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Critical Peak Rebates for Residential Gas: Effectiveness and Selection During the European Energy Crisis

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Critical Peak Rebates for Residential Gas: Effectiveness and Selection during the European Energy Crisis

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Abstract

The abrupt shortage of natural gas imports during the 2022/2023 energy crisis following Russia's war against Ukraine forced European countries to rapidly cut consumption. In response, governments and energy providers introduced voluntary gas-saving programs offering financial incentives to residential customers. We study one such program – a critical peak rebate (CPR) launched by one of Germany's largest energy providers – that offered a six-month per-unit bonus for demand reductions at a time when wholesale gas prices spiked but regulated retail prices remained fixed, muting the price signal households actually faced. Combining household meter readings with survey data, we use a difference-in-differences design to "stress test" a CPR scheme. We show that the program-induced average gas savings amount to 13.2 to 17 percent. Participation was more likely among higher consumption, higher income and pro-socially motivated households, who also achieved larger absolute savings. This reveals a trade-off between program effectiveness and distributional considerations in the design of demand flexibility programs.

JEL Classification: C21; D12; D91; Q41; Q48

Keywords: Critical peak rebates; residential energy savings; energy crises; program enrollment; difference-in-differences.

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1 Introduction

When energy crises triggered by international conflict and uncertainty over energy imports drive wholesale prices to extreme levels, rigid retail tariffs keep the market signal from reaching households – and demand flexibility programs designed to close this gap gain momentum in public policy. Among the set of possible demand-side management instruments, critical peak rebates (CPR) -– that is offering financial incentives to voluntarily reduce energy consumption during typically short peak price periods – appear attractive for policy makers. While the economic effects of this instrument are well understood under ordinary market conditions with hourly peak price periods (e.g., Wolak 2011; Faruqui and Sergici 2010; Burkhardt et al. 2023; Bernard et al. 2026), little is known about its effectiveness during abrupt, longer lasting high-price periods, when both CPR program participants and non-participants *observe* market signals through public debate and media coverage but the prices they face mostly remain rigid.

We "stress test" the effectiveness of a CPR program launched by one of the largest energy providers in Germany (annual sales: >7.5 billion euros in 2023) during the EU energy crisis caused by the Russian war against Ukraine. As a result of the abrupt shortages of gas imports, wholesale prices for natural gas skyrocketed: in Germany, the largest importer of Russian gas, gas procurement costs rose to as much as 560 percent of their pre-crisis level (BDEW, 2023). Due to fixed customer contracts, however, energy providers could not fully pass these cost increases through to consumers, distorting the price charged for each kilowatt-hour (kWh) of natural gas sold within existing customer relationships.

We study a six-month CPR program in which participants received 0.05 EUR from the energy provider for each kWh natural gas saved (up to 2,500 kWh) in the period from October 1, 2022 to March 31, 2023 compared to their consumption levels in the prior two years. We address the program's effectiveness in two ways: First, we use a difference-in-differences design to estimate the causal effect of the CPR program on additional residential gas savings during a high-price period of several months. Second, we study selection into the program as a mechanism explaining its effectiveness: as common in opt-in demand flexibility programs, the effectiveness crucially depends upon which households actively enroll for participation (Ito et al., 2023; Gerster et al., 2025). We assess selection into the CPR program by comparing baseline consumption levels as well as survey-based responses of eligible households which voluntarily decided to enroll in the CPR program against those who did not enroll. This allows us to shed light on socio-demographic characteristics as well as motivational drivers that correlate with enrollment. We then contrast our findings to a program which offers a lump-sum payment conditional on a relative saving threshold.

We report two main results. First, average program-induced savings range from 13.2 to 17 percent. This effect holds in several robustness checks, including weather-corrected consumption, propensity score matching and honest difference-in-differences approaches (Rambachan and Roth, 2023). Second, selection into the program is strongly favorable. Comparing participants before and during the program suggests average savings of 29 percent – well above our preferred estimate – and part of this gap reflects who enrolls rather than what the program achieves. Participants show higher levels of pre-crisis gas consumption than non-participants, demonstrating larger absolute saving potentials. This is further reflected by differences in their socio-demographic characteristics. Participants possess comparatively higher incomes, live in larger dwellings and are more likely to be retired compared to those who did not opt-into the program. In addition, participants state more ambitious energy saving goals and are more strongly motivated to save gas for societal reasons.

Our results reveal important insights for public policy and the design of demand flexibility programs: Voluntary CPR schemes do survive a "stress test" in a setting where both participants and non-participants already observe high market prices but individual prices are rigid. That is, CPR schemes can foster additional energy savings in high-price periods. The observed selection pattern is consistent with favorable selection contributing to program effectiveness, as the program appears particularly attractive to high-income households with relatively high baseline consumption. In our setting, in absolute terms, these households benefit most from program participation. Public policy-makers have to balance these additional savings against potential distributional concerns: Low-income households with relatively lower baseline usage are less likely to become program beneficiaries and receive lower payments.

Our empirical findings contribute to three literature strands. First, the effectiveness of gas saving programs during the energy crisis is also discussed in Amberg et al. (2025) and Dertwinkel-Kalt et al. (2024), while Ahlvik et al. (2026), Behr et al. (2025), Ruhnau et al. (2023) explore price responsiveness during the crisis beyond specific programs. Our study is the first to study the effectiveness of a CPR incentive scheme on residential gas savings during an energy crisis. Dertwinkel-Kalt et al. (2024) investigate the impact of a fixed reward program – participants received a cash premium if they reached an assigned target of 10 or 20 percent of savings – and crisis communication on residential gas consumption, comparing program participants with survey responses from non-participants. They report financial incentives in general, and the reward program in particular, to be largely irrelevant for residential gas savings in Germany during the energy crisis. Closest to our work within this literature strand, Amberg et al. (2025) conduct an empirical analysis of a residential gas saving program in Germany, which – contrary to our CPR program but similar to the program studied by Dertwinkel-Kalt et al. (2024) – introduced a fixed reward: Participants received 100 EUR if they saved at least 10 percent. Using exact and nearest-neighbor Mahalanobis distance matching, Amberg et al. (2025) identify program-induced savings of 6.4 percentage points. One explanation for the lower saving levels compared to our results is differential selection into the program, favoring relatively low-consuming households as compared to high-consuming households in our study.

Second, a large body of evidence has studied critical peak pricing (CPP) and CPR programs at non-crisis times.[1] Following the seminal paper by Wolak (2011), Faruqui and Sergici (2010) synthesize results from fifteen pricing pilots and find average peak reductions on the order of 13–20 percent, with the magnitude depending on the size of the price signal, the availability of enabling technology such as programmable thermostats, and household characteristics. More recent literature moved towards investigating appliance-level adjustments in response to the CPP/CPR programs (Burkhardt et al., 2023; Bernard et al., 2026) as well as understanding the selection of customers into such dynamic pricing programs (Ito et al., 2023), including the role of default enrollment (Fowlie et al., 2021) and optimal targeting of customers (Ida et al., 2026). Close to our research question, Ito et al. (2018) compare the effectiveness of a group receiving a CPP incentive to that of a 'moral suasion' group, which likewise receives alerts about peak price periods but the alerts are coupled with appeals to the societal need to save energy. While both groups reduce consumption during the peak periods, the reduction is significantly larger in the CPP

[1] Theoretically, both CPP and CPR programs imply an increase in the marginal energy price, which is why the literature often treats them interchangeably (e.g., Wolak 2011). Following arguments from the behavioral environmental economics literature, the frequently observed gaps between Willingness-to-Accept (WTA) and Willingness-to-Pay (WTP) suggest that households respond differently to receiving a reward (CPR) versus paying a penalty (CPP). As a consequence, the two program types may lead to different empirical observations in practice (e.g., Kahneman et al. 1990; Horowitz and McConnell 2002; Tunçel and Hammitt 2014).

group and not subject to habituation. Most recently, Bernard et al. (2026) study the effects of a CPR on electricity consumption during periods of system stress within the UK's Demand Flexibility Service (DFS). Using a randomized encouragement design within a nation-wide field experiment, participants – after sign-up – actively opt into different peak rebate events.

We contribute to this literature by evaluating a CPR program for residential gas savings in a setting with two distinctive features: (i) the market signal and societal urgency of saving energy were salient to participants and non-participants alike, and (ii) the peak-price event lasted for six months rather than a few hours of the day. We further investigate who selects into the program.

Third, with respect to these selection effects, Ito et al. (2023) show that price-responsive consumers are more likely to select into a CPR program, which the authors interpret as favorable and welfare enhancing selection. Related to this argument, Allcott (2015) shows favorable selection at the utility site level: Uptake of a home energy report (HER) program is positively correlated with effect sizes. Studying the uptake of energy efficiency subsidies, Allcott et al. (2015) observe that pro-environmental consumers are more likely to request a subsidy for energy-efficient investments which is in line with our empirical observations. Here, Allcott et al. (2015) argue in favor of unfavorable selection; such consumers have likely little distortion in demand and would not need the subsidy to decide in favor of the green investment. Further, Löschel et al. (2023) investigate selection into an energy-saving app that randomizes a goal-setting nudge. Löschel et al. (2023) interpret the observation of higher take-up rates by high-income households with smaller energy savings potential, who are neither loss-averse nor present-biased, as unfavorable selection. Within the context of the energy crisis, using a hypothetical survey experiment, Gerster et al. (2025) study selection into a rebate program: Only 11 percent of households opt-in, using the program as a commitment device. We contribute to this literature by empirically investigating selection into a CPR program during an energy crisis of several months, characterizing program participants along both sociodemographic and motivational dimensions as well as assessing whether this selection is favorable or unfavorable for program effectiveness.

2 The Gas Bonus Program

2.1 Set-up

This study is based on a collaboration with one of Germany's largest energy providers (annual sales: $>$ 7.5 billion euros in 2023). The energy provider is based in a large German city with more than 300,000 inhabitants.

Following the Russian war against Ukraine and resulting gas shortages, the energy provider set up a CPR program – called the Gas Bonus Program (GBP) – with the aim of reducing the consumption of natural gas for residential heating. Within the program, participants received economic incentives stimulating additional natural gas consumption reductions compared to a reference level indicated by their gas consumption in the previous two billing periods. Participants' monetary rewards were composed of two factors: individual-level and collective ("community") savings. Through their individual efforts, participants were able to earn a maximum bonus of 125 euros by receiving 0.05 euros for each kWh of gas saved (up to 2,500 kWh), compared to the weather-adjusted average of the two preceding billing periods. Community savings, which are determined by the average gas savings of all program participants, resulted in a bonus of 20 euros if the average savings rate reached 10 percent or a bonus of 40 euros if the average savings rate reached 15 percent.

Figure 1 illustrates the program and study timeline. During the summer of 2022, the energy provider launched an extensive marketing campaign aimed at reaching consumers through various means, including direct mailings, distribution of posters and flyers throughout the city, and social media promotions. Figure A.1 displays one of the posters. An important feature of the campaign was that every household was eligible for enrollment. Participation was neither restricted to being a registered customer of the energy supplier nor to any geographical region. Registration required households to provide their previous two gas bills, their gender and the type of housing.(i.e., single-family home or multi-family home). Registration was completed via a web-based form. The sign-up period was from the beginning of August 2022 to the beginning of October 2022.

Initially, the energy provider limited registration to 1,500 participants. At the end of August, the energy provider announced an extension of the registration limit to 3,000 participants. At the end of the registration period, 2,598 participants signed up for the GBP. The large majority of 75 percent of program participants live in the direct city districts, 25 percent live in surrounding counties, about 89 percent of GBP participants are customers of the energy provider. The energy provider supplies gas to approximately 54,000 households in and around the city. Consequently, the participants who joined the GBP represent 5 percent of the total gas-consuming customer base.

The GBP launched in October 2022 and spanned a total of six months until the end of March 2023. The participants reported their meter readings at the time of sign-up and again at the end of the GBP. These readings enabled a direct calculation of gas consumption within the program during a period of six months.[2] In December, we conducted a survey with participants (N=469) and non-participants (N=1,370) as described in the next section.

2.2 Design of surveys

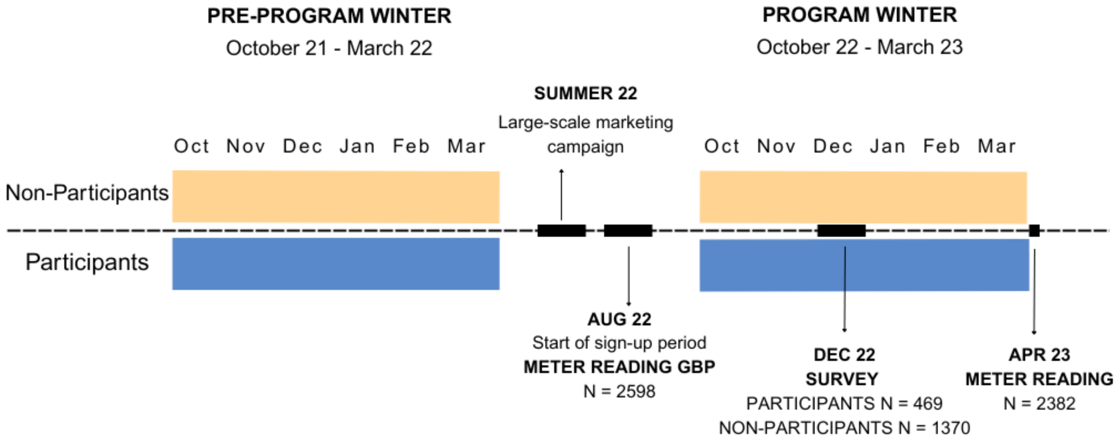
In December 2022, surveys were conducted among both program participants and non-participants. The surveys were administered online, survey respondents had the chance to win a 50 Euro shopping voucher for a local clothing shop. Participation in the survey was voluntary. GBP participants were invited via email to participate in the survey, resulting in N=469 survey responses, approximately 18 percent of all signed-up GBP participants. Non-participants were also recruited by the provider sending an email to randomly selected households in their customer base, resulting in N=1,370 survey responses.

The survey questions are divided into four sets: (1) household and individual characteristics, (2) energy-related beliefs, (3) crisis-related beliefs, and (4) motivational beliefs for saving energy. The set of household and individual characteristics includes questions on ownership status, household size, number of children in the household, year in which the house was constructed, and square meters of the house. Additionally, individual characteristics are assessed using questions on education, employment and income.

Energy-related beliefs included questions about planned energy savings, energy literacy, and previously implemented energy-saving measures. In this question set, respondents are asked to estimate the amount of energy they plan to save in their households between October 2022 and the end of March

[2] Participants received two mailings from the energy provider during the program (December and February), which we used to deliver behaviorally-informed interventions. We study these interventions separately in Tinnefeld et al. (2025). As the interventions had only limited effects on gas consumption, we do not interpret the estimated program effects reported in Section 4 as being substantially driven by them.

Figure 1: Program and study timeline



2023, with answer options ranging from 0 to more than 25% in increments of 5%. The question on 'Dezemberhilfe' serves as a proxy for energy literacy and understanding of energy policies, as it queries participants' understanding of a subsidy program providing a one-time bonus for households and small businesses to help with the costs of natural gas in December 2022 due to the energy crisis. The question aims to assess the respondents' understanding of that policy by asking, 'Can your gas consumption in December affect the one-time payment?' We provide four answer options, with the correct option being 'No.' The other choices were: 'Yes, high consumption in December will increase the amount of the one-time payment.', 'Yes, high consumption in December will decrease the amount of the one-time payment.', and 'I am not certain.' The sum of actions refers to the total number of energy-saving actions already taken, including measures such as lowering the room temperature, replacing shower heads, and reducing shower temperatures.

The third set of questions relating to crisis-related beliefs assesses the impact of the crisis on the financial situation and the estimated duration of the crisis. Regarding the financial situation, the question seeks to determine whether the energy crisis affected the financial situation of the respondent. Answer options range from 'no effect' to 'I won't be able to pay my energy bill.' Additionally, respondents are asked to estimate the duration of the crisis, with answer options ranging from spring 2023 to 2026.

The fourth set of questions assesses motivational beliefs, focusing on respondents' motivations for saving energy. Respondents evaluate their level of motivation to save gas on a scale of 1-5, with 1 indicating 'no motivation' and 5 indicating 'very strong motivation.' This evaluation is done for five different statements, which we categorize into three main motivational dimensions: individual costs, politics, and climate. The individual cost dimension is derived from the answer to the statement, 'I save energy to reduce my individual costs.' The political dimension is determined by averaging responses to two statements, 'I reduce energy for independence from Russia' and 'I reduce energy to reduce societal costs.' The climate dimension is calculated as the average of the answers to the statements 'I reduce energy to be in alignment with climate protection goals' and 'I reduce energy to avoid the usage of fossil fuels.' Additionally, respondents were asked to estimate the savings in Germany during the program period.

3 Data and empirical strategy

To evaluate the GBP, our analysis proceeds in four steps. We first document average gas savings among program participants using the energy provider's own savings measure, which forms the basis for bonus payments. We then estimate the causal, program-induced savings using a difference-in-differences design that compares consumption changes between program participants and non-participants across two winters. Third, we study selection into the program to understand who participates and why, drawing on our survey data including socio-demographic characteristics, beliefs, and motivational factors. Finally, we study heterogeneous gas savings within the participant group.

We present two approaches to measure savings. The energy provider calculates gas savings by comparing each participant's gas consumption during the GBP period (October 2022 to March 2023) to a weather-adjusted reference level based on the two prior billing periods. Formally, the reference consumption is defined as

$$kWh_{ref} = \frac{kWh_{t-1} + kWh_{t-2}}{HDD_{t-1} + HDD_{t-2}} \cdot HDD_{10/22-3/23},$$

whereby kWh_{t-1} and kWh_{t-2} represent the gas consumption of the last billing period $(t-1)$ and of the second-to-last billing period $(t-2)$, HDD_{t-1} and HDD_{t-2} the heating degree days of the same time frame, and $HDD_{10/22-3/23}$ the heating degree days of the GBP period from October 2022 to March 2023.[3] Based on this reference, absolute savings are defined as

$$Savings_{kWh} = kWh_{ref} - kWh_{GBP},$$

and savings in percentage terms as

$$Savings_{\%} = 1 - \frac{kWh_{GBP}}{kWh_{ref}}.$$

We discuss the results of this approach in Section 4.1. While this approach is transparent and directly tied to program payments, it relies solely on participants' own prior consumption as a counterfactual and cannot account for general consumption trends that would have occurred absent the program.

To address these limitations, our second approach estimates program-induced savings using household-level billing data for both participants ($N = 2,382$) and non-participants ($N = 1,998$). The analysis covers two winters (see Figure 1): Winter 1 (October 2021 to March 2022) represents the winter before the GBP, and Winter 2 (October 2022 to March 2023) represents the winter during the program. Billing records

[3] The energy provider provided us with the prior gas consumption, the heating degree days, kWh_{ref}, $Savings_{kWh}$ and $Savings_{\%}$.

typically cover extended periods, often one year. Since we do not have smart meter data, monthly consumption is therefore reconstructed by dividing the total consumption within a billing period by the sum of heating degree days in the billing period and multiplying this value by the heating degree days for each calendar month included in the bill:

$$kWh_m = \frac{kWh_{bill}}{HDD_{bill}} \cdot HDD_m,$$

whereby kWh_m denotes the reconstructed gas consumption in month m, kWh_{bill} the total consumption recorded in the billing period, and HDD_m the heating degree days in month m. We apply this reconstruction conservatively and include a monthly consumption value only if the respective calendar month is fully covered by at least one billing period. The HDD-based scaling adjusts for temperature differences between billing period and target month, but it cannot correct for consumption patterns that do not scale with heating degree days, such as delayed onset of heating or temperature-independent baseline use. If a billing period started or ended within a given month, the reconstructed partial values from the overlapping billing periods are summed to obtain the monthly consumption for that month.

This reconstruction of monthly consumption is central to our empirical approach: it allows us to exploit within-household variation across months and thereby implement a difference-in-differences design with household and month fixed effects. In addition, we construct a weather-corrected predicted consumption measure by applying the same HDD-based scaling to predict what consumption in Winter 2 would have been based solely on temperature differences relative to Winter 1, absent any behavioral change. We use this weather-corrected consumption measure only as an alternative outcome in a robustness specification.

Table A.1 in the Appendix reports summary statistics of monthly gas consumption for both participants and non-participants across the two winter periods, as well as the weather-corrected predicted consumption. To limit extreme values arising from the HDD-based reconstruction, the reconstructed monthly consumption is truncated at group- and month-specific 5th and 95th percentiles of raw consumption. Using group- and month-specific thresholds rather than a single threshold across the whole heating period accounts for the fact that consumption levels vary considerably across months, reflecting seasonality, and between participants and non-participants, reflecting systematic differences in dwelling size and baseline usage.

We estimate the effect of the CPR program on gas consumption using the following two-way fixed effects model:

$$kWh_{i,m} = \alpha_i + \gamma_m + \beta \cdot (Participant_i \times Post_m) + \varepsilon_{i,m},$$

where $kWh_{i,m}$ is the monthly gas consumption of household i in month m, α_i are household fixed effects absorbing all time-invariant differences between households, γ_m are month fixed effects capturing common seasonal patterns and aggregate trends, $Post_m$ is an indicator equal to one for months in Winter 2 (October 2022 to March 2023), and $Participant_i$ is an indicator equal to one for GBP participants. The coefficient of interest β captures the average effect of GBP participation on monthly gas consumption during the program period. Standard errors are clustered at the household level.

To further address pre-treatment differences in baseline consumption between the two groups, we implement propensity score matching (PSM) and nearest-neighbor covariate matching (nnmatch) as robustness checks, both based on pre-treatment mean consumption. In both cases, we then re-estimate the same two-way fixed effects model on the matched sample only.

The identifying assumption is that, absent the program, participants and non-participants would have followed parallel trends in gas consumption. We assess this assumption graphically and via a formal pre-trend test, and additionally apply the HonestDiD approach of Rambachan and Roth (2023) to assess robustness against potential violations.

To study selection into the GBP, we draw on the December 2022 survey data described in Section 2.2, covering both GBP participants (N=469) and non-participants (N=1370) across four sets of variables: household and individual characteristics, energy-related beliefs, crisis-related beliefs, and motivational beliefs.

To identify the correlates of GBP participation, we estimate the following linear probability model:

$$GBP_i = \beta_0 + \beta_1 Hous.C._i + \beta_2 Indv.C._i + [\beta_3 EnergyBeliefs_i] + [\beta_4 CrisisBeliefs_i] + [\beta_5 Motivation_i] + \varepsilon_i,$$

where GBP_i is a binary indicator equal to one if respondent i participated in the GBP, and the right-hand side variables correspond to the four survey question sets described above. Household and individual characteristics serve as controls throughout.

4 Program effectiveness

4.1 Savings among participants: a pre-post comparison

Table 1 provides descriptive evidence of the natural gas savings of the 2,382 households who participated in the GBP and submitted the meter readings at sign-up and at the end of the GBP. On average, program participants achieved a reduction of approximately 29 percent in gas consumption during the GBP period compared to a reference consumption based on their own consumption in the two previous billing periods. However, there is a significant degree of variability, as indicated by the standard deviation of 62 percent. It is worth noting that some individuals increased gas consumption, as evidenced by the negative savings of $-1{,}600$ percent. The median savings percentage is 31 percent.

Turning to the payments of the GBP, the average savings imply that every participating household received the 40 euros community bonus. Further, the individual bonuses paid by the utility are substantial. As shown in Table 1, participants received an individual payment of on average 106.33 euros, with a standard deviation of 35.97 euros. The median payment is 125 euros, which corresponds to the maximum payment that was achievable in the program. Notably, 72 percent of the participants received that

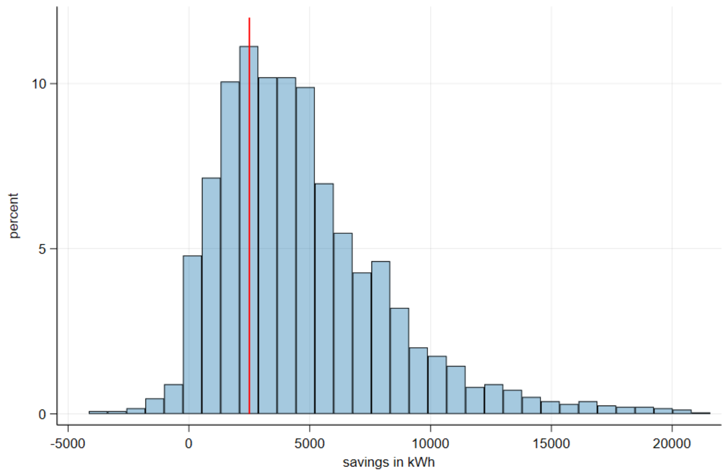
Table 1: Summary statistics of gas savings

	Mean	Min	p10	p25	p50	p75	p90	Max	N
Savings (in %)	0.29	-16	0.13	0.22	0.31	0.41	0.55	1	2,382
	(0.62)								
Ind. payment	106.33	0	42.53	108.63	125.00	125.00	125.00	125	2,382
	(35.97)								

Note: All participants who submitted meter readings at sign-up and at program end. Savings are calculated by comparing participants' consumption pre- and during the program. Standard deviations in parenthesis.

maximum bonus. According to public announcements, the energy provider distributed a total amount of 350,000 euros to program participants, whose savings additionally realized a reduction of gas bills by 1,250,000 euros.[4]

Figure 2: Distribution of gas savings in kWh



Note: To account for outliers, we remove the upper and lower 1-percentile of the savings distribution. The vertical red line indicates savings of 2,500 kWh, which map onto receiving the maximum bonus of 125 euros.

Figure 2 displays the distribution of savings in kWh. Savings of 2,500 kWh are highlighted by the red line, as these are the savings which map onto the maximum payment of 125 euros. Any savings beyond the 2,500 kWh were not incentivized through the GBP. The key insight from Figure 2 is that about 70 percent of participants save more than the 2,500 kWh, i.e., more than financially incentivized. While this can be interpreted as substantial non-financial motivation to save gas, it is important to note that participants do not have access to real-time consumption information, making it highly difficult for them to track their savings in comparison to that threshold.

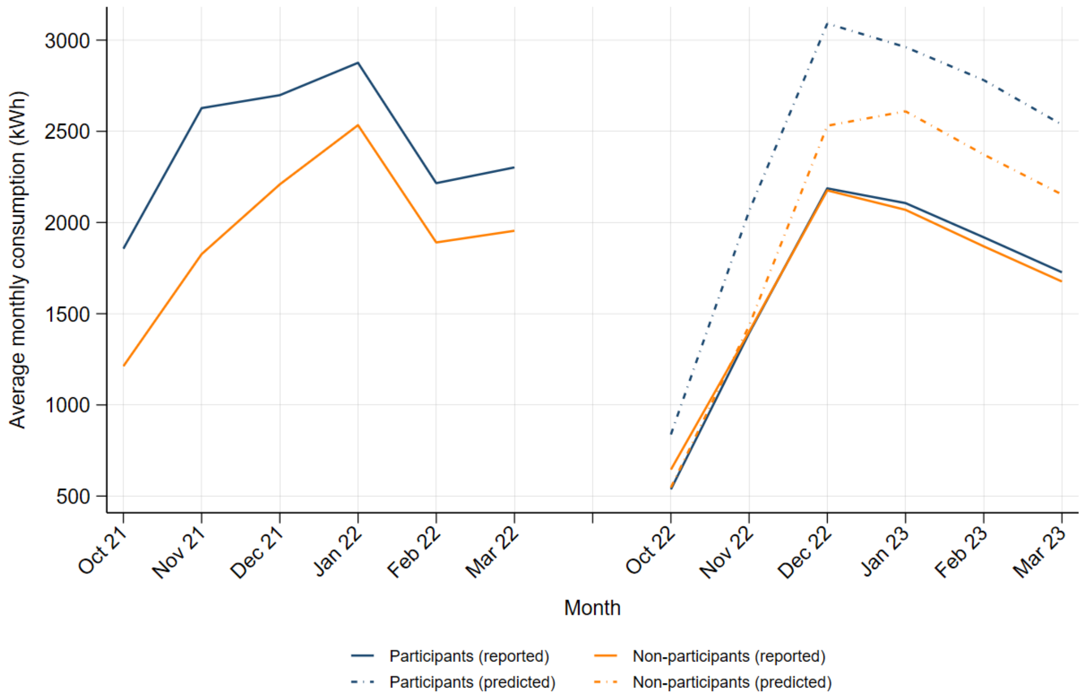
Further, when interpreting these savings, one might be concerned by the energy provider's approach of estimating savings based on comparing consumption of program participants in winter 2022/2023 to their consumption in 2020-2022. As one example, savings might be upward biased by higher levels of reference consumption due to the COVID-19 pandemic and stay-at-home orders in 2020-2022. This is why we next turn to the monthly reconstructed consumption data and compare both participants and non-participants.

4.2 Program-induced savings: participants versus non-participants

The average monthly consumption for participants and non-participants during both winters is displayed in Table A.1 and in Figure 3. In the pre-program period (winter 2021/2022), program participants consumed a monthly average of 2,397 kWh. Non-participants consumed an average of 1,992 kWh. The gap of 405 kWh between participants' and non-participants' energy consumption is statistically significant ($p < 0.001$, two-sided t-test). During the program, in winter 2022/2023, participants reduced their average consumption to a monthly average of 1,645 kWh, and non-participants reduced their consumption to 1,639 kWh. The gap in energy consumption between participants and non-participants thus decreases

[4]Figure A.3 displays the communication of program success by the energy provider at the end of the program.

Figure 3: Gas consumption in Winter 21/22 and Winter 22/23



to 6 kWh in the crisis winter, which is economically negligible and statistically insignificant ($p = 0.729$, two-sided t-test). This closing of the gap between participants and non-participants can be considered first evidence suggesting a positive program effect. Within group and across time, we identify a significant reduction of 751 kWh ($p < 0.001$, two-sided t-test) for participants and of 352 kWh ($p < 0.001$, two-sided t-test) for non-participants from winter 2021/2022 to winter 2022/2023.

Figure 3 visualizes these trends. The solid lines represent the reported consumption, and the dashed lines represent the predicted weather-corrected consumption for winter 2022/2023 based on the data from the 2021/2022 period. As Figure 3 reveals, the beginning of winter 2022/2023 was warmer than the prior winter, as indicated by lower predicted consumption for both groups. Further, behavioral change becomes evident from November 2022 onwards, shown by the growing gap between predicted and reported consumption (right side of Figure 3).

The graphical evidence indicates parallel trends between participants and non-participants during the pre-intervention winter 2021/2022 (left side of Figure 3). The global linear pre-trend test confirms the absence of systematic differences before the intervention ($p = 0.258$).

We next estimate the program effect using a two-way fixed effects model, with month and household fixed effects. The results are presented in Table 2. Column (1) is our preferred specification, using reported monthly natural gas consumption with household and month fixed effects. We estimate an average monthly program effect of -406.7 kWh ($p < 0.001$), which aggregates to approximately 2,440 kWh per participating household over the six-month program period, corresponding to a 17.0 percent reduction relative to participants' pre-treatment consumption over the same period.[5] Columns (2) and

[5] Alternative specifications confirm the robustness of this finding: the raw data specification yields an estimate of -457.6 kWh per month (17.4 percent), and truncating the top and bottom 1 percent gives an estimate of -419.2 kWh per month (16.8 percent). All estimates are statistically significant at the 1-percent level.

Table 2: Difference in Differences results

	(1) Monthly consumption (kWh)	(2) Monthly consumption (kWh)	(3) Monthly consumption (kWh)	(4) Weather-corrected monthly consumption (kWh)
DiD	-406.65^{***}	-294.72^{***}	-353.52^{***}	-328.66^{***}
	(23.34)	(25.09)	(28.99)	(23.28)
Matching	None	PSM	nnmatch	None
HH & Month fixed effects	Yes	Yes	Yes	Yes
Program-induced savings (%)	−17.0%	−13.2%	−14.8%	−15.0%
Observations	38,212	26,806	27,678	38,212
Households	4,008	2,563	3,000	4,008

Note: All specifications use monthly gas consumption truncated at the group- and month-specific 5th and 95th percentiles of raw consumption. Column (4) uses weather-corrected predicted consumption as the dependent variable. Matching in columns (2) and (3) is based on pre-treatment mean consumption. Program-induced savings (%) are calculated as the DiD estimate divided by the pre-treatment mean consumption of participants in Winter 2021/2022, using the specification-specific consumption measure and sample. For column (1), the denominator is the pre-treatment mean of all participants (2,397 kWh). For column (2), the denominator is the pre-treatment mean of PSM-matched participants (2,241 kWh). For column (3), the denominator is the pre-treatment mean of all participants (2,397 kWh), as nearest-neighbor matching retains all treated units. For column (4), the denominator is the pre-treatment mean of weather-corrected consumption (2,196 kWh). The program-induced savings in % are calculated by dividing the estimated monthly DiD coefficient by the average pre-treatment monthly consumption of GBP participants in the corresponding estimation sample and multiplying by 100. The estimation sample of N=4,008 households is smaller than the total of 2,382 participants and 1,998 non-participants, as households whose billing records do not fully cover at least one month in the pre-program winter are excluded from the estimation sample. Robust standard errors in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

(3) address potential pre-treatment differences in baseline consumption between participants and non-participants by combining the DiD specification with propensity score matching (PSM) and nearest-neighbor matching (nnmatch), both based on pre-treatment mean consumption in Winter 1. The matched estimates are somewhat smaller in magnitude, at -294.7 kWh (PSM) and -353.5 kWh (nnmatch) per month. Column (4) provides an additional robustness check using weather-corrected predicted monthly consumption as the dependent variable. The resulting estimate of -328.7 kWh per month, corresponding to 15.0 percent, is somewhat smaller but remains close to the preferred estimate.

We apply the HonestDiD approach of Rambachan and Roth (2023) to further assess robustness against potential violations of the parallel trends assumption. The sensitivity parameter $\bar{M}$ captures the maximum allowable deviation from parallel trends in the post-treatment period, expressed as a multiple of the maximum pre-treatment deviation. Our results indicate that the confidence intervals remain entirely negative for $\bar{M} \leq 1.6$, with a confidence interval ranging from -834.9 kWh to -19.9 kWh at $\bar{M} = 1.6$. This implies that our estimates remain robust even if post-treatment violations of parallel trends were up to 1.6 times as large as the observed pre-treatment deviations. For larger deviations ($\bar{M} > 1.6$), the upper bound becomes positive, indicating that the sign of the effects cannot be guaranteed under very large departures from parallel trends.

These findings provide strong and consistent evidence that the GBP induced significant reductions in residential gas consumption. The estimated effects are robust across consumption measures, truncation strategies, matching approaches, and robustness checks for violations of parallel trends.

4.3 Heterogeneity in program effects

Beyond average treatment effects, we investigate whether program-induced savings differ systematically across the pre-treatment consumption distribution. A median split based on pre-treatment consumption (median: 1,931 kWh/month) reveals that households above the median reduce consumption by -340.2 kWh per month, compared to -300.4 kWh for households below the median, suggesting that higher-consumption households achieve somewhat larger absolute savings. A quartile analysis provides a more granular picture. In absolute terms, the DiD estimates increase monotonically in magnitude from the first to fourth quartile of the consumption distribution: -206.6 kWh/month (Q1), -252.4 kWh/month

(Q2), -308.0 kWh/month (Q3), and -407.6 kWh/month (Q4). The aggregate average treatment effect is thus primarily driven by high-baseline-consumption households, which have greater absolute saving potential.

However, the picture reverses when considering relative savings. In log-linear specifications, Q1 pre-consumption households reduce consumption by 28.3%, Q2 by 19.9%, Q3 by 15.1%, and Q4 by 17.4%.[6] Low-consumption households thus respond more strongly in relative terms despite having lower absolute saving potential.

This divergence between absolute and relative program effectiveness has direct implications for the program's distributional profile. Since the GBP rewards absolute kWh savings, high-consumption households, who tend to have higher incomes and larger dwellings, systematically receive larger financial transfers. Low-consumption households, by contrast, save fewer kWh in absolute terms and receive lower payments despite making relatively larger behavioral adjustments.

As a further exploratory test of this distributional program implication, Table A.2 correlates savings and bonus payments with participants' income as elicited in our survey. Accordingly, individuals with above-median income receive a bonus that is at the 10-percent level significantly higher compared to a below-median income reference group. The coefficient suggests an 8.8 euro higher payment to the above-median participants. Figure A.4 visually explores this link. The fraction of participants receiving the maximum payment of 125 euros tends to increase with increasing income category: A total of 60.61 percent of individuals in the below-median-income group received the full 125 euros bonus. This is followed by a slightly higher percentage of 63.49 percent in the median-income group and a considerably larger proportion of 77.27 percent in the high-income bracket.

5 Selection into program

5.1 Descriptive differences between participants and non-participants

Table 3 presents the summary statistics of the household and individual characteristics of the participants and non-participants.[7] It is noteworthy that a lower percentage of non-participants live in family houses (47 percent) and are homeowners (59 percent) compared to participants (61 percent and 78 percent, respectively). Participants and non-participants have a similar household size, with an average of 2.30 individuals per household for participants and a standard deviation of 0.92, compared to non-participants who have an average size of 2.28 individuals per household and a standard deviation of 1.03. Additionally, participants are less likely to have minors living with them, with an average of 0.28 children and a standard deviation of 0.67, compared to non-participants, with an average of 0.43 children and a standard deviation of 0.88. In terms of education, participants generally have a higher educational background than non-participants, with the median category being 'qualification for applied-science college' for non-participants and 'university qualification' for participants. Regarding employment status, most participants are retired, whereas the majority of non-participants are employed on a full-time basis.

[6] Percentage changes are computed as $(e^{\hat{\beta}} - 1) \times 100\%$, where $\hat{\beta}$ denotes the estimated coefficient on the difference-in-difference interaction term in a log-linear two-way fixed effects specification with household and month fixed effects. Note that these relative effects are based on log specifications, whereas the aggregate percentage effect reported in Table 2 is computed as the level difference-in-difference coefficient divided by participants' pre-treatment mean.

[7] Among GBP participants, survey respondents and non-respondents do not differ significantly in their pre-program consumption ($p = 0.101$), suggesting the survey subsample is not systematically selected on prior usage.

Table 3: Summary statistics of program adopters and non-adopters

	Mean	p50	Std. Dev.	N
Non-participants				
Family house (yes=1)	0.47	0.00	0.50	1044
Owner (yes=1)	0.59	1.00	0.49	1041
Persons in hh (count)	2.28	2.00	1.03	1046
Children in hh (count)	0.43	0.00	0.88	1046
Education (1-7)	4.36	4.00	1.60	949
Employment (1-7)	2.62	2.00	1.90	1029
Income (1-9)	3.80	3.00	1.80	799
Participants				
Family house (yes=1)	0.61	1.00	0.49	2598
Owner (yes=1)	0.78	1.00	0.42	428
Persons in hh (count)	2.30	2.00	0.92	430
Children in hh (count)	0.28	0.00	0.67	430
Education (1-7)	4.69	5.00	1.55	387
Employment (1-7)	2.81	4.00	1.73	426
Income (1-9)	4.37	4.00	1.77	295

Note: Dwelling type was a mandatory question during sign-up. All other characteristics stem from the survey and are subject to item non-response, resulting in a lower N.

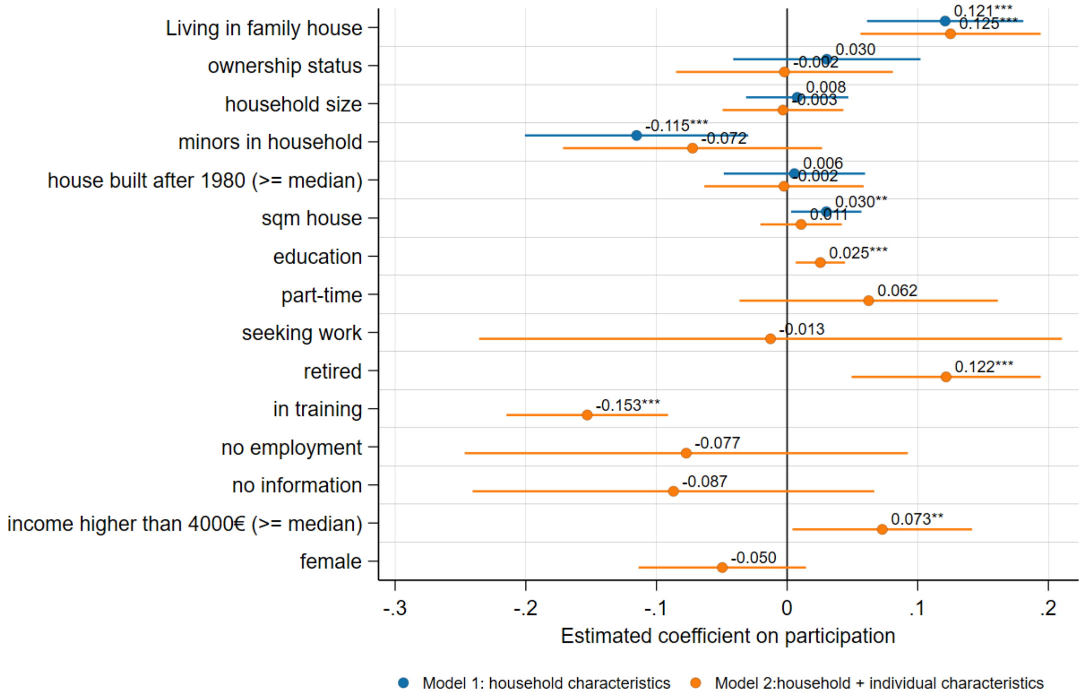
Finally, it is worth noting that participants generally reported higher incomes, with median incomes of 2,000 euros – 3,000 euros for non-participants and 3,000 euros – 4,000 euros for participants.

Additionally, the descriptive analysis of the planned savings, the estimated savings of other German households, and the 'Dezemberhilfe'-quiz-question offers valuable insights. On average, a GBP participant plans to save about 15-20 percent of their household gas consumption during the GBP compared to 10-15 percent planned savings among non-participants. This suggests a higher inclination for savings among participants. Participants believed that other GBP participants and residents in Germany would save approximately 10-15 percent, indicating a perception of moderate saving behavior in the broader community. 56 percent of GBP participants correctly understood the Dezemberhilfe, in contrast to 45 percent among non-participants, highlighting a better knowledge about current energy policy among the former.

5.2 Correlates of program enrollment

We now study the characteristics which explain selection into the GBP program. Such analysis helps in understanding both the effectiveness and the distributional consequences of the program. Section 4.3 already showed that consumers with higher baseline consumption and higher income generated the largest program effects. This is consistent with Schulte and Heindl (2017), showing that high-income households display a larger price elasticity of electricity demand than low-income households. Such argumentation may be even more true in the context of residential heating, just to name a few reasons, (1) high-income households will more likely be homeowners, as opposed to tenants, and thus are able to invest in insulation and new heating systems, (2) high-income households will likely live in larger

Figure 4: Program adoption by house and socio-demographic characteristics



Note: Table A.3 displays the full regression results.

apartments and thus have more square meters for which heating temperature can be reduced, (3) to save costs, low-income households may have already fully exploited their savings potential before the GBP. Hence, program enrollment by high-income homeowners, living in larger dwellings, and having a high savings potential is likely beneficial for program effectiveness – yet, questionable from a distributional perspective as it implies (public) utility payments to an already richer population group.

Figure 4 illustrates the estimated coefficients of the household and the socio-demographic characteristics on program enrollment. The figure shows the results from two different econometric specifications. Model 1 uses household characteristics and Model 2 incorporates both household and individual characteristics. While the variable education is treated as a continuous variable, we present 'employment' as binary indicators, which take the value of 1 for each of the respective categories: 'full-time,' 'part-time,' 'seeking work,' 'retired,' 'in training,' 'no employment,' and 'no information,' whereby 'full-time' is the omitted reference category in the regression.

The 'house built after 1980' variable is binary, indicating whether a house was constructed after 1980 or not. The median of the variable 'year house was built' is in the category 1980-1989. Therefore, this variable we used for the regression categorizes houses as 'built in or after 1980' or 'built before the 1980.' Similarly, for the income variable, a binary category was created to indicate whether income was equal to or above the median income of 3,000 euros - 4,000 euros in the regression analysis.

The coefficients in the models demonstrate noteworthy disparities between participants and non-participants when considering the household and sociodemographic characteristics. The binary variable 'Living in a family home' has coefficients of 0.121 (Model 1) and 0.125 (Model 2), and displays a relationship with GBP participation that is significant at the 1-percent level. Program participants are more likely to reside in family homes. In Model 1, the continuous variable 'minors' has a significant and negative coefficient of -0.115, indicating that households with more minors are less likely to participate in the GBP. The variable 'sqm house' suggests that an increase in the square meters of a house is significantly linked to a higher likelihood of GBP participation. Further, participants are more likely to have a higher educational degree and are more likely to be retired. The binary variable 'income higher than 4000 euros' is also significantly positively associated with GBP participation, suggesting that participants are more likely to have above-median income levels.

Figure 5 displays the estimated coefficients on program participation for the set 'energy-related beliefs' and encompasses five models. The first three models sequentially include the variables of household saving estimates, correct understanding of the "Dezemberhilfe"-policy, and sum of energy saving actions. To test the robustness of our findings, we add household and individual characteristics in the following models: Model 4 controls for household variables, while Model 5 incorporates both household and individual controls. In all models, the planned natural gas savings shows a significant and positive relation to GBP participation (ranging from 0.022 to 0.040), suggesting that participants in the GBP have higher saving intentions.[8] GBP participants also tend to be better informed about energy policy, as evidenced by the positive and statistically significant coefficients for 'correct understanding Dezemberhilfe.'

We do not find a robust relation between the number of actions conducted to save natural gas and program participation. While the coefficient is positive and significant in the first model, indicating more energy saving actions among program participants, the coefficient loses significance once we control for household characteristics. In part, this may be due to the relation between GBP participation and 'living in a family house' on the one hand, and 'living in a family house' and the potential of conducting more actions on the other hand.

The estimated coefficients for the set 'crisis-related beliefs' are illustrated in Figure 6. The figure depicts four different models, with Models 1 and 2 built sequentially. In Models 3 and 4, robustness tests were conducted by including the control variables. The most notable finding in this set of models is the variable 'financial situation,' which exhibits a significant difference between the groups in Models 1 to 3. Respondents who participate in the GBP are less likely to indicate financial constraints due to the crisis than those who do not participate. We do not find a significant relation in the anticipated duration of the crisis between participants and non-participants.

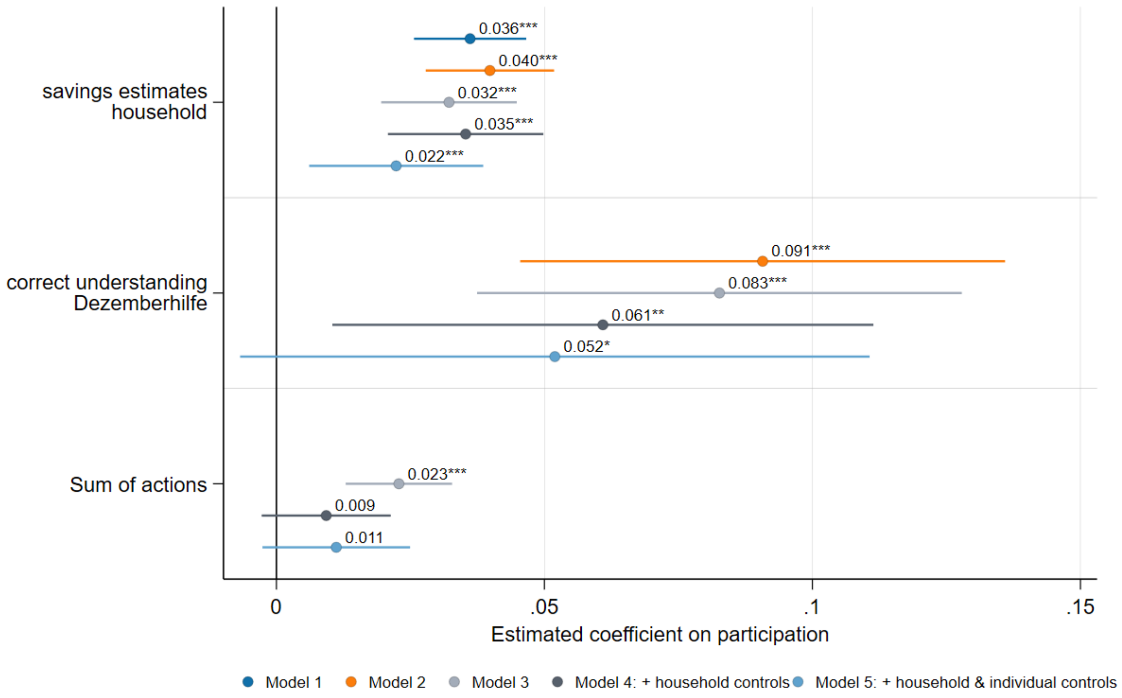
Figure 7 displays the estimated coefficients for the set 'motivational beliefs.' The first model includes the variables 'individual costs', 'politics', and 'climate'. Model 2 was designed to control for experimental demand effects through including the variables 'peer effects'[9] and 'expectations'[10]. Model 3 instead controls for respondents' estimates of gas savings in Germany. Model 4 extends Model 3 by including household characteristics and Model 5 controls for both household and individual factors. Our findings indicate that while there was no significant difference between the groups based on individual costs as a motive to save gas, there was a significant positive difference in political and climate motives. This suggests that GBP participants are more likely to be motivated to save gas by political and climate-related, i.e., pro-social, factors compared to non-participants.

[8] Figure A.5 maps participants' actual program savings against their planned savings. Visual inspection denotes most observations above the 45-degree line and, hence, suggests that the majority of participants actually achieve greater savings than planned or anticipated.

[9] The exact wording of the question is "It is important for me to fit in with my social group."

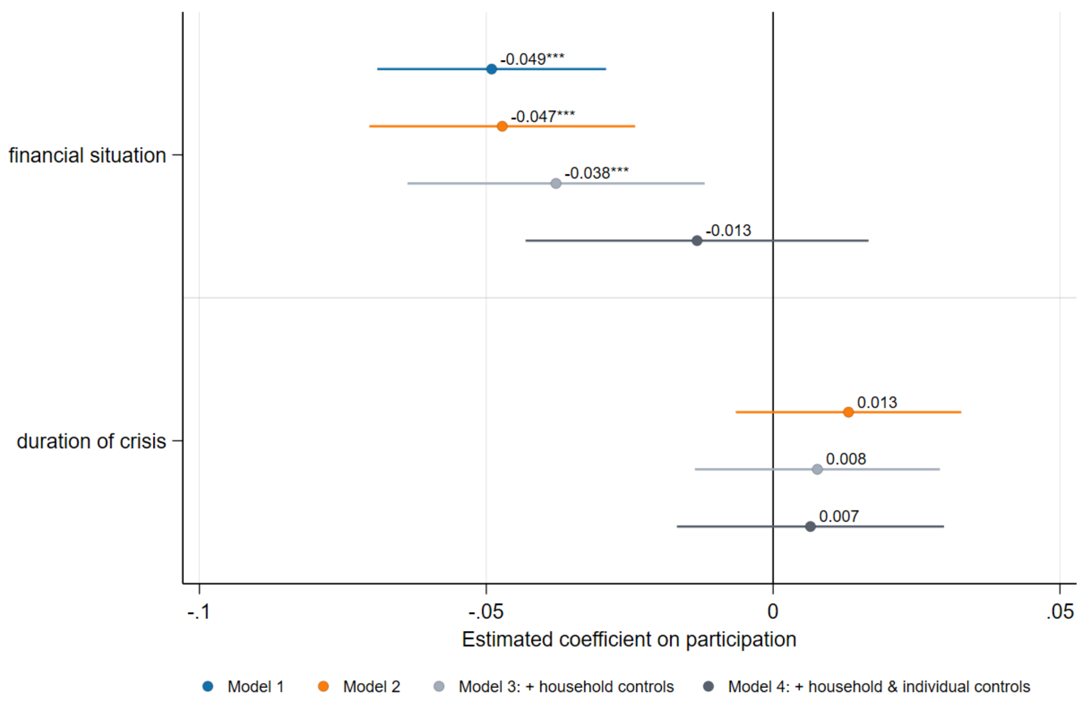
[10] The exact wording is "My behavior is influenced by the expectations of others."

Figure 5: Program adoption by energy-related beliefs



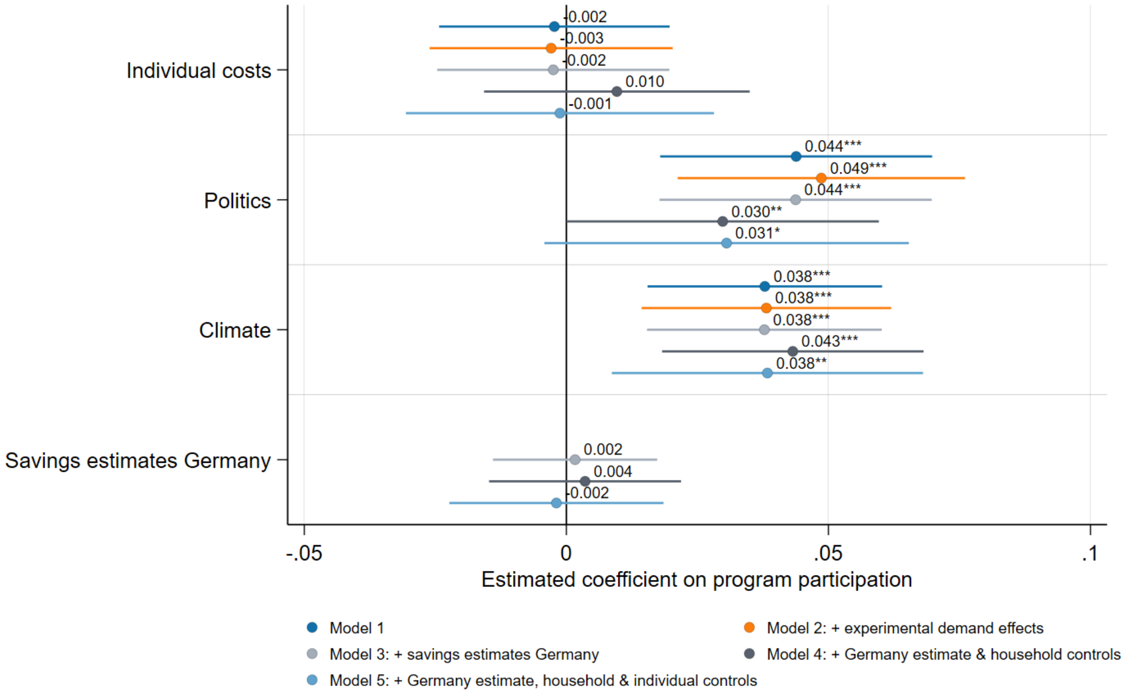
Note: Table A.4 displays the full regression results.

Figure 6: Program adoption by crisis-related beliefs



Note: Table A.5 displays the full regression results.

Figure 7: Program adoption by motivational beliefs



Note: Table A.6 displays the full regression results.

In sum, our data shows that program participants have higher incomes, reside in larger houses, and are rather retired.[11] GBP adopters exhibit a proactive approach to gas conservation and possess a better understanding of the energy policies. While financial motivation is the strongest motive in both groups, program participants are distinguished by their stronger societal motivation. Participants are also less likely to report financial constraints resulting from the energy crisis.

Our analysis thus suggests that selection into the program itself may constitute an important mechanism shaping program effectiveness. The finding that households with higher income tend to have higher program enrollment rates speaks in favor of favorable selection into GBP participation. Their financial stability and larger living spaces may enhance their capacity to implement energy-saving measures, leading them to contribute disproportionately to the savings achieved by the GBP program – consistent with the heterogeneous program effects documented in Section 4.3.

6 Alternative program design

Our analysis of the GBP shows that the per-unit CPR is particularly attractive for participants with high pre-intervention gas consumption. A program designer or policy maker who prioritizes targeting low-consumption (e.g., low-income) households might instead consider introducing a fixed saving reward: If a household achieves a certain savings threshold s of its baseline energy consumption E, it receives a lump-sum payment P. The implied marginal rebate per kWh saved then decreases in baseline consumption E, making such a fixed reward program more advantageous for low-consumption households.

[11] Similar selection patterns emerge in other settings: Bernard et al. (2026) document higher enrollment among homeowners and residents of houses rather than flats in a nationwide electricity program.

To illustrate the mechanics of these two different approaches, we compare our results to the fixed reward program analyzed by Amberg et al. (2025). The program was rolled out in Germany at the same time as our intervention. Participants received a lump-sum payment of 100 euros if they saved at least 10 percent compared to the pre-intervention period.

With a per-unit payment of $p = 0.05$ euros/kWh and a cap of 2,500 kWh, our CPR program leads to higher individual payments compared to the fixed reward program with $s = 0.1$ and $P = 100$ euros for all households with

(i) $0 < s < 0.1$, since households with positive savings below the 10 percent threshold receive no payment under the fixed reward scheme but a positive payment under CPR,

(ii) $E < 20,000$ kWh and high individual saving rates: e.g. at $E = 10,000$ kWh and $s \in (0.2, 0.25)$ or $E = 5,000$ kWh and $s \in (0.4, 0.5)$,

(iii) $E > 20,000$ kWh and $s \geq 0.1$.

In our data, we observe $E > 20,000$ kWh for about 25 percent of all participating households and $0 < s < 0.1$ for about 6 percent of all households. About 70 percent of all participating households have $E < 20,000$ kWh and $s > 0.1$. Among those 70 percent, 23 percent would be better off in the fixed reward scheme while 77 percent benefit more in the CPR program (net of the community bonus).

This comparison shows a fundamental trade-off in program design. A per-unit payment scheme, such as the GBP, rewards each kWh saved relative to prior consumption equally. Total payments thus scale with absolute savings and the scheme is more attractive for high-consumption households. In contrast, a fixed reward ties a lump-sum payment to reaching a savings threshold rather than rewarding an absolute savings quantity, generating higher payments for low-consumption households that meet the threshold. The choice between the two schemes thus depends on whether the policy or program objective is to maximize aggregate gas savings, which favors the CPR given its attractiveness for high-consumption households, or to reach low-consumption households with meaningful financial incentives, which favors the fixed reward scheme.

7 Conclusion

Designing energy-saving programs involves multiple challenges and even more so during high-price periods with little time for preparation. We report empirical evidence from a natural gas saving program launched during the energy crisis in 2022/2023 by one of the largest energy providers in Germany. Our study can be interpreted as a stress test of a CPR program and results show that the CPR survives the test: the program induced significant gas savings of 13.2% - 17.0% – even in a setting where both participants and non-participants already observe high market prices through public debate and media coverage.

One mechanism of the program success is favorable selection. We find program participants to have a comparably higher pre-program energy consumption, higher income, to live in larger dwellings, and to be more likely to be retired compared to non-participants. Regarding their motivation, participants have more ambitious energy saving intentions and are more strongly motivated to save gas for societal reasons.

However, our observation that high-income households are more likely to select into the program and receive larger payments raises distributional concerns. At the same time, exactly those high-income households also tend to be more price-elastic and respond most to the program, which speaks in favor of the program successfully targeting households with the largest ability to save gas. Public policy-makers thus have to balance program effectiveness against distributional concerns.

Comparing the per-unit CPR to a fixed reward scheme – where a lump-sum payment is granted for reaching a relative savings threshold – shows that the fixed reward scheme generates higher payments for low-consumption households. The choice between the two simple schemes therefore depends on the policy objective: maximizing aggregate gas savings favors the CPR, given its appeal to high-consumption households, whereas reaching low-consumption households with meaningful financial incentives favors the fixed reward scheme.

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Appendix

A Figures

Figure A.1: Recruitment campaign: Poster 1

Figure A.2: Sign-up distribution

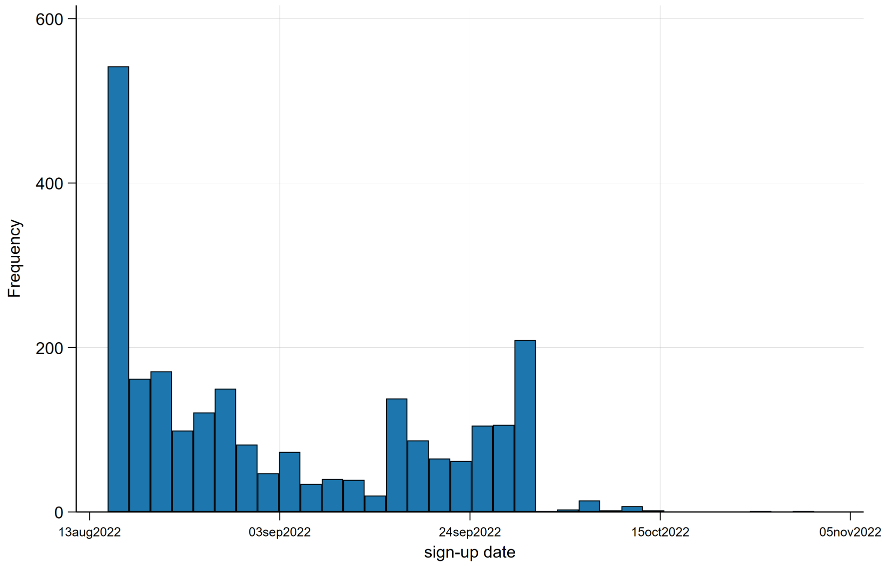


Figure A.3: Utility communication: Gas savings

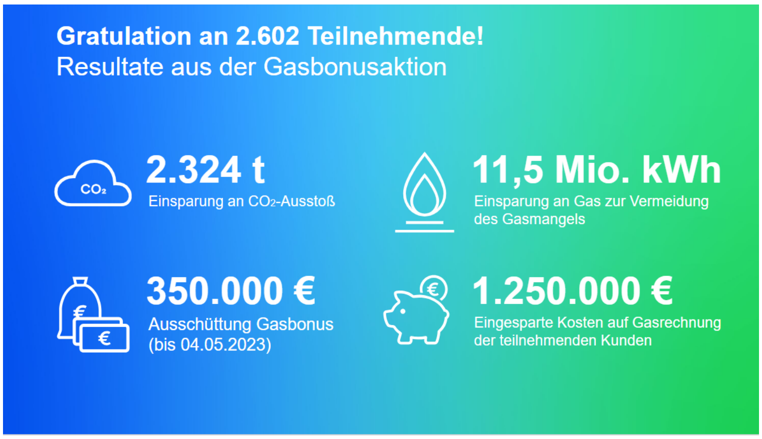


Figure A.4: Individual payment by income group

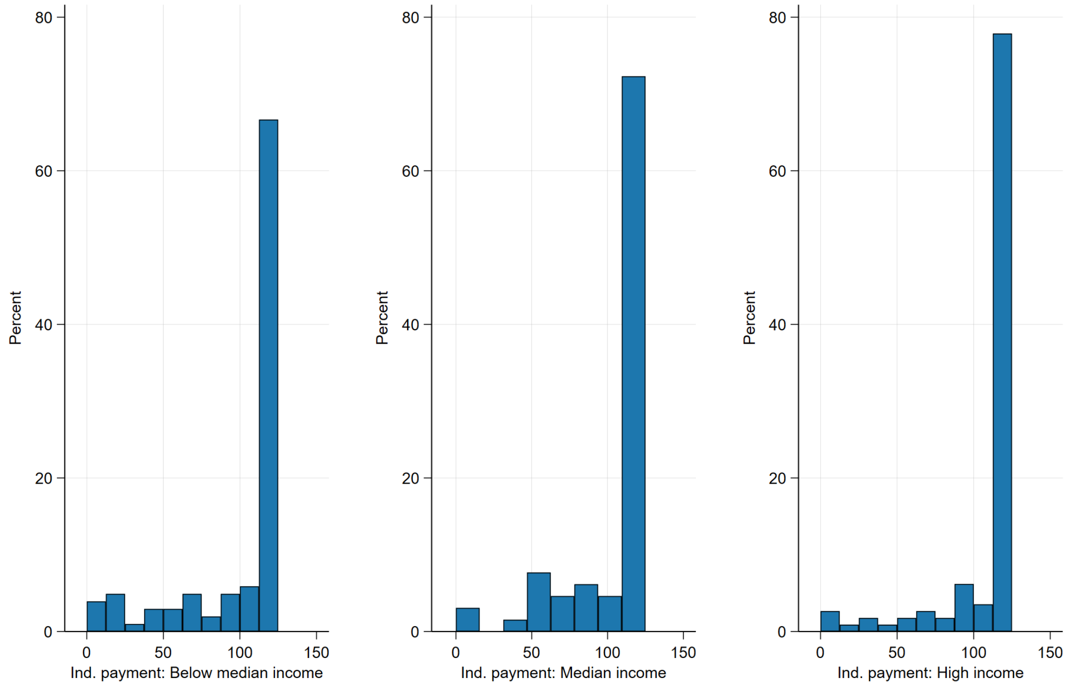
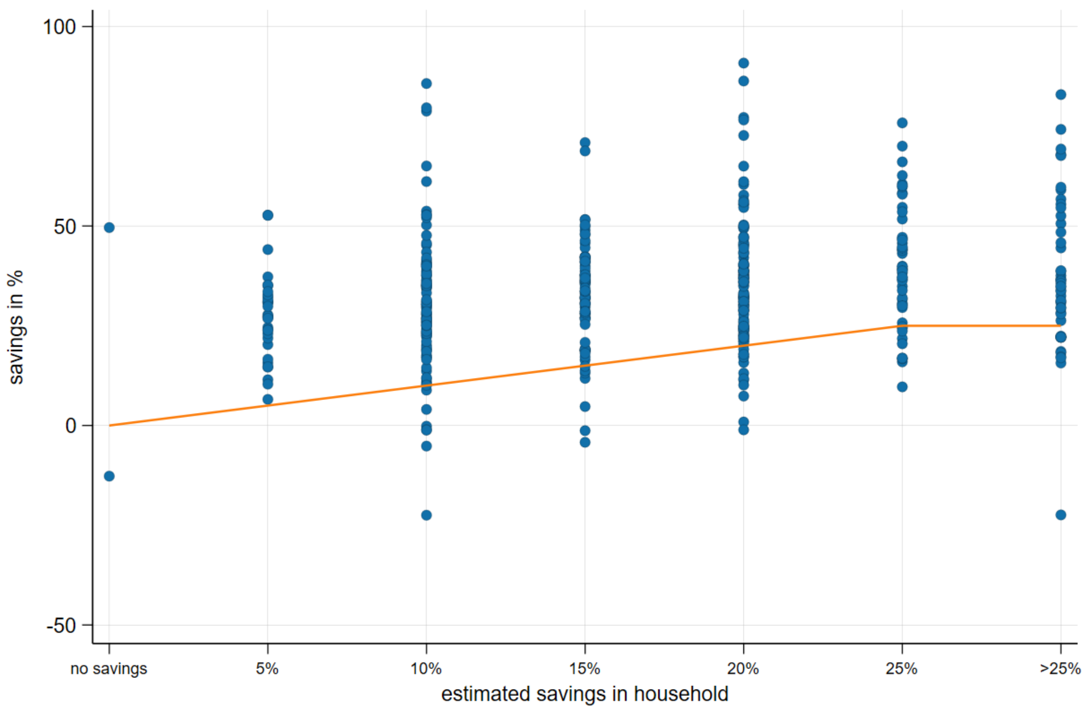


Figure A.5: Actual versus planned savings



Note: To account for outliers, we remove the upper and lower 1-percentile of the savings distribution.

B Tables

Table A.1: Summary statistics of monthly gas consumption

	Participants			Non-participants		
Month	N	Mean	SD	N	Mean	SD
Panel A: Reported consumption Winter 1						
Oct 21	1,459	1,856	947	1,093	1,212	1,042
Nov 21	1,226	2,627	1,384	1,240	1,827	1,517
Dec 21	1,008	2,698	1,419	1,657	2,209	1,675
Jan 22	809	2,876	1,469	1,730	2,534	1,942
Feb 22	702	2,216	1,107	1,735	1,891	1,461
Mar 22	629	2,302	1,142	1,736	1,955	1,513
Total	5,833	2,397	1,303	9,191	1,992	1,622
Panel B: Reported consumption Winter 2						
Oct 22	2,142	537	281	1,729	645	527
Nov 22	2,144	1,394	732	1,729	1,402	1,092
Dec 22	2,143	2,187	1,147	1,727	2,176	1,692
Jan 23	2,144	2,106	1,106	1,727	2,070	1,593
Feb 23	2,144	1,919	1,007	1,727	1,869	1,435
Mar 23	2,144	1,727	907	1,728	1,676	1,287
Total	12,861	1,645	1,070	10,367	1,639	1,423
Panel C: Weather-corrected, predicted consumption						
Oct 22	1,459	838	427	1,093	547	470
Nov 22	1,226	2,063	1,087	1,240	1,434	1,191
Dec 22	1,008	3,091	1,626	1,657	2,530	1,919
Jan 23	809	2,962	1,513	1,730	2,610	2,000
Feb 23	702	2,780	1,389	1,735	2,373	1,834
Mar 23	629	2,536	1,258	1,736	2,154	1,667
Total	5,833	2,196	1,486	9,191	2,061	1,798

Note: Reported consumption is truncated at group- and month-specific 5th and 95th percentiles.

Table A.2: Savings and payments received by income group

	(1) Savings (in kWh)	(2) Savings (in %)	(3) Ind. payment
Median income	-691.427	-0.009	5.067
	(558.694)	(0.026)	(5.216)
Above median	998.113	0.002	8.798*
	(624.641)	(0.024)	(4.576)
Constant	4361.152***	0.339***	103.192***
	(495.426)	(0.018)	(3.664)
Observations	280	280	280

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

Table A.3: Program enrollment by house and socio-demographic characteristics

	(1) gas bonus program	(2) gas bonus program
Living in family house	0.121***	0.125***
	(0.030)	(0.035)
ownership status	0.030	-0.002
	(0.037)	(0.042)
household size	0.008	-0.003
	(0.020)	(0.024)
minors in household	-0.115***	-0.072
	(0.044)	(0.051)
house built after 1980 ($\geq$ median)	0.006	-0.002
	(0.028)	(0.031)
sqm house	0.030**	0.011
	(0.014)	(0.016)
education		0.025***
		(0.010)
full-time		0.000
		(.)
part-time		0.062
		(0.050)
seeking work		-0.013
		(0.114)
retired		0.122***
		(0.037)
in training		-0.153***
		(0.032)
no employment		-0.077
		(0.086)
no information		-0.087
		(0.078)
income higher than 4000€ ($\geq$ median)		0.073**
		(0.035)
female		-0.050
		(0.033)
Constant	0.086*	0.025
	(0.045)	(0.069)
Observations	1274	933

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

Table A.4: Program enrollment by energy-related beliefs

	(1) gas bonus program	(2) gas bonus program	(3) gas bonus program	(4) gas bonus program	(5) gas bonus program
savings estimates household	0.036***	0.040***	0.032***	0.035***	0.022***
	(0.005)	(0.006)	(0.006)	(0.007)	(0.008)
correct understanding Dezemberhilfe		0.091***	0.083***	0.061**	0.052*
		(0.023)	(0.023)	(0.026)	(0.030)
Sum of actions			0.023***	0.009	0.011
			(0.005)	(0.006)	(0.007)
Constant	0.112***	0.081***	-0.033	-0.113**	-0.152***
	(0.022)	(0.027)	(0.034)	(0.056)	(0.077)
Household controls	No	No	No	Yes	Yes
Individual controls	No	No	No	No	Yes
Observations	1734	1507	1507	1274	934

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. Robust standard errors in parentheses.

Table A.5: Program enrollment by crisis-related beliefs

	(1) gas bonus program	(2) gas bonus program	(3) gas bonus program	(4) gas bonus program
financial situation	-0.049***	-0.047***	-0.038***	-0.013
	(0.010)	(0.012)	(0.013)	(0.015)
duration of crisis		0.013	0.008	0.007
		(0.010)	(0.011)	(0.012)
Constant	0.455***	0.385***	0.190**	0.031
	(0.037)	(0.062)	(0.089)	(0.114)
Household controls	No	No	Yes	Yes
Individual controls	No	No	No	Yes
Observations	1393	1079	960	743

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. Robust standard errors in parentheses.

Table A.6: Program enrollment by motivational beliefs

	(1) gas bonus program	(2) gas bonus program	(3) gas bonus program	(4) gas bonus program	(5) gas bonus program
individual costs	-0.002	-0.003	-0.002	0.010	-0.001
	(0.011)	(0.012)	(0.011)	(0.013)	(0.015)
politics	0.044***	0.049***	0.044***	0.030**	0.031*
	(0.013)	(0.014)	(0.013)	(0.015)	(0.018)
climate	0.038***	0.038***	0.038***	0.043***	0.038**
	(0.011)	(0.012)	(0.011)	(0.013)	(0.015)
savings estimates Germany			0.002	0.004	-0.002
			(0.008)	(0.009)	(0.010)
Constant	-0.027	0.033	-0.032	-0.236***	-0.201**
	(0.049)	(0.057)	(0.053)	(0.078)	(0.102)
Household controls	No	No	No	Yes	Yes
Individual controls	No	No	No	No	Yes
Experimental demand effects	No	Yes	No	No	No
Observations	1542	1426	1542	1274	933

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

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