1,204,420
Panel C: Rural area												
Price	-0.189***	-0.229***	0.0178**	0.0136	0.00404	0.00697*	0.251***	0.275***	0.00426**	0.00497**	-0.0611***	-0.0627***
	(0.00396)	(0.00479)	(0.00645)	(0.00837)	(0.00263)	(0.00320)	(0.0222)	(0.0282)	(0.00150)	(0.00179)	(0.00350)	(0.00432)
...x income		-0.00135***		-0.000511		0.000244		-0.00244***		0.0000136		0.000811***
		(0.000179)		(0.000295)		(0.000187)		(0.000672)		(0.0000609)		(0.000157)
...x use		-0.0760***		0.0125		-0.00791		0.410***		0.00537		-0.0505***
		(0.00943)		(0.0129)		(0.00595)		(0.0413)		(0.00313)		(0.00721)
...x lag		-0.0574***		-0.000527		0.00199		0.0240		0.00081		0.000757
		(0.00261)		(0.00458)		(0.00158)		(0.0159)		(0.00093)		(0.00237)
Anticipation	-0.0141***	-0.0323***	0.00375	0.00393	0.000204	0.000745	-0.0378***	-0.0297*	0.000377	0.000648	-0.00325	-0.00299
	(0.00206)	(0.00222)	(0.00392)	(0.00430)	(0.000922)	(0.00109)	(0.0111)	(0.0118)	(0.000583)	(0.000706)	(0.00192)	(0.00213)
N	1,163,947	1,156,444	596,351	592,389	619,866	615,640	481,171	478,765	1,164,788	1,157,284	1,122,208	1,114,960
Panel D: Electricity heating												
Price	-0.179***	-0.224***	0.00811*	0.0108*	0.00106	0.00144	0.229***	0.239***	0.00362***	0.00428***	-0.0556***	-0.0533***
	(0.00254)	(0.00309)	(0.00397)	(0.00522)	(0.00195)	(0.00244)	(0.0146)	(0.0187)	(0.000947)	(0.00117)	(0.00230)	(0.00288)
...x income		-0.000829***		-0.000756***		0.000406***		-0.00296***		-0.0000459		0.000556***
		(0.000103)		(0.000171)		(0.000122)		(0.000469)		(0.0000344)		(0.0000916)
...x use		-0.0799***		0.00896		-0.00306		0.391***		0.00309		-0.0496***
		(0.00592)		(0.00794)		(0.00409)		(0.0285)		(0.00198)		(0.00468)
...x lag		-0.0609***		0.00404		0.000460		-0.000248		0.0010		0.00341*
		(0.00175)		(0.00290)		(0.00124)		(0.0107)		(0.00064)		(0.00161)
Anticipation	-0.0156***	-0.0340***	0.000208	0.00103	0.000677	0.000831	-0.0353***	-0.0361***	0.000562	0.000856*	-0.00417**	-0.00323*
	(0.00127)	(0.00137)	(0.00229)	(0.00253)	(0.000728)	(0.000867)	(0.00677)	(0.00731)	(0.000357)	(0.000436)	(0.00128)	(0.00142)
N	2,563,966	2,529,908	1,492,045	1,471,680	1,202,935	1,186,684	1,119,933	1,105,330	2,565,090	2,531,016	2,491,135	2,457,959

Table A.2: Price elasticity, full data and various subsamples (continued)

	Electricity use		Labor earnings		Pensions		Benefits		Defaults		Residual consumption	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel E: Indebted households												
Price	-0.194***	-0.243***	0.0123**	0.0181**	0.0128	0.0131	0.0558***	0.0226	0.00719***	0.00767***	-0.0365***	-0.0317***
	(0.0040)	(0.0050)	(0.0046)	(0.0061)	(0.00703)	(0.00924)	(0.0141)	(0.0185)	(0.0016)	(0.0020)	(0.0040)	(0.0052)
...x income		-0.000589***		-0.000691***		0.000220		0.00286***		-0.00000351		-0.000106
		(0.0002)		(0.0002)		(0.0004)		(0.0005)		(0.00006)		(0.00017)
...x use		-0.0817***		0.0173		-0.00776		0.225***		0.00849**		-0.0224**
		(0.0083)		(0.0090)		(0.0139)		(0.0274)		(0.0030)		(0.0078)
...x lag		-0.0664***		0.00833*		0.00338		-0.0451***		0.00047		0.00690*
		(0.0028)		(0.0034)		(0.0047)		(0.0103)		(0.00112)		(0.0029)
Anticipation	-0.0154***	-0.0336***	0.00185	0.00426	0.00386	0.00495	-0.0223***	-0.0343***	0.00106*	0.00130*	-0.00676**	-0.00493*
	(0.0018)	(0.0020)	(0.0025)	(0.0028)	(0.00235)	(0.0028)	(0.0061)	(0.0070)	(0.0005)	(0.0006)	(0.0021)	(0.0023)
N	1,266,100	1,251,569	1,079,424	1,066,939	178,658	175,882	701,826	694,278	1,266,533	1,251,997	1,226,995	1,213,022
Panel F: Social assistance												
Price	-0.0846***	-0.0949***	0.0950*	0.102*	0.0188	0.0225	-0.0122	-0.0122	-0.0124	-0.0182	-0.0473**	-0.0474*
	(0.0107)	(0.0126)	(0.0372)	(0.0446)	(0.0161)	(0.0185)	(0.0197)	(0.0233)	(0.00949)	(0.0113)	(0.0168)	(0.0197)
...x income		-0.00156*		-0.00185		-0.00204*		-0.00363*		-0.000870		0.00109
		(0.000665)		(0.00155)		(0.000867)		(0.00147)		(0.000561)		(0.000870)
...x use		-0.115***		0.0383		-0.0385		0.0567		.0.00831		-0.0676*
		(0.0223)		(0.0742)		(0.0291)		(0.0398)		(0.0185)		(0.0336)
...x lag		-0.0183**		0.0269		0.0156		0.00699		-0.0116*		0.00876
		(0.00698)		(0.0235)		(0.0111)		(0.0120)		(0.0058)		(0.0108)
Anticipation	-0.00777	-0.0144*	0.0198	0.0241	0.00502	0.00876	-0.00984	-0.0104	-0.00863*	-0.0137**	-0.0121	-0.00958
	(0.00543)	(0.00595)	(0.0192)	(0.0221)	(0.00718)	(0.00829)	(0.00972)	(0.0107)	(0.00368)	(0.00450)	(0.00836)	(0.00940)
N	214394	209112	68531	64295	29810	28657	191628	187796	214613	209329	206797	201669
Panel G: Tenants												
Price	-0.0756***	-0.0888***	0.0371***	0.0401***	0.00300	0.00419	-0.0165	-0.0232	0.00526*	0.00596	-0.0288***	-0.0342***
	(0.00425)	(0.00504)	(0.00844)	(0.0101)	(0.00331)	(0.00394)	(0.0106)	(0.0126)	(0.00260)	(0.00305)	(0.00506)	(0.00596)
...x income		-0.000973**		-0.00183***		0.000302		-0.00296***		-0.000103		0.000122
		(0.000300)		(0.000436)		(0.000324)		(0.000720)		(0.000144)		(0.000269)
...x use		-0.0844***		-0.0173		-0.00762		0.102***		-0.00129		-0.0587***
		(0.0110)		(0.0228)		(0.00841)		(0.0248)		(0.00594)		(0.0124)
...x lag		-0.0247***		0.00882		0.000519		-0.000751		0.00083		-0.00242
		(0.00281)		(0.00538)		(0.00232)		(0.00644)		(0.00160)		(0.00324)
Anticipation	-0.00180	-0.0106***	0.00467	0.00727	0.00147	0.00168	-0.0116*	-0.0121*	-0.000203	-0.0000421	-0.00285	-0.00314
	(0.00218)	(0.00240)	(0.00482)	(0.00530)	(0.00140)	(0.00158)	(0.00490)	(0.00551)	(0.000989)	(0.00122)	(0.00270)	(0.00299)
N	1,055,452	1,051,933	528,120	526,245	343,581	342,229	616,149	614,300	1,056,172	1,052,650	1,024,678	1,021,268
Panel H: Non-native speaker												
Price	-0.120***	-0.146***	0.0306*	0.0400*	0.00429	-0.00139	0.0358	0.0317	0.00525	0.00468	-0.0362***	-0.0289**
	(0.00911)	(0.0105)	(0.0136)	(0.0161)	(0.00851)	(0.00972)	(0.0277)	(0.0330)	(0.00380)	(0.00444)	(0.00912)	(0.0106)
...x income		-0.000800*		-0.000834		-0.0000878		0.000975		0.0000751		0.000719
		(0.000368)		(0.000543)		(0.000487)		(0.00102)		(0.000126)		(0.000391)
...x use		-0.136***		-0.0436		-0.0248		0.395***		0.00386		-0.0752***
		(0.0178)		(0.0264)		(0.0164)		(0.0601)		(0.00672)		(0.0174)
...x lag		-0.0341***		0.0111		-0.00438		-0.0127		-0.00125		0.00822
		(0.00574)		(0.00863)		(0.00496)		(0.0180)		(0.0240)		(0.00576)
Anticipation	-0.00554	-0.0162**	0.00917	0.0128	0.000406	-0.000720	-0.0187	-0.0242	-0.000220	-0.000638	0.000744	0.00339
	(0.00455)	(0.00492)	(0.00723)	(0.00793)	(0.00327)	(0.00351)	(0.0125)	(0.0138)	(0.00141)	(0.00172)	(0.00481)	(0.00526)
N	313,885	312,395	201,768	200,777	89,956	89,457	179,227	178,443	314,114	312,620	304,832	303,373

Notes: The dependent variable is the natural logarithm of electricity consumption (columns 1-2), labor earnings (columns 3-4), pension payments (5-6), benefits (columns 7-8), the level of defaults indicator (columns 9-10) and the natural logarithm of residual consumption (columns 11-12). The table estimates price elasticities following eqs. (3)-(4), where Price is the logarithm of contract price. Panel A uses the full sample, Panel B only households where the person who pays the bill is born before 1952, Panel C households living in rural area (classified as M4-M7), Panel D households whose heating is reported to be dependent on electreciti (in Datahub), Panel E only for households whose debt-to-annual income ratio exceeds 100%, Panel F only for households who received social assistance (*toimeentulotuki*), Panel G only households who are renting their home, and Panel H only households whose mother tongue is not Finnish or Swedish. All panels include interactions with income (in 10,000 euros, difference to sample mean), electricity use (an indicator equal to one if electricity consumption is above median for a given income quintile, difference to sample mean), and lag, where lag is defined as the month of the contract ending (difference to sample mean). All columns control for household-stack (ih), stack-month (ht) and match-id fixed effects. Heterogeneity results also control for post- and treatment- interactions (for example, post-earnings and treatment-earnings). Standard errors, clustered by households, are shown in parentheses. * p<.05, ** for p<.01, and *** for p<.001.

(a) Raw data: Electricity use



(b) Event study graphs: Electricity use

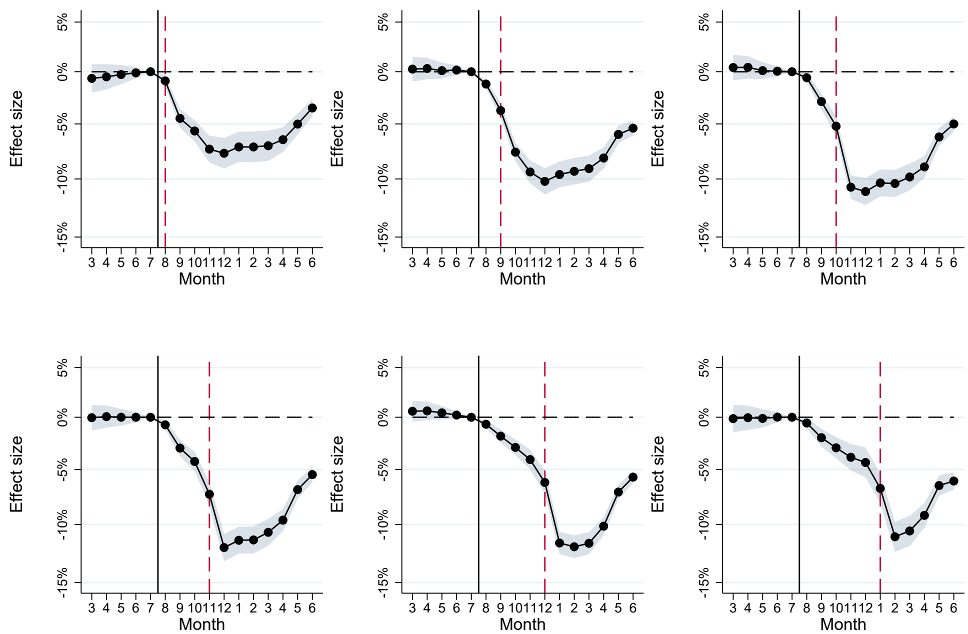
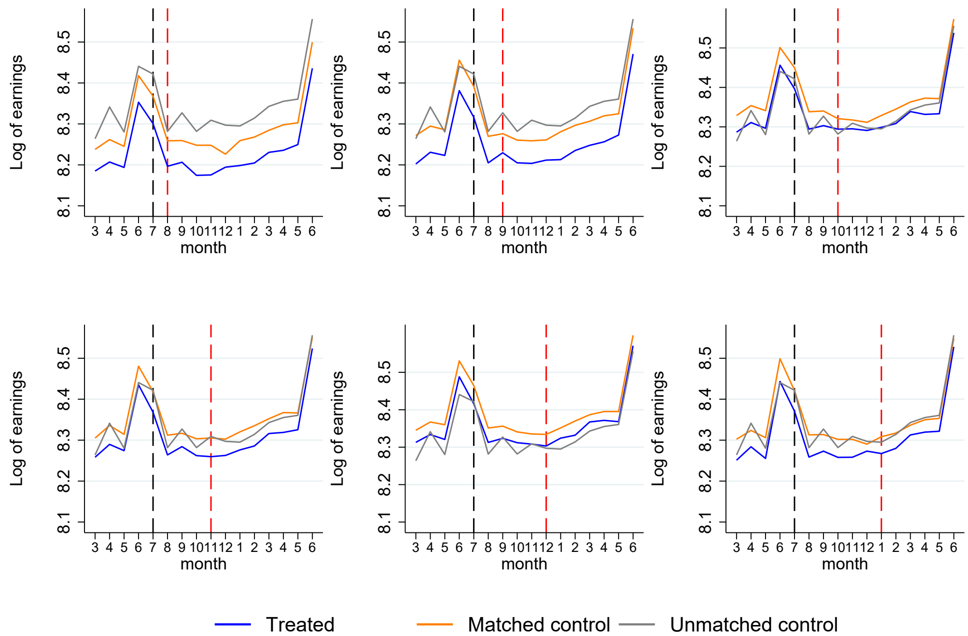


Figure B.1: Raw electricity use data plot for all treatment stacks (panel a), and the corresponding event study figures (panel b).

Notes: Panel (a) shows the raw data plot of the logarithmic transformation of electrcity use for treated (blue line) and matched (orange line), as well as unmatched (grey line) control groups without adjustment for covariates. Panel (b) reports coefficients per calendar month following equation (1). Shaded areas show the 95% confidence intervals. Standard errors are clustered at the household level.

(a) Raw data: Labor earnings



(b) Event study graphs: Labor earnings

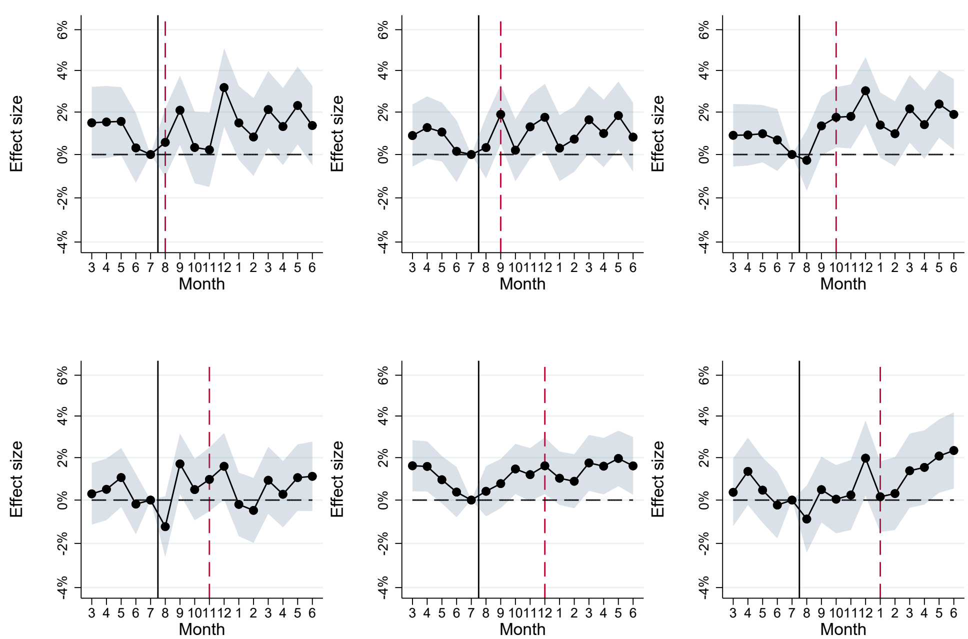
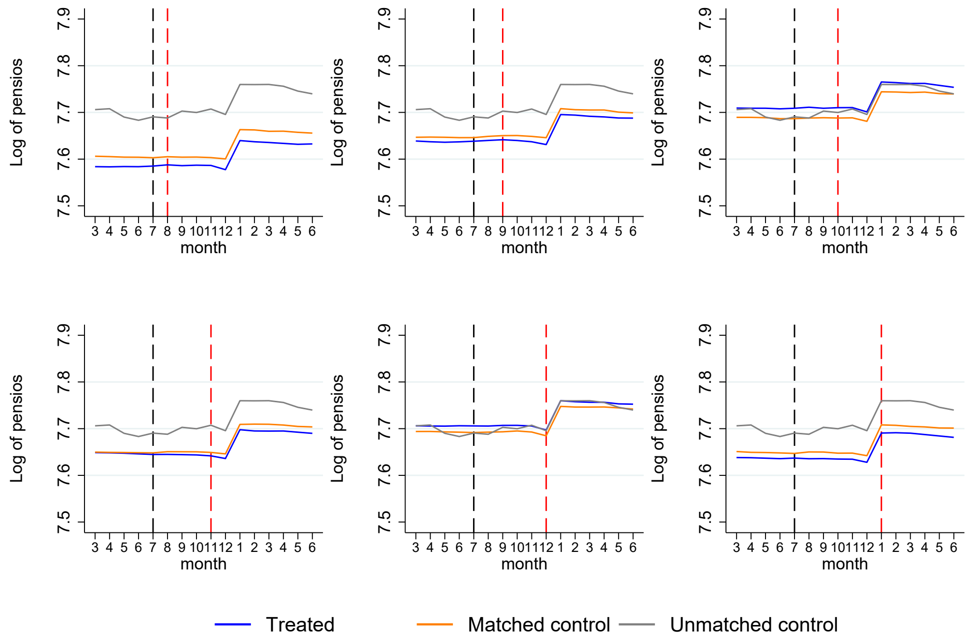


Figure B.2: Raw labor earnings data plot for all treatment stacks (panel a), and the corresponding event study figures (panel b).

Notes: Panel (a) shows the raw data plot of the logarithmic transformation of labor earnings for treated (blue line) and matched (orange line), as well as unmatched (grey line) control groups without adjustment for covariates. Panel (b) reports coefficients per calendar month following equation (1). Shaded areas show the 95% confidence intervals. Standard errors are clustered at the household level.

(a) Raw data: Pensions



(b) Event study graphs: Pensions

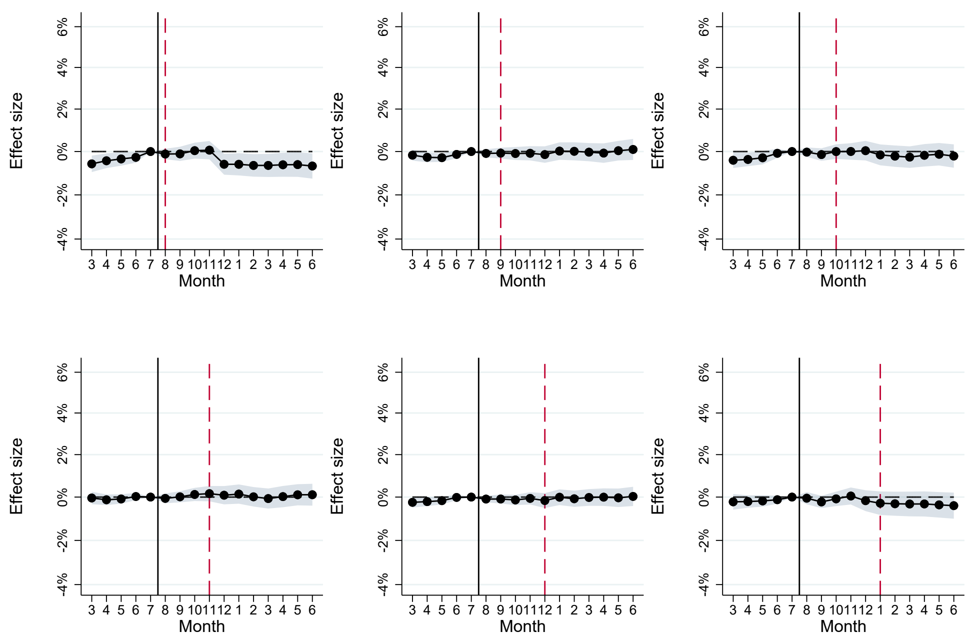
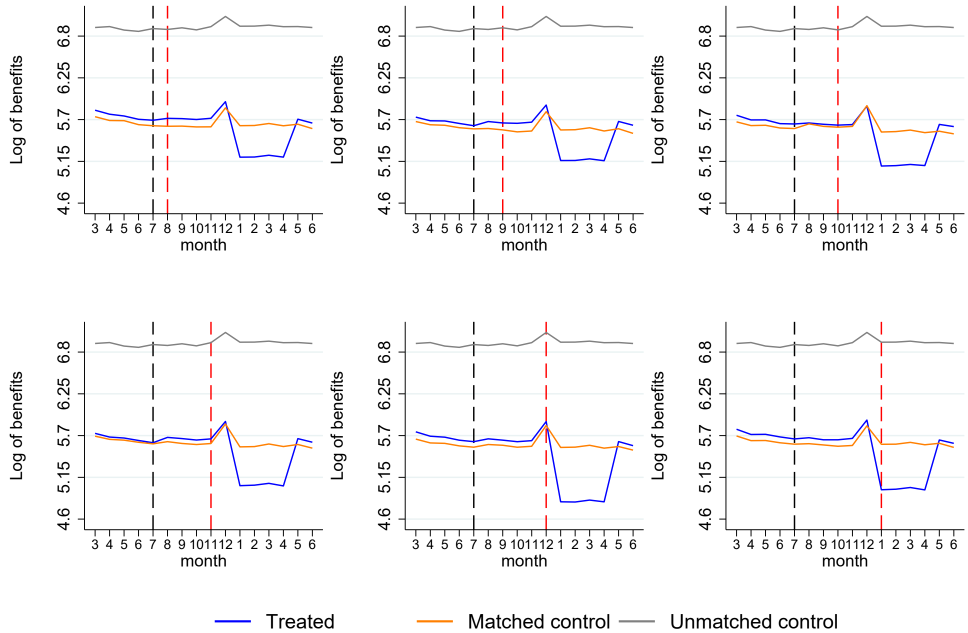


Figure B.3: Pension data, raw plot for all treatment stacks (panel a), and the corresponding event study figures (panel b).

Notes: Panel (a) shows the raw data plot of the logarithmic transformation of pensions for treated (blue line) and matched (orange line), as well as unmatched (grey line) control groups without adjustment for covariates. Panel (b) reports coefficients per calendar month following equation (1). Shaded areas show the 95% confidence intervals. Standard errors are clustered at the household level.

(a) Raw data: Benefits



(b) Event study graphs: Benefits

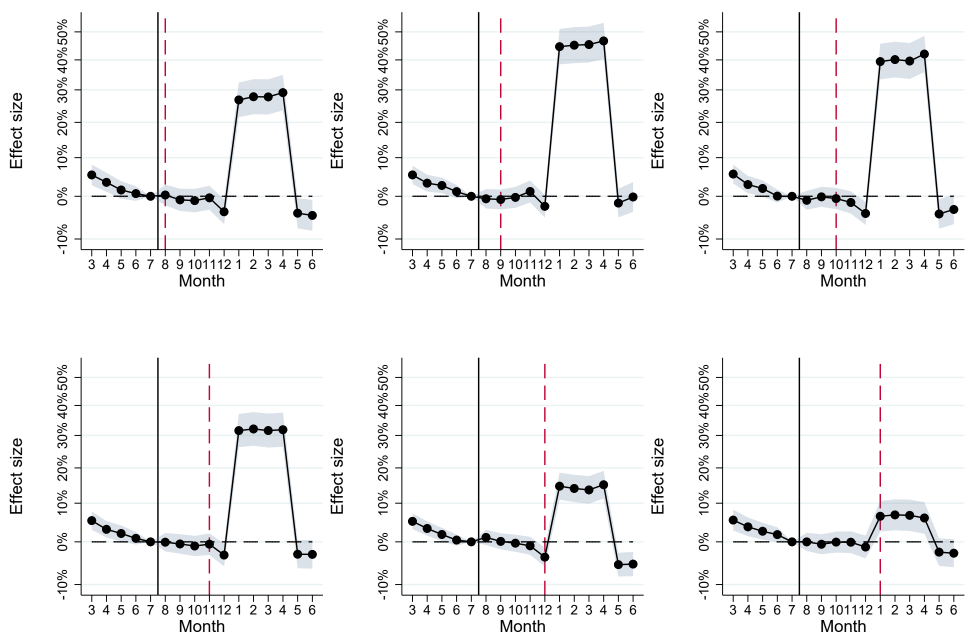
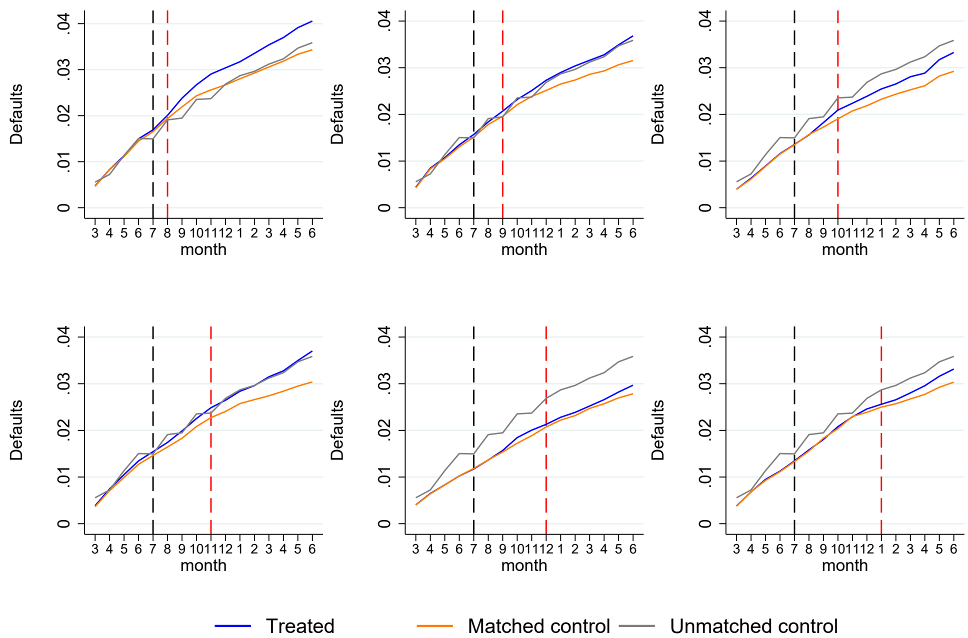


Figure B.4: Benefits data, raw plot for all treatment stacks (panel a), and the corresponding event study figures (panel b).

Notes: Panel (a) shows the raw data plot of the logarithmic transformation of benefits, including the electricity support paid out in months 1-4/2023 (blue line) and matched (orange line), as well as unmatched (grey line) control groups without adjustment for covariates. Since only a subset of the treated group receives electricity support, the average benefit across the group is less than one. Due to the logarithmic transformation, and the fact the majority of households receiving electricity support do not receive any other benefits, the raw data plot shows the effect electricity support as negative. Panel (b) reports coefficients per calendar month following equation (1). Shaded areas show the 95% confidence intervals. Standard errors are clustered at the household level.

(a) Raw data: Defaults



(b) Event study graphs: Defaults

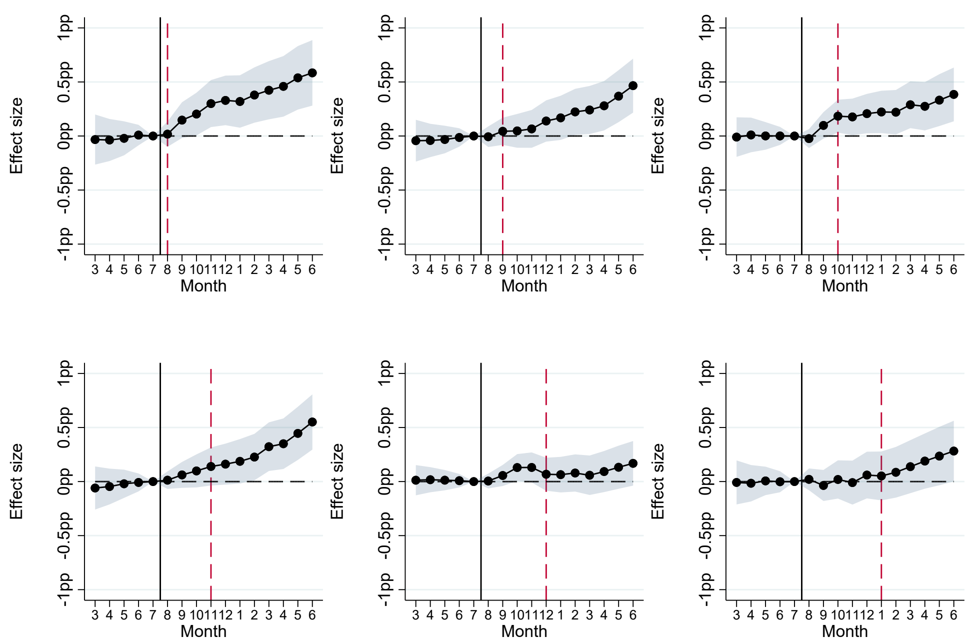
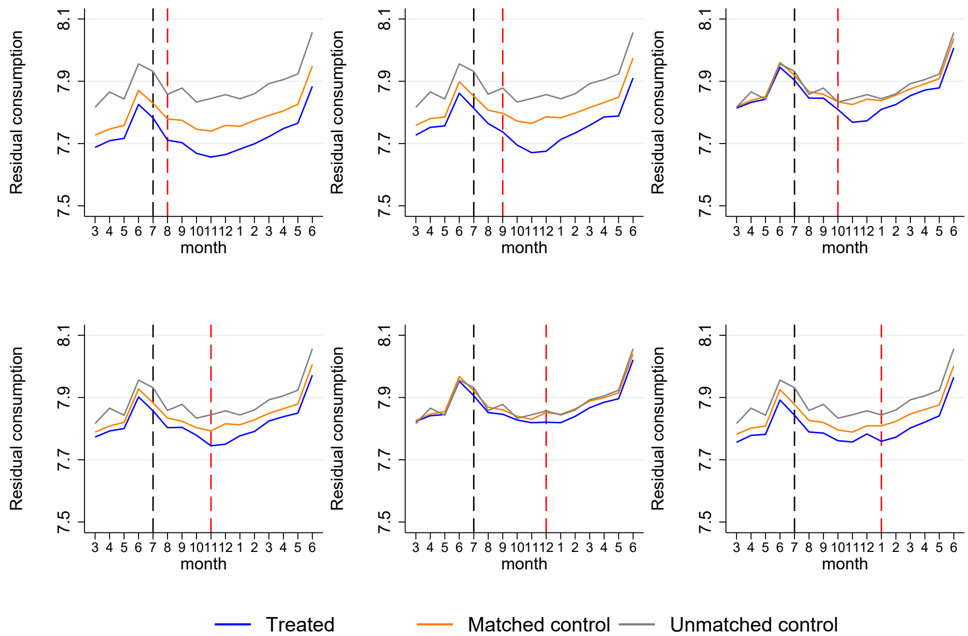


Figure B.5: Cumulative defaults, raw data plot for all treatment stacks (panel a), and the corresponding event study figures (panel b).

Notes: Panel (a) shows the raw data plot of cumulative defaults for treated (blue line) and matched (orange line), as well as unmatched (grey line) control groups without adjustment for covariates. Panel (b) reports coefficients per calendar month following equation (1). Shaded areas show the 95% confidence intervals. Standard errors are clustered at the household level.

(a) Raw data: Residual consumption



(b) Event study graphs: Residual consumption

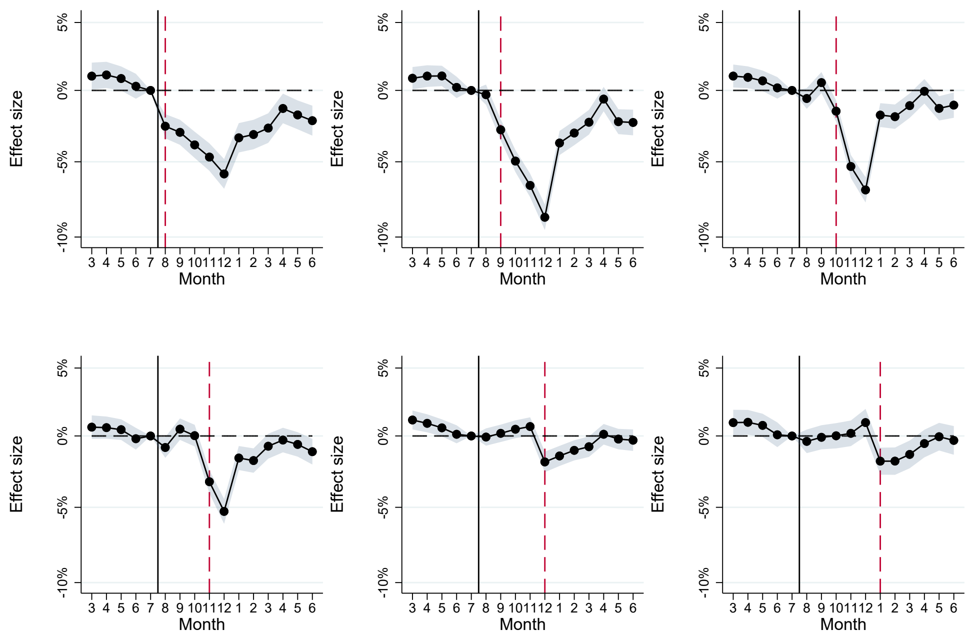


Figure B.6: Residual consumption, raw data plot for all treatment stacks (panel a), and the corresponding event study figures (panel b).

Notes: Panel (a) shows the raw data plot of the logarithmic transformation of residual consumption (blue line) and matched (orange line), as well as unmatched (grey line) control groups without adjustment for covariates. Panel (b) reports coefficients per calendar month following equation (1). Shaded areas show the 95% confidence intervals. Standard errors are clustered at the household level.

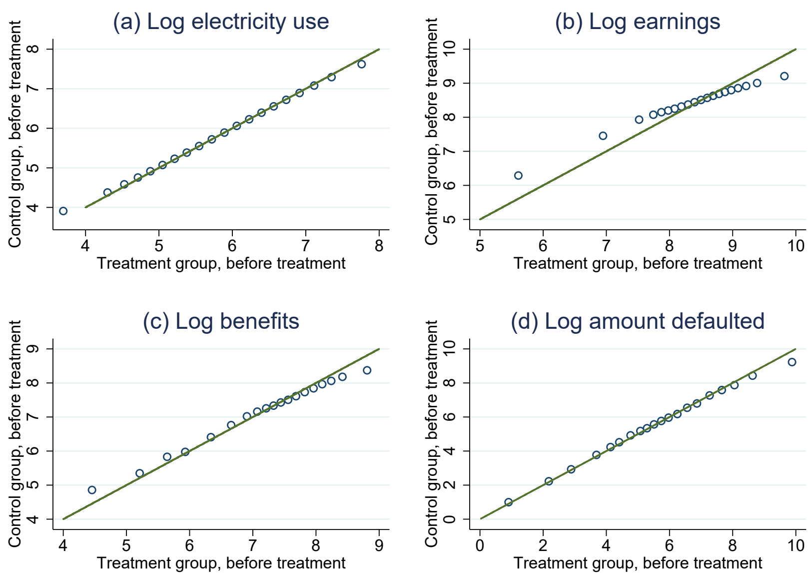


Figure B.7: Treatment vs. matched control group, binscatter plot

Notes: The figure shows treatment and the matched control group values of electricity use, earnings, benefits and defaults, all in logs. If both sets of households have the same distribution of outcomes, the dots are close to the 45-degree line; drawn in green.

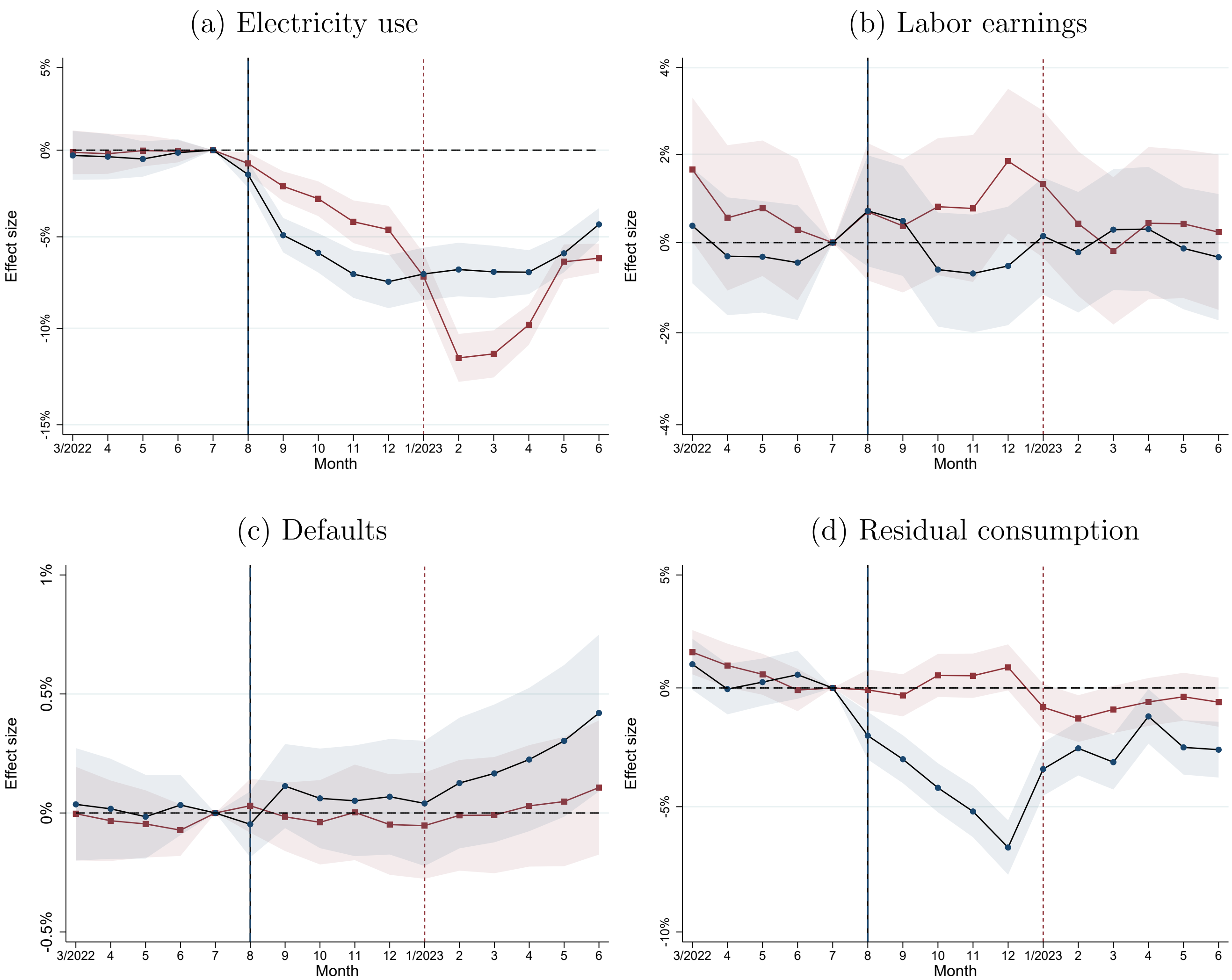


Figure B.8: Robustness of main outcome variables to simple matching

Notes: This Figure shows the effects for four main outcome variables using the simple matching data, where matching is done using only the first month of our data (March 2022). Matching is based on household heating technology, electricity use, default indicator variable, benefits and earnings. Shaded areas show 95% confidence intervals and standard errors are clustered at the household level.

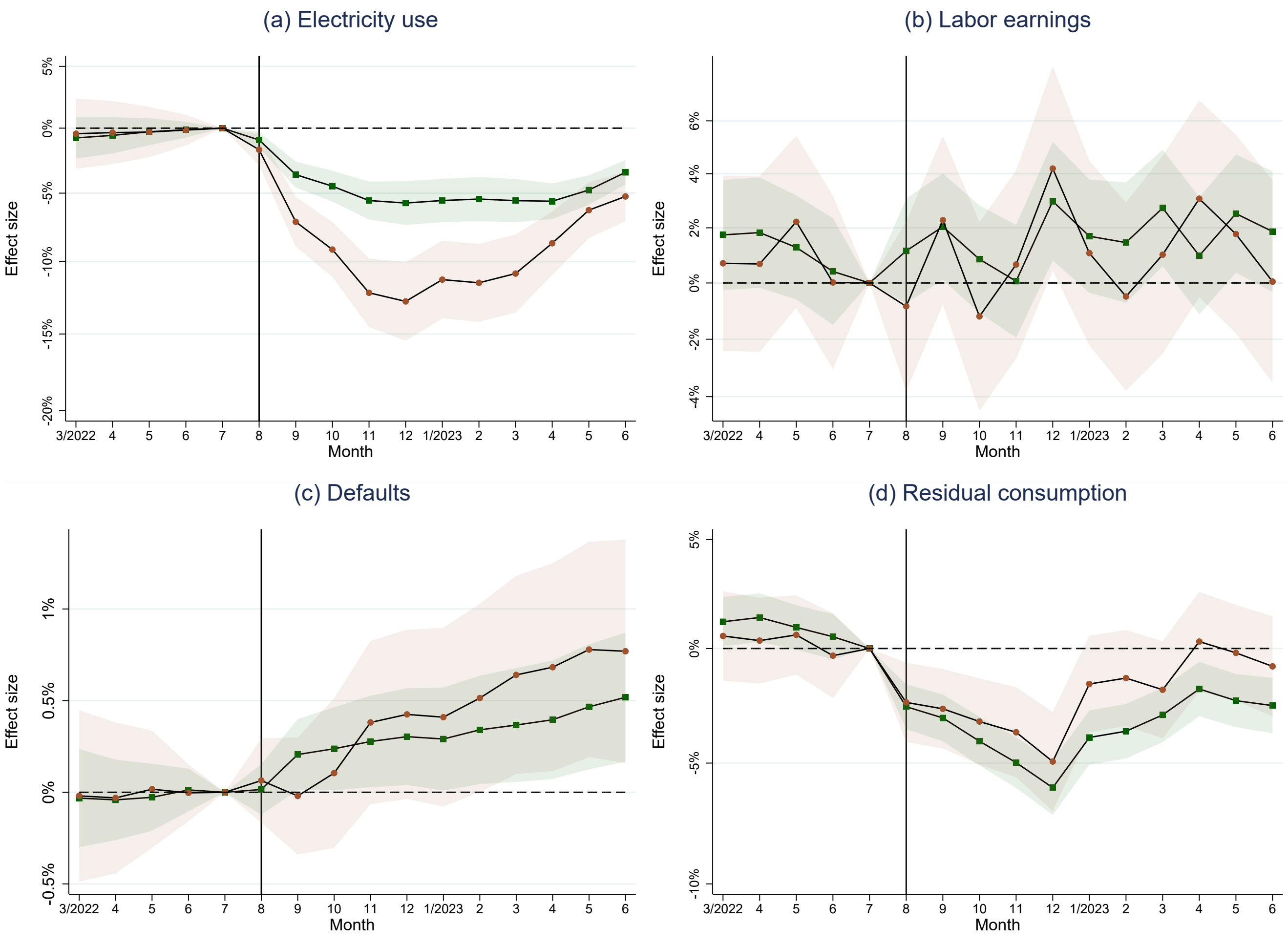


Figure B.9: Main results, split between variable- and fixed-price contracts

Notes: This Figure shows the effects for four main outcome variables. We split households who change to variable-price contract (gray) and fixed-price contract (brown) and show results only for households whose contracts end in August. Shaded areas show 95% confidence intervals and standard errors are clustered at the household level.

(a) Bankruptcy: No anticipation

(b) Contract ending as planned

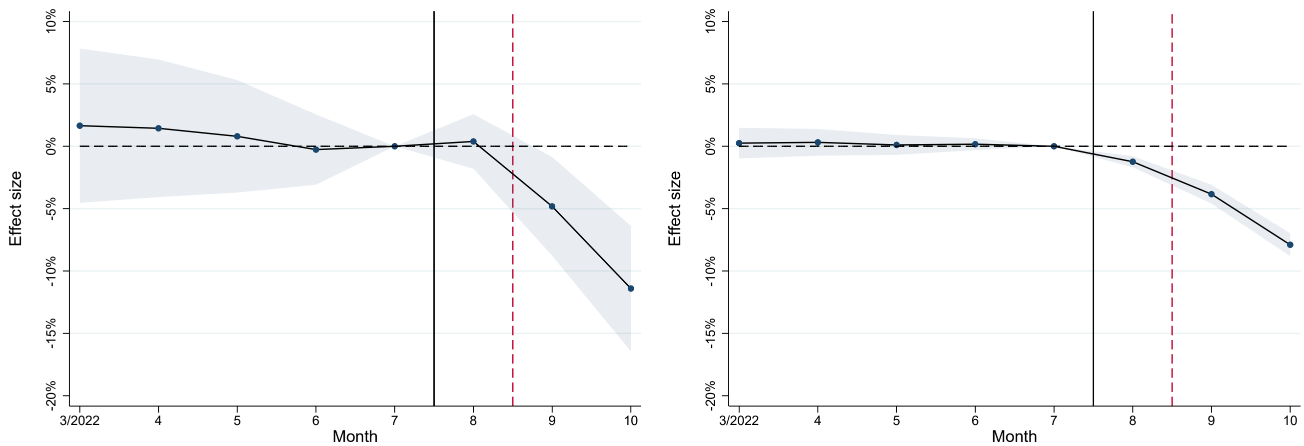


Figure B.10: Robustness for anticipation: Impact of contract termination on electricity consumption for households that are (a) unaware and (b) aware of their contract expiration date.

Notes: The left panel (a) shows households with abrupt contract terminations due to the bankruptcy of the electricity retailer in September 2022. The right panel (b) shows households that knew the termination date in advance, corresponding to our main event study Figue 2. Shaded areas show 95% confidence intervals and standard errors are clustered at the household level.