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Money versus procedures — Evidence from an energy efficiency assistance program[☆]

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ABSTRACT

In many countries, governments have put in place targeted programs intended to support energy efficiency investments by low-income households, but have encountered low take-up even when subsidies are high. Using evidence from a large energy efficiency assistance program, we demonstrate that seemingly small procedural changes can substantially improve take-up and that these changes have effects comparable to significantly raising subsidies. Observing 77,305 durable goods purchase decisions in a refrigerator replacement program, our RD design exploits two quasi-exogenous temporal discontinuities in voucher value and procedures. Despite seeming disadvantageous, the procedural changes actually raise replacement rates among the target demographic of low-income households, an effect roughly equivalent to raising voucher values by 35 Euro. These results suggest that even under fixed budgets, the performance of energy efficiency assistance programs can be improved through empirically guided procedural design.

1. Introduction

In recent years, electricity retail prices for residential customers have been increasing steeply across much of the developed world (U.S. Energy Information Administration, 2023; Eurostat, 2024), bringing the adverse distributional effects of high prices on low-income households to the attention of researchers (Fabra and Reguant, 2024; Frondel et al., 2019) and public entities (Levinson and Silva, 2022; Sirin et al., 2023). Policy-makers have responded by designing programs intended to attenuate the adverse distributional effects of rising energy prices by helping low-income households become more energy-efficient.[1] At a conceptual level, these programs appear simple: They combine technical advice and practical help to households with economic incentives, such as subsidies. At a more detailed level, however, they reveal at times astonishing procedural complexity for all involved parties. For example, the 2014 evaluation report of Weatherization Assistance Program (WAP) dedicates an entire section to 'program complexity' as experienced by households, agencies, auditors, and weatherization crews (Tonn et al., 2014).[2] Onerous design features are an intuitive explanation for low take-up of privately beneficial assistance programs among low-income households (Fowlie et al.,

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[1] Examples are the Weatherization Assistance Program (WAP) by the U.S. Department of Energy, Services Locaux d'Intervention pour la Maîtrise de l'Énergie (SLIME) of the French Ministry for Ecological Transition, and the Electricity Savings Check (SSC) by the German Ministry for the Environment.

[2] As an illustration, the report points out that the program's knowledge base comprises more than 100 work categories and more than 800 gradable actions.

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2018). It would seem obvious that thinking carefully about how to design a program may be as important as setting the right economic incentives. Yet, the contribution of program design[3] to program performance is rarely substantiated, let alone quantified, in policy discussions.[4] To fill this gap, we exploit an empirical opportunity presented by one of the world's largest energy efficiency assistance programs to show that procedural design is impactful: Even seemingly small and arguably cost-saving procedural changes can substantially substitute for monetary inducements.

The empirical opportunity for studying and monetizing the effects of procedural change on household behaviour arises in the context of a nation-wide energy efficiency assistance program targeting low-income households in Germany. Since 2009, the Refrigerator Replacement Program (RRP) has subsidized the modernization of household refrigeration appliances. There, refrigerators are the consumer durable that accounts for the largest share (about 25 percent) of household electricity consumption (BDEW, 2019).[5] The RRP is embedded in a larger initiative called "Energy-Saving-Check" (SSC), funded by the German Ministry for the Environment. Between 2009 and 2020, the 150 local branches of the SSC actively recruited more than 360,000 low-income households through a variety of channels and conducted energy audits in their homes to help them reduce energy and water consumption. Appliance inventory data collected as part of the audit are used to screen for eligibility for the RRP.[6] Three criteria determine eligibility: a welfare recipient status, refrigerator age, and expected energy savings from refrigerator replacement. In its first twelve years, the SSC identified 77,305 eligible households. Eligible households are actively targeted for enrolment into the RRP in a follow-up visit by the team of SSC advisors. Enrolled households receive a voucher that is redeemed in cash upon successful refrigerator replacement by the household. Average program take-up among eligible households is between 25 and 30 percent for an average payback period of 3.5 years.[7]

In this setting, we study the impact of varying subsidies and of varying procedures on the probability that an eligible household successfully replaces their refrigerator. This probability, referred to as the "replacement rate", is the key performance indicator of the RRP, not least because of the considerable cost of each home energy audit to the program. Three aspects of this setting help enrich the literature on program design for low-income households. First, the RRP experienced two quasi-exogenous shocks that changed different dimensions of the program design unexpectedly and at short notice. The shocks mean that we observe the RRP in three distinct regimes over time. Proceeding conservatively and making use of the rolling nature of the program, our empirical strategy shows that much of the change in replacement rates across the three regimes can be attributed to the program design changes.

Second, the design dimensions changed by each of the policy shocks were essentially orthogonal. One shock changed the level of the cash subsidy from €150 to €100.[8] The paper can therefore speak to the effects of large relative changes in financial incentives on program performance among low-income households.[9] The other shock changed program procedures from automatic enrolment (every eligible household received the voucher by default) to elective enrolment (vouchers had to be requested) and voucher terms from flexible (three-month validity, unlimited renewability) to rigid (two-month validity, non-renewable). The paper can therefore speak to the effects of procedural changes on program performance among low-income households, including the role of "psychological frictions" (Bhargava and Manoli, 2015), "hassle" (Bertrand et al., 2006), and deadlines (Bertrand et al., 2010; Shu and Gneezy, 2010; Altmann et al., 2021). Importantly, we are able to benchmark the effect of these procedural changes against the variation in cash subsidies, providing an intuitive but novel metric of comparison.

Third, low-income households take investment decisions in our setting, rather than consumption or labour supply decisions typically studied. This decision constitutes a particularly challenging problem for all owners of energy-intensive consumer durables who pay their own electricity bills (Rapson, 2014; Wang and Matsumoto, 2021): Due to wear and tear in use, the durables become less energy-efficient over time while increasingly energy-efficient devices become available and affordable on the market due to technological progress. Both dynamics play out against a background of short- and long-term changes in electricity prices, further complicating the decision. Compared to high-income groups, low-income households have most to gain from getting the replacement timing right because a larger share of their income is exposed to the cost of energy. At the same time, they are at particular risk of mis-timing: The cognitive challenges of optimal replacement timing accentuate lower financial literacy, specifically to energy-related questions, leading to errors in decision-making (Calvet et al., 2009; Brent and Ward, 2018; Blasch et al., 2021). Low-income

[3] "Program design" here refers to the totality of features of a policy, from budget-relevant economic incentives to purely situational aspects (Bertrand et al., 2004)

[4] This is despite important examples in other policy areas, from procedural hassles in food stamp programs (Bertrand et al., 2006), information provision in school choice (Hastings and Weinstein, 2008) and variations in tax mailings (Bhargava and Manoli, 2015) to the local presence of Social Security field offices (Deshpande and Li, 2019) and electronic food vouchers (Banerjee et al., 2022).

[5] In the US, air conditioners are the most energy-intensive home durable, with 12 percent of total home energy expenditures in 2015 (EIA, 2018). In Germany, AC units remain rare.

[6] In Germany, the vast majority of low-income households own their refrigerators. In our sample, only 2.6% of households do not, making them ineligible for the RRP.

[7] In 2020 for example, average electricity prices were €0.289 and annual savings 342 kWh per replaced refrigerator, implying annual electricity bill reductions of €99. The take-up rate compares favourably to that induced by financial incentives of WAP, which is minimal, even for shorter payback (Fowlie et al., 2015, 2018; Hancevic and Sandoval, 2022). Evidence on appliance replacement programs is only available for episodic campaigns directed at the general population: A 36-month campaign in Mexico between 2009 and 2012 achieved 17 percent take-up (Davis et al., 2014), increasing by 34 percent following an increase in the subsidy of $80 (Boomhower and Davis, 2014). For a similar, but shorter U.S. campaign (26 weeks on average), take-up rates are difficult to compute (Houde and Aldy, 2017).

[8] This corresponds to a drop from 37 percent of the appliance price to 24 percent, on average.

[9] To our knowledge, empirical evidence on such effects is surprisingly scarce, with the exception of the effects of social benefits on labour supply (Ellwood, 2000).

households are also forced, as a result of being poor, to devote a greater share of their cognitive resources to psychologically salient short-term problems (Shah et al., 2012; Mani et al., 2013). This makes it likelier that households overlook longer-term problems and miss optimal replacement points, a particularly costly mistake for German low-income households due to high electricity prices,[10] lower investments in energy-efficiency consumer durables (Ameli and Brandt, 2015; Schleich, 2019), and an annual billing cycle.[11]

On the basis of twelve years of RRP data on home energy audits, program enrolment, and voucher redemption in three distinct program regimes, we have three main results on how subsidy and procedural variations in the RRP affected replacement rates among eligible low-income households. First, we find that a 50 percent higher subsidy is associated with a likelihood of refrigerator replacement that is 5 to 7 percentage points higher. This "subsidy elasticity" underscores that program performance is demonstrably a question of subsidy levels. Program administrators will want to take note that the elasticity operates only at the enrolment stage, but not at the redemption stage: Higher-value vouchers make more households enrol, but higher-value vouchers are not redeemed more frequently.

Second, we find that the procedural changes from automatic enrolment with flexible voucher terms to elective enrolment with rigid voucher terms in the RRP cause replacement rates to rise by 4 to 15 percentage points. The direction of this effect is as interesting as its composition, magnitude, and dynamics. At the enrolment stage, the share of enrolled households drops from 100 percent under automatic to just under 40 percent under elective enrolment. Through the lens of the behavioural economics of assistance programs, the size of this decrease is consistent with a change in the default (Thaler and Sunstein, 2021) and with procedural "hassle" being imposed on eligible households (Bertrand et al., 2006). At the same time, electively enrolled households exhibit – under the rigid two-month deadline – vigorous program take-up at the redemption stage. Compared to automatically enrolled households, a greater share of enrolled households replaces their refrigerator, and they replace more quickly following the second visit. Selection effects trivially explain some of the intensive-margin difference. They cannot explain, however, why cumulative replacement rates among eligible households after the procedural change dominate those before the change for every point in time following the second home visit. Through the lens of behavioural economics, this evidence is consistent with deliberate 'opt-ins' facilitating effective "goal-setting" (Locke and Latham, 1990) towards replacement and with rigid deadlines helping households to overcome time management problems (Bertrand et al., 2006).[12] Jointly, they lead to an intensive-margin effect that more than compensates for the changes in the enrolment mechanism.

Third, we conduct back-of-the-envelope calculations of the merits of alternative program design. Comparing effect sizes,[13] we find that the procedural changes improved replacement rates equivalent to an estimated subsidy increase of about €50 per replacing household while adding little to no cost to the program.[14] As a conservative illustration, bringing these procedural changes forward to 2013 rather than 2018 would have realized 2,000 additional replacements by low-income households at the same budgetary cost, leading to average additional savings of €99 in annual electricity bills of replacing households, or aggregate annual savings of €201,800.

We proceed as follows: In the following Section 2 we provide the necessary background on the Refrigerator Replacement Program. In Section 3, we explain the data on which the analysis is based. Section 4 lays out the empirical challenges and the empirical strategy. In Section 5, we present the main effects of the variation in the subsidy levels and the procedures on the success rate of the RRP. We then discuss the underlying mechanisms in Section 6. In Section 7, we compare the effects of subsidy and procedural change to each other and compute the effects of the alternative, untried regime on program success. Section 8 concludes.

2. The refrigerator replacement program

Since January 2009, the Refrigerator Replacement Program (RRP; German: *Kühlgeräte - Tauschprogramm*) has been offering cash vouchers to households on federal income support[15] in order to encourage replacing their old and inefficient refrigeration devices with modern, highly efficient models. The program is embedded within a wider initiative, the "Energy-Saving-Check" (SSC, German: *Stromspar-Check*) that provides support to low-income households for reducing their energy and water consumption by conducting home energy audits. These 'SSC households' constitute the pool of households that are screened for participation in the RRP. RRP and SSC are implemented jointly by the German Caritas Association, one of the largest social welfare organizations in the country, and the Association of Energy and Climate Protection Agencies (eaD). Caritas and eaD operate around 150 local branches throughout the country. Annual funding of around €10-15 million is provided by the German Federal Ministry for the Environment on the basis

[10] At €0.37 per kWh in July 2022 Germany has some of the highest retail prices for electricity in the world. Consumer electricity prices have more than doubled since 2002. In July 2022, wholesale prices peaked at a new all-time high. In consequence, some providers started to charge prices of close to €1.00 per kWh. In addition, German low-income households tend to face higher retail prices for electricity than the average German household.

[11] As a result, households learn about their electricity consumption only with significant delay and with little hope of being able to attribute the annual total to specific appliances, such as refrigerators, or consumption episodes, such as hot weather periods.

[12] *Prima facie,* the effect of deadlines is far from clear: (Bertrand et al., 2010) find a negative effect of deadlines on loan take-up among general-population households in South Africa. Shu and Gneezy (2010) and Altmann et al. (2021), on the other hand, find positive effects.

[13] Examples of such comparisons for the general population are interest rate equivalents to changes in deadlines and in advertising content in loan marketing (Bertrand et al., 2010) or monetary equivalents to product information in the purchase of energy-efficient light bulbs (Allcott and Taubinski, 2015).

[14] The impact on costs could plausibly even be negative due to reductions in administrative work load.

[15] To qualify, the household needs to receive one of the following types of federal income support such as unemployment benefits ("Arbeitslosengeld II"), housing allowances ("Wohngeld", "Sozialhilfe"), low pensions ("Grundsicherung"), child supplements ("Kinderzuschlag") or benefits for asylum seekers ("Leistungen nach Asylbewerberleistungsgesetz"), or the household's income must be below the income limit for attachment. In 2020, more than 7 percent of German households qualified on this basis (Bundesagentur für Arbeit, 2020).

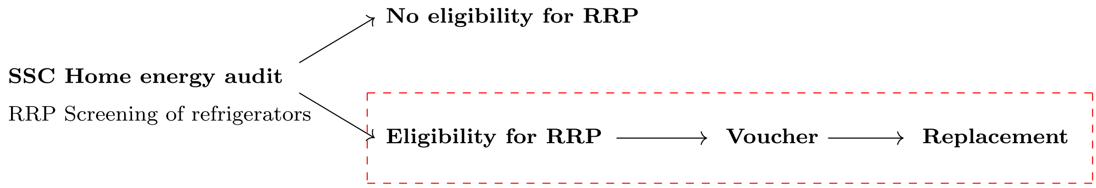

Fig. 1. Sequence of procedures in SSC and RRP.
Notes: Schematic flow chart of the sequence of procedures in Stromspar-Check (SSC) and Refrigerator Replacement Program (RRP). The red box (dashed lines) defines the sample used for the analysis in this paper.

of program grants with a funding cycle of three years, subject to successful (re-)application by the implementing agencies. The RRP was scaled up to its current size with the start of the second funding cycle of the SSC ("SSC plus") in April 2013. The last funding cycle that we observe in the data started on April 1, 2019 and lasted until early 2022 ("SSC active", German: *Stromspar-Check Aktiv*). Recruitment of qualified households into the SSC's home energy audits takes place through a variety of channels.[16] The program has no systematic understanding of how its different channels contribute to overall recruitment, but since 2009, more than 360,000 households have participated in the SSC and undergone, free of charge, a home energy audit by staff employed by one of the local branches.

The typical home energy audit of the SSC consists of two visits to the household by a two-person team within a period of not more than two weeks, with the schedule driven by program logistics and under control of the local branch. During the first visit, the "energy advisors" inventory all electric devices and their usage in the household, collect utility bill information, assess the electricity consumption of refrigerators and freezers, and educate the household on electricity-saving behaviour. Upon return to the branch office, the advisors use the inventory and electricity consumption assessment to screen for eligibility of the household for the RRP. The screening leads to differences in the second visit: Both eligible and non-eligible households receive approximately €70 worth of energy-saving kit.[17] Non-eligible households then exit the SSC. For eligible households, the second visit contains additional components through which they are specifically targeted for enrolment in the RRP.[18]

The rationale for enrolling households in the RRP is the large contribution, roughly 25 percent (BDEW, 2019), that refrigeration appliances make to the electricity consumption of the average German household.[19] Differences in refrigerator efficiency can therefore significantly impact residential electricity bills. To be eligible for enrolment, the low-income household has to own a refrigerator older than 10 years and be expected to save at least 200 kWh annually from a replacement with the most energy-efficient class of devices on the market.[20] The expected savings are part of the information shared with the household at the occasion of the second visit. As we explain below, the specific enrolment procedures changed between 2017 and 2018, but enrolment always concludes with the receipt of a voucher. Enrolled households, i.e., households in possession of a voucher, can redeem their voucher for cash only after meeting a number of criteria. They need to present the purchase receipt; document that the purchased device is of energy efficiency class A+++; and provide proof that the original refrigerator has entered the recycling chain.[21] Households have to handle all steps of the refrigerator replacement on their own, including identifying and selecting a model that fulfils the requirements, pre-financing the purchase, and organizing the logistics of delivering the new and of disposing of the old refrigerator. Fig. 1 provides a flow chart of the sequence of procedures in the SSC and RRP. The red box in dashed lines marks the sample of interest for our analysis.

The RRP is the only federal scheme for replacing refrigerators in low-income households. At the same time, complementary programs exist in four of the sixteen states (*Länder*) and in a number of municipalities.[22] This coexistence of programs is one feature of the policy landscape that requires an appropriate empirical strategy. Another feature are cyclical dynamics at the federal level that are driven by the starting and ending of the funding cycles: Vouchers are cycle-specific and do not carry over from one funding

[16] SSC and RRP are actively promoted in many employment and social assistance agencies across the country through printed and audiovisual material. They are also present with pop-up booths in shopping streets and malls, with active staffers providing individualized education about the program. Some local branches of the social assistance agency mandate the participation of households with excessively high energy bills. The SSC also maintains a website where information is available about the RRP in eleven languages. Additionally, recruitment takes place directly through the local branches.

[17] The kit features LED light bulbs, switchable socket strips, TV standby cut-off switches, timers and water flow regulators. These items are directly installed by the two advisors.

[18] Completion of the first visit is necessary to become eligible for the RRP.

[19] "Refrigerator" refers to refrigerators, freezers, and combination units within the program.

[20] The savings expectations are based on engineering estimates: Based on the inventory data from the first visit, SSC staff use a custom database to calculate expected savings based on a comparison between the current device and a reference device of equivalent size and features that fulfils the A+++ standard, the most efficient class of devices on the EU scale in force between 2009 to 2021. Since March 2021, a revised EU scale has been in force that puts devices previously rated as A+++ predominantly in the classes B, C and D.

[21] A further requirement during the first and second funding cycle up to March 2016 was that the volume and type of the new refrigerator had to be identical with the original refrigerator.

[22] At the level of the federal states, Berlin has offered a complementary subsidy of €50 since December 2020, Saxony-Anhalt of €75 since May 2020, and Hamburg of €100 since September 2010. North Rhine-Westphalia has complemented the federal subsidy with an additional €50 per person (up to €200 per household and up to the purchasing price less €50) since July 2016.

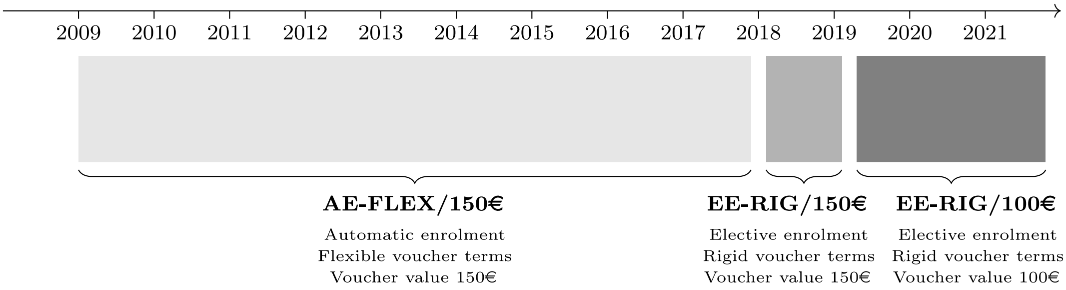

Fig. 2. Timeline of changes in program design.

cycle to the next. As one cycle ends, staff at local branches increase their efforts to encourage enrolled households to redeem their vouchers during the final months of the program. At the same time, enrolment activities cease in the final two to three months before being ramped up again at the beginning of the new cycle.

The policy landscape also gave rise to two unexpected changes in the RRP, one on January 1, 2018 and one on April 1, 2019 (see Fig. 2 for a timeline). The first change, within the third funding cycle of the SSC, simultaneously affected specific procedures of the program, namely the enrolment mode via which households enter the RRP, and the terms of the voucher. The enrolment mode switched from automatic enrolment (AE) until the end of 2017 to elective enrolment (EE) from 2018 onward. Under AE, all eligible households automatically received the RRP voucher on the second visit. Under EE, on the second visit eligible households have been receiving an *invitation to request* a voucher from the local branch. EE hence requires households to take the active step of contacting the local branch and asking for the voucher to be mailed to them. In addition, the terms of the voucher changed: Until the end of 2017, the voucher handed out to all eligible households was valid for three months and renewable for additional periods of three months. From 2018 onward, the voucher has been valid for two months, without the option to renew. The reason for the change from flexible three-month renewable (FLEX) to rigid two-month non-renewable (RIG) terms in January 2018 was the discovery in late 2017 that the combination of an automatic enrolment mode and an implicit right for voucher renewal had left the RRP open to possible oversubscription and a resulting budget shortfall as the funding cycle approached its end in March 2019. As a result of this discovery, the implementing agencies resolved, at short notice, to alter the enrolment mode and voucher terms as an 'emergency brake'.

The second unexpected change, when turning from the third to the fourth funding cycle on April 1, 2019, affected the value of the voucher. Since the start of the RRP in 2009, vouchers had always been worth €150 to a redeeming household. The implementing agencies' 2018 application for the fourth funding cycle starting 2019 foresaw the same voucher value. Instead, the Federal Ministry's funding approval at the end of 2018 cut its support to €100 per replaced refrigerator, the first such change in the history of the RRP.[23]

Taken together, the voucher-based subsidy scheme has therefore experienced three distinct regimes since 2009 (see Fig. 2): A regime *AE-FLEX/EUR150* with automatic enrolment, flexible terms, and a subsidy of €150 up to December 2017, a regime *EE-RIG/EUR150* with elective enrolment, rigid terms and a subsidy of €150 up to January 2019,[24] and – finally – a regime *EE-RIG/EUR100* with elective enrolment, rigid terms, and a subsidy of €100 from February 1, 2019 onwards.

3. Data

Our data include more than 360,000 households that participated in an SSC audit between January 2009 and December 2020 (repeated cross-section). Of these, about 77,000 households were eligible for the RRP, the sample of interest for our analysis (see Figure B.1 in the Appendix for the distribution of audits over the program period). About 20,000 households actually replaced their refrigerator. The take-up rate is therefore around 26 percent (see Table 1: Program variables). This statistic is important: It implies that for three out of four low-income households owning an old and inefficient refrigerator, the efforts of the RRP do not lead to subsidized replacement. At the level of the household, this means a continuation of paying high electricity bills. At the program level, it means that for one successful replacement, the RRP has to bear the costs of screening and enrolling four households. It also means bearing the costs of issuing and administrating thousands of vouchers that go unused.

For each eligible household, the dataset contains demographic information, such as the number of persons in the household, the type of federal income support received, living space, and location by postal code. Documentation from the audit includes the date of the first and second visit, the responsible local branch, auditor IDs, annual electricity consumption and price paid per kWh. For

[23] As a result, the subsidy covered 37% of the purchasing price of the average new refrigerator before and 26% after the change, or 44% and 29%, respectively, when also considering the complementary state programs. See Appendix Figure B.2.

[24] The fourth funding cycle with the new €100 voucher value started on April 1, 2019. Between February 1 and March 31 the RRP paused and no vouchers were issued. Households that underwent a home energy audit during the interim period could request a voucher no sooner than April 1 and thus they received a voucher for €100. Therefore, we set the day for the regime change on February 1, 2019 in our analysis.

Table 1
Descriptive statistics.

	Observations	Mean	Median	Std. Dev.	Min	Max
RRP variables						
Total no. of eligible households (2009–2020)	77,305					
– Automatic enrolment yes/no (2009–2017)	49,182	0.99	1	0.04	0	1
– Elective enrolment yes/no (since 2018)	28,123	0.40	0	0.49	0	1
Voucher redemption yes/no	77,305	0.26	0	0.44	0	1
– Regime AE-FLEX/EUR150 (2009–2017)	49,182	0.26	0	0.44	0	1
– Regime EE-RIG/EUR150 (2018–January 2019)	14,945	0.32	0	0.47	0	1
– Regime EE-RIG/EUR100 (February 2019–2020)	13,178	0.19	0	0.39	0	1
Federal subsidy rate (share of purchase price)	19,909	0.35	0.32	0.16	0.07	1
– Subsidy rate €150 (2009–January 2019)	17,428	0.37	0.34	0.16	0.09	1
– Subsidy rate €100 (February 2019–2020)	2,481	0.24	0.21	0.10	0.07	1
Household variables						
Number of inhabitants	77,305	2.79	2	1.73	1	10
Electricity price per kWh	77,270	0.28	0.28	0.02	0.03	0.90
Living space in square metre	77,305	69.38	65	24.65	11	300
Annual electricity consumption in kWh	71,513	3,021.18	2,571	1,846.97	0	54,329.15
Old refrigerator variables						
Annual consumption in kWh	29,679	479.62	430	6.57	1	5,840
Age in years	77,305	17.30	16	4.69	11	45
Volume in litres	77,305	239.29	238	76.88	37	600
Estimated savings from replacement in kWh	77,305	336.07	286	166.93	0	5,736

AE-FLEX denotes the automatic enrolment mode with flexible voucher terms and EE-RIG denotes the elective enrolment mode with rigid voucher terms. The federal subsidy rate is the share that the federal subsidy accounts for in the purchase price for the new refrigerator. Appendix Figure B.2 shows the distribution of the subsidy rate summing up the federal and, if applicable, the respective complementary state subsidy.

the RRP, status of eligibility, enrolment (i.e. voucher request) and voucher redemption after refrigerator replacement is available. So is information on the old refrigerators, such as age, kWh consumption as measured during the audit, and volume. Finally, the data contain information on the newly purchased refrigerator, including the purchasing price, volume and kWh consumption as specified by the manufacturer.

To prepare the data for the analysis, we remove implausible observations.[25] In households where more than one appliance is marked eligible for replacement we use the first of those as "old refrigerator". For households whose audits were administered by only one advisor (10,505 observations) we introduce an ID in place of the second advisor ID to not lose these observations when introducing auditor fixed effects in the analysis. We also recode implausible refrigerator characteristics as missing. The database truncates values of some variables at a maximum cutoff. This cutoff changes for a few variables over time. We harmonize truncation and set a consistent maximum value over the sample period. Table 1 presents descriptive statistics for the prepared dataset on the sample of eligible households, 77,305 observations in total. On average, eligible households consist of 2.8 household members which live on 69 square metres.[26] Their refrigerators and freezers have an average age of 17.3 years, a capacity of 239 L and consume around 480 kWh annually. For comparison, a state-of-the-art large A+++ combined refrigerator–freezer consumes around 200 kWh annually. The difference of 280 kWh per year, equivalent to around €84, illustrates the energy efficiency gap present in eligible households.

Of the eligible households, 35 percent live together in families with at least one child in the household; more than a third of these families have more than two kids. 29 percent in the sample are single households, with about a third retired. 14 percent are single parent households with one or more children and 6 percent are retired couples. The remaining 16 percent in the sample have a different household composition. Virtually all eligible households are on some type of federal income support: 75 percent receive unemployment benefits, 12 percent basic income,[27], 5 percent a housing allowance,[28] and 4 percent other public benefits.

The RRP measurably reduces the energy bills of households that take up the program: Their average estimated reduction in annual energy consumption between 2009–2020 amounts to 336 kWh (see Table 1), with little trend across the observed period (see Appendix Figure B.5). Replacement refrigerators grow in size over the sample period (see Appendix Figure B.9) while the electricity price paid by target households increases from an average of €0.205 in 2009 to €0.289 in 2020 (see Appendix Figure B.8), mirroring the general trend in Germany. As a result, average savings in electricity bills of replacing households increase from €70 in 2009 to €99 in 2020.[29]

[25] For example, we drop observations that report 0 inhabitants in the household (1884 observations) and observations with a date of the second visit prior to January 1, 2009 (45 observations).

[26] An average German household consists of 2.03 members (Destatis, 2020) and lives on 93 square metres (Destatis, 2018).

[27] Retired households with a pension below the minimal income and households with a reduced earning capacity are entitled to basic income. Unemployment benefits and basic income contain a fixed amount for electricity costs which depends on the number of persons in the households. For instance, in 2022 unemployment benefit "ALGII" grants €36.42 for monthly electricity costs for a single household. ALGII also includes a monthly grant of €1.89 to save as investment into a new refrigerator. Some job centers offer interest-free loans to finance durable replacements.

[28] Households with sufficiently low income qualify for a partial or total grant of their rent costs.

We complement the dataset by a weighted index of cooling appliance prices. We collect data on price indices for refrigerators, freezers, and refrigerator–freezers in Germany (base year 2015) from the Federal Statistical Office (Destatis, 2022) and we weight each index according to the share of each RRP category in all newly purchased durables within the program.[30]

4. Empirical strategy

4.1. Identification

To estimate the effect of varying subsidies and procedures on refrigerator replacement rates, we exploit the temporal variation in the enrolment mode and voucher terms (the procedural change) and in the voucher value (the subsidy change). We consequently observe eligible households making replacement decisions in three distinct regimes. Our identification strategy therefore translates into a pre/post analysis of the procedural and the subsidy change while controlling for as many confounding factors as possible around the regime change. Our main analysis relies on two different econometric approaches – OLS and RD-in-time – that are suitable for such a setting, but address the empirical challenges in different ways.

The OLS analysis provides a comparison in means before and after a regime change, considering all observations in the full sample. The approach controls for potentially time-varying observable confounding factors by considering household characteristics as well as time and local fixed effects. The RD-in-time approach considers observations located close to both sides of the regime change within a certain bandwidth. It can allow for a more flexible form of the underlying model that accounts for the temporal distance of individual observations to the threshold. By restricting the analysis to observations within an appropriate time window around the regime change, confounding factors are expected to be less likely to vary significantly.

The continuity requirements of both OLS and RDD-in-time are threatened by possible selection effects. For continuity to hold, households need to have been quasi-randomly assigned to the three regimes of the program. We have three reasons for a justified belief that selection effects do not compromise our analysis. The first reason is institutional: Both regime changes were unexpected and deviated from the RRP's implementation plan both in terms of substance and timing. Local branches, let alone households, were not given advance information about the discovery of a potential funding shortfall in 2017 or the cut in the federal subsidy at the end of 2018 (see Section 2 for a detailed description). The second reason is empirical: To test formally for evidence that households strategically selected out of or into regimes around program changes, we look for bunching and discontinuities in household observables around the cutoff points. These tests reveal no visual clues for bunching around the thresholds (see Appendix Figures B.10 and B.11), and based on McCrary tests, we cannot reject the hypothesis that there is no bunching around the thresholds (see Appendix Tables A.1 and A.2). We also do not find any discontinuities in household observables (see Appendix Figures B.12 and B.13). The third reason is the dynamic nature of the program: New households become continuously eligible for enrolment into the program as their refrigerators age while the transparent recruitment process and eligibility criteria remain constant over time. If households responded strategically to the regime, the characteristics of households found eligible would be expected to differ across regimes. Instead, we find that the characteristics of RRP-eligible households, including the features of the refrigerator slated for replacement, do not vary strongly over time (see Appendix Figures B.3 to B.7). This supports the notion that there is no evidence for clear selection effects and that observations can be treated as independent.

Irrespective of whether OLS or RD-in-time is used, the empirical strategy has to take into account that the conditions under which households take the replacement decision can vary over time and space. Our approach accounts for a range of temporal and spatial factors: Persistent trends such as rising electricity prices during the sample period, cyclical effects such as seasonal variations in refrigerator prices and seasonally varying household liquidity. Changing conditions on the German refrigeration appliance market do not pose an obvious threat.[31] We nevertheless control for short-term fluctuations in purchase prices using a retail price index by the German Federal Statistical Office. We also account for the presence of complementary programs at the state and municipal level that coexist with the RRP. In addition, temporal and spatial factors inside the program affect replacement decisions: One example are differences between local branches in program practices and differences in audit quality between advisors, even at the same branch. Interim periods between funding cycles and around unexpected program changes similarly need to be accounted for. The relevance of such interim periods is visible in the data. For example, both right around January 2018 and February 2019, when changes are implemented, the share of audited households that are subsequently enrolled into the RRP drops. The drop can be explained by a significant share of eligible households being denied enrolment. At the same time, the share of redeeming households among eligible households inches higher, especially around the procedural change (see Appendix Figure B.14).[32] Both

[29] In January 2022, the average price per kWh paid in Germany further increased to €0.362 (BDEW, 2022) resulting in average annual savings of €123. At these rates at an average purchase price of €478 less the program grant of €100, the investment amortizes after about three years.

[30] Refrigerator–freezers make up 77 percent of all purchased appliances, refrigerators make up 18 percent, and freezers account for 5 percent.

[31] Unit sales (ZVEI, 2023) and purchase patterns (Destatis, 2021) have not changed perceptibly from year to year. Sales figures remain constant between 2015 and 2018, with data for 2019 unavailable. Purchase data from the representative Household Income and Consumption Survey conducted by the German Federal Statistical Office records virtually constant amounts of cooling appliances bought between 2016 and 2019, with data for 2018 unavailable. This is consistent with the absence of reported institutional or regulatory changes on the appliance market.

[32] In the interim period starting around two months before and ending around two months after the implementation of the procedural change, 6,000 households that fulfilled the eligibility criteria did not receive an invitation to join in the program and to request a voucher (consisting of 2423 eligible households before the design change and 3,577 households after, and making up 63 percent of all households that fulfil the eligibility criteria during this period). In the interim period 2 months around the change in subsidy levels, 2,676 eligible households did not receive an invitation to join in the program (consisting of 1,888 households before the change and 788 households after, and making up 53 percent of all households that fulfil the eligibility criteria during this period).

observations suggest a potential bias of selection towards households with a high propensity to replace their refrigerator in the interim period.[33] By controlling for a broad range of factors, we are confident that the assumption of constant treatment effects important for identification in RD designs holds in our setting.[34]

4.2. Specifications

First, we estimate an OLS model that includes the full set of observations (2009–2020) before and after the policy change. The OLS approach both takes into account a set of control variables and fixed effects for energy advisor ID, branch, month and 2-year indicators. We add relevant controls which could influence the individual replacement decision of households, such as the price paid per kWh, the number of persons in the household, the type of income support received, living space, total electricity consumption, the age and size of the old refrigerator, and the calculated savings after replacement.[35] We also add a refrigerator price index as control for changes in refrigerator purchase prices over time.

We estimate the following model separately for the subsidy and procedural variations:

$$Outcome_{it} = \beta_0 + \beta_1 Regime_t + \beta_2 X_i + \gamma_t + \delta_b + \zeta_a + \varepsilon_{it} \tag{1}$$

$Regime$ indicates the current regime as a binary treatment variable: for the change in voucher value, the variable is coded 1 for a €150 and 0 for a €100 subsidy (automatic enrolment and flexible voucher terms in both regimes); for the procedural change, the variable is coded 0 for automatic enrolment and flexible voucher terms, and 1 for elective enrolment and rigid voucher terms (€150 subsidy in both regimes). X is a vector of controls. The subscripts t and i denote time in days and individual households, b denotes the local branch and a the advisor the audit is administered from. We cluster standard errors at the branch level.

Second, we employ an RD-in-time within a bandwidth of nine months.[36] As a robustness check, we illustrate in bandwidth plots how the choice affects the coefficient of interest for both RD estimations for all outcomes in the Appendix (see Figures B.19 to B.22). The running variable $DayCount$ counts the number of days from the program change in both directions. To allow the slope of the linear time trend to vary on both sides of the threshold, we interact the treatment indicator $Regime$ with the running variable. We also add location fixed effects at the branch and advisor level. The first RD specification is estimated according to the following equation:

$$Outcome_{it} = \beta_0 + \beta_1 Regime_t + \beta_2 DayCount_t + \delta_b + \zeta_a + \varepsilon_{it} \tag{2}$$

Standard errors are clustered at the branch level.

Third, we present results of a RD specification that adds a Donut design as proposed by Barreca et al. (2011) and an Augmented Local Linear (ALL) design as proposed by Hausman and Rapson (2018). When applying RD to a setting which is prone to irregularities in the observations closely around the policy change, observations in this period might be better excluded from the sample on each side of the threshold, creating a "Donut hole".[37] We construct a donut that excludes two months of observations on each side of the threshold (program change) as we observe a drop in eligibility rates in this period.[38] The design controls for a potential bias in the selection towards households with a high propensity to redeem the voucher during the interim periods. We additionally apply an ALL design to adjust our outcome variable for location effects, thereby increasing the precision of our estimation. In a two-step approach, we first regress the outcome of interest on location indicators using the full sample (2009–2020). We then use the residuals obtained from this first step as outcome in the second step — the RD estimation (Hausman and Rapson, 2018).[39] We apply ALL using a set of spatial indicators. We control for different practices at the local branches as well as for complementary programs by states, municipalities and local energy providers by including branch indicators and for audits conducted by different advisors by including fixed effects for each of the two advisors who conducted the audit. Combining ALL with the RD specification also mitigates the need for a flexible functional form and diminishes potential concerns for overfitting as the use of higher order polynomials puts high weight on observations far away from the cutoff (Gelman and Imbens, 2019; Hausman and Rapson, 2018).

We estimate the second stage of the ALL-RD as shown in the following equation:

$$Outcome_{it}^{Residuals} = \beta_0 + \beta_1 Regime_t + \beta_2 DayCount_t + \varepsilon_{it} \tag{3}$$

---

33 This is despite the fact that selection into treatment is not biased as bunching and discontinuity tests indicate.

34 Hausman and Rapson (2018) discuss the assumption in the context of RD-in-time and conclude that the threat of violation of the assumption tends to be larger in designs that use bandwidths of several years around policy changes. As we restrict the bandwidth in our estimation to under a year, the threat of violation in our setting should be less severe. As an empirical test, we do not find that the choice of bandwidth strongly affects our estimates.

35 Table A.3 provides a comparison in means for relevant covariates before and after each program change (subsidy level and procedures). The imbalances in some of the variables capture secular changes in the economic environment of the RRP that are exogenous to the program.

36 To test for optimal bandwidth in our setting we follow (Calonico et al., 2017). The test indicates an optimal bandwidth of 206 days (about 7 months) for the estimation of the subsidy effect and 178 days (about 6 months) for the procedural effect. However, we cannot explicitly test the optimal bandwidth taking into account the Donut design we use in our third specification. Therefore, we add two months of bandwidth on top for both RD specifications, which leaves us with a bandwidth of around 9 months for the subsidy estimation and around 8 months for the procedural estimation. For symmetry and comparability, we apply a bandwidth of 9 months for both effects for both RD specifications. Nine months is also the upper bound of available bandwidth for the subsidy effect estimation as the start of the first SARS-CoV-2 lockdown that may have confounded replacement rates puts a ceiling to bandwidth choice.

37 Examples for applications are Ost et al. (2018), Kim and Koh (2020), and Gillingham and Huang (2021).

38 We observed that a significant share of households participating in audits in the interim periods around the program changes does not receive the information letter as invitation to join the replacement scheme, even though these households fulfil the eligibility criteria. We examine the sensitivity of results to this choice in Section 5.

39 Examples for applications of ALL are Li et al. (2020) and Gillingham and Huang (2021).

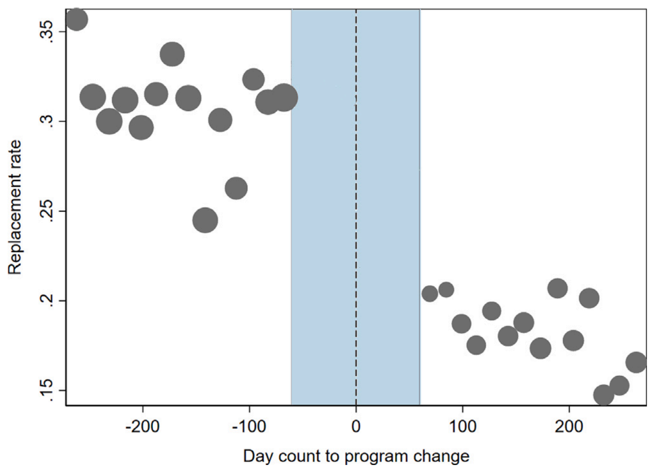

Fig. 3. Subsidy variation, replacement rate: Discontinuity.
Notes: This figure shows the rate of households that successfully complete refrigerator replacement out of all households that are eligible for the RRP around the reduction of the voucher value by €50 on April 1, 2019. Replacement rates are binned and averaged over 15 days in a bandwidth of 270 days around the program change. The blue-shaded area marks the interim period of 2 months around the change. We exclude data points that fall in this period from the analysis in a RD Donut Design (see Figure B.15 in the Appendix for the raw data plot).

where the outcome uses the residuals from the first ALL stage that adjusts for location effects. We bootstrap standard errors to account for the ALL two-step approach, using 500 repetitions.

We estimate Eqs. (1) to (3) for three outcomes of interest:

1. The replacement rate: the share of households that redeem the voucher out of all eligible households. The variable of interest is the binary decision to replace the refrigerator, estimated on the sample of eligible households.
2. The enrolment rate: the share of households that enrol in the program out of all eligible households. The variable of interest is the binary decision to enrol, estimated on the sample of eligible households. We only observe this outcome for the period as of 2018.
3. The redemption rate: the share of households that redeem the voucher at the second stage of the program out of all enrolled households. The variable of interest is the binary decision to redeem the voucher and replace the refrigerator, estimated on the sample of enrolled households. We only observe this outcome for the period as of 2018.

In robustness checks, we systematically test the impact of different specification choices on the RD estimates along four dimensions: inclusion of the Donut design, inclusion of the ALL approach, bandwidth at lower bound of 6 months or upper bound of 9 months, as well as inclusion of an interaction term between the treatment indicator and the running variable. Results are presented in Figures C.2 to C.5 in Appendix A. We find the estimates to be robust in sign and statistical significance across all specifications.

5. Main results

5.1. Subsidy variations

We first investigate to what extent replacement decisions among eligible households respond to a large relative variation in the voucher-based subsidy. Fig. 3 shows the replacement rate around the subsidy change from €150 to €100. Day 0 is February 1, 2019. Negative day counts cover the period when the voucher value is €150, positive day counts the period when the voucher value is €100. Each bubble captures the average replacement rate within a 15-day interval, with larger bubbles signifying more observations. The blue-shaded area marks the interim period of two months around the change. We exclude data points that fall in this period from the analysis in the Donut design. By inspection, replacement rates respond to subsidy levels as expected. They vary around 0.3 for negative day counts: About one in three eligible households elects to enrol and redeems the €150 voucher. For positive day counts, replacement rates vary around 0.2: About one in five households elects to enrol and redeems the €100 voucher. This suggests that the reduction in the subsidy is associated with roughly a 10 percentage point reduction in the share of eligible households replacing their refrigerator. A simple comparison in means for the average replacement rate in the two regimes results in a reduction of 13 percentage points (from 0.32 to 0.19, see Table 1).

Table 2 provides our estimation results across three specifications. All models indicate the treatment indicator of subsidy variation (= 1 for the subsidy of €150, 0 for €100) to be positive, confirming the visual impression of Fig. 3 and the difference in means: Households react to prices, leading to a lower replacement rate after the reduction of the subsidy level to €100. In our preferred specification (column 3) that includes both the Donut design as well as the ALL approach we estimate the replacement rate to be 4.9 percentage points higher for a voucher that has a €50 higher value (p= 0.010). In the more simplified RDD without Donut and ALL,

Table 2
Estimated effect of subsidy variation on the replacement rate.

	1	2	3
Subsidy (€150 = 1)	0.073 (0.027)	0.048 (0.028)	0.049 (0.019)
Day count		Yes	Yes
Day count×Subsidy		Yes	Yes
Location fixed effects	Yes	Yes	
Time fixed effects	Yes		
Controls	Yes		
ALL			Yes
Donut			Yes
No. observations	70,426	16,832	14,890

Notes: Standard errors in parentheses, clustered by branch or bootstrapped (ALL). Location fixed effects include energy advisor ID and local branch. Time fixed effects include month and 2-year indicators. Augmented Local Linear includes advisor IDs and branch indicators. The Donut design excludes 2 months around the program change. Column 1 uses the sample over the sample period 2009–2021. RDD estimates in columns 2 and 3 use the sample of eligible households in a bandwidth of 9 months around February 1, 2019.

the effect is very similar at 4.8 percentage points (p= 0.087). In the basic OLS specification, the effect is slightly larger in magnitude at 7.3 percentage points ($p = 0.008$).[40] In Figure B.19, we show how the treatment effect changes as function of the bandwidth. For models 2 and 3, the effect ranges from 3 (185 days bandwidth, model 2) to 8 percentage points (225 days bandwidth, model 3). In other words, a 33 percent lower subsidy level is associated with a likelihood of appliance replacement that is around 3 to 8 percentage points lower.

We compare whether households that replace their refrigerators with a €150 versus a €100 subsidy change in terms of their observable characteristics (see Table A.5). Households that successfully complete the replacement with the €100 subsidy are smaller but their old refrigerators are larger. The difference seems to be driven by households in NRW that receive additional funding by the state government. Potentially, the lower federal subsidy makes the replacement less attractive for larger households in NRW which had a small own contribution to the purchasing price when the federal subsidy was set at €150.

5.2. Procedural variations

Fig. 4 shows the replacement rate around the simultaneous procedural changes from automatic to elective enrolment and from flexible to rigid voucher terms. Day 0 is January 1, 2018. Negative day counts cover the period when enrolment was automatic and voucher terms flexible, positive day counts the period when enrolment was elective and voucher terms rigid. As before, each bubble captures the average replacement rate within a 15-day interval. The blue-shaded area marks the interim period of two months around the change. We exclude data points that fall in this period from the analysis in the Donut design. By inspection, the average replacement rate lies around 0.25 before the interim period: About a quarter of automatically enrolled eligible households redeem the €150 voucher upon replacing their refrigerator. After the interim period, the replacement rate rises to around 0.3: Around a third of eligible households elect to enrol in the RRP and successfully redeem the €150 voucher with rigid terms. A simple comparison in means for the average replacement rate in both regimes shows an increase of 6 percentage points (from 0.26 to 0.32, see Table 1).

Table 3 provides our estimation results. The specifications are analogous to the estimation of the subsidy effect. We estimate a positive coefficient that is statistically significant in all three specifications ($p = 0.008$, $p < 0.001$ and $p = 0.015$ respectively), confirming the visual impression and the difference in means. In our preferred specification (column 3) including both the Donut design and the ALL, we estimate the effect of changing procedures at 4.2 percentage points.[41] In the more simplified RDD without Donut and ALL (column 2), the effect is larger in magnitude at 15 percentage points.[42] In the basic OLS specification (column 1), the effect is, at 4.6 percentage points, similar to column 3. Figure B.20 shows how the treatment effect changes as function of the bandwidth. For models 2 and 3, the effect ranges from 3 (235 days bandwidth, model 3) to 19 percentage points (170 days bandwidth, model 2). The direction and size of the effect of the procedural variations merit attention, in particular in light of their small, possibly negative costs to the program. Comparing the effects of procedural to those of subsidy variation in a back-of-the-envelope calculation illustrates the merits of alternative program designs: The procedural variation had a positive effect on the adoption of energy-efficient appliances that measured 0.7 to 2.5 times that of a €50 increase in the subsidy.[43] We do however not find both coefficients significantly different from each other at any bandwidth (see Figure B.24 in the Appendix).

We compare whether households that replace their refrigerators under automatic enrolment and flexible voucher terms versus elective enrolment and rigid voucher terms change in their observable characteristics (see Table A.4). Mean comparisons suggest

40 Appendix Table C.2 provides robustness check results in a specification chart and Figure C.1 provides placebo tests.

41 The 2-month bandwidth of the Donut returns conservative estimates of the effect sizes: Narrower bandwidths lead to higher effect estimates that capture more of the transient noise and adjustments around the change. Wider Donut bandwidths also have elevated point estimates and greater variance.

42 Appendix Table C.3 provides robustness check results in a specification chart and Figure C.1 provides placebo tests.

43 The range is based on specification 3. The procedural effect is smallest in comparison to the subsidy effect at 185 days bandwidth and largest at 225 days.

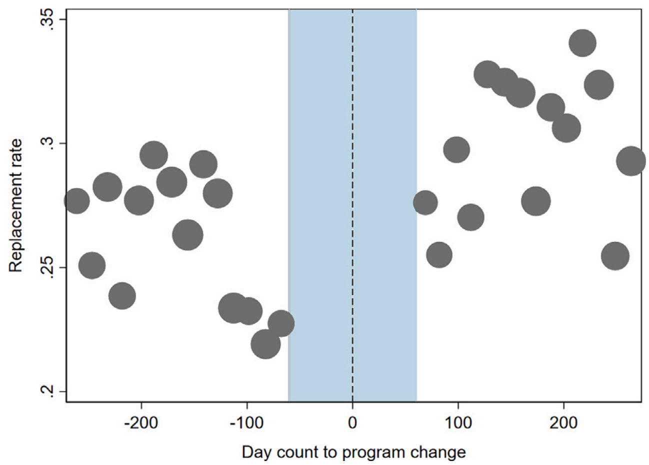

Fig. 4. Procedural variation, replacement rate: Discontinuity.
Notes: This figure shows the rate of households that successfully complete refrigerator replacement out of all households that are eligible for the RRP around the change in program procedures on January 1, 2018. Replacement rates are binned and averaged over 15 days in a bandwidth of 270 days around the program change. The blue-shaded area marks the interim period of 2 months around the change. In our main specification, we exclude data points that fall in this period from the analysis in a RD Donut Design (see Figure B.16 in the Appendix for the raw data plot).

Table 3
Estimated effect of procedural variation on the replacement rate.

	1	2	3
Procedural change (EE-RIG = 1)	0.046 (0.012)	0.150 (0.022)	0.042 (0.017)
Day count		Yes	Yes
Day count×Subsidy		Yes	Yes
Location fixed effects	Yes	Yes	
Time fixed effects	Yes		
Controls	Yes		
ALL			Yes
Donut			Yes
No. observations	70,426	21,534	18,406

Notes: Standard errors in parentheses, clustered by branch or bootstrapped (ALL). Location fixed effects include energy advisor ID and local branch. Time fixed effects include month and 2-year indicators. Augmented Local Linear includes advisor IDs and branch indicators. The Donut design excludes 2 months around the program change. Column 1 uses the sample over the sample period 2009–2021. RDD estimates in columns 2 and 3 use the sample of eligible households in a bandwidth of 9 months around January 1, 2018.

that households that successfully complete replacement under elective enrolment/rigid voucher terms are slightly larger (3.0 vs. 2.9 household members) and possess slightly larger (249 vs. 241 L) and older (18.4 vs. 17.9 years) refrigerators. Their new refrigerators are also larger (268 vs. 259 L) and consequently a bit more expensive (€476 vs. €462) with a higher kWh consumption (142 kWh vs. 139 kWh). Even though these mean comparisons are statistically significant, the magnitude of the differences is small from an economic point of view.[44]

6. Mechanisms

6.1. Subsidy variations: Enrolment and redemption effects

The procedures in place when the subsidy is changed from € 150 to € 100 are elective enrolment and rigid voucher terms. Since RRP records register whether a household enrolled and whether the enrolled households redeemed the voucher, we are able to examine the effect of varying the subsidy on refrigerator replacement more closely by decomposing it into two distinct effects, one at the enrolment stage and one at the redemption stage.

[44] We also check whether procedural change was accompanied by changes in program timing. Comparing the distributions of days passed between the first and second visit under the two regimes (see Figure B.25, the patterns are statistically indistinguishable. This speaks against the conjecture that households managed to alter local branches' timing of the second visit after EE-RIG procedures had been introduced.

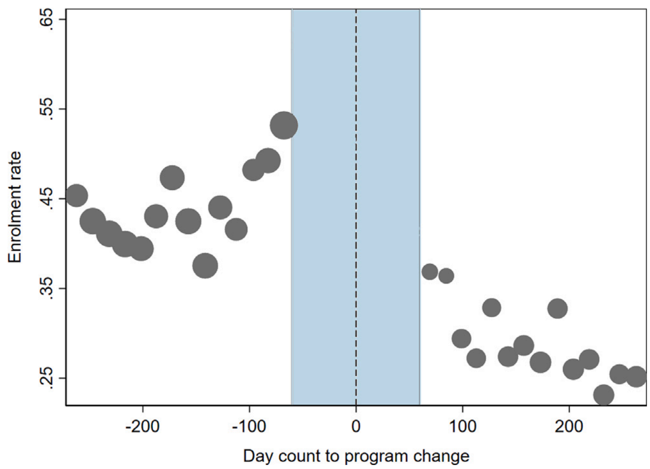

Fig. 5. Subsidy variation, enrolment rate: Discontinuity.
Notes: This figure shows the rate of households that request a voucher for refrigerator replacement and enrol in the program out of all households that are eligible for the RRP over time around the reduction of the voucher value by €50 on April 1, 2019. Enrolment rates are binned and averaged over 15 days in a bandwidth of 270 days around the program change. The light-grey shaded area marks the interim period of 2 months around the change. In our main specification, we exclude data points that fall in this period from the analysis in a RD Donut Design (see Figure B.17 in the Appendix for the raw data plot).

Table 4
Estimated effect of subsidy variation on the enrolment rate.

	1	2	3
Subsidy (€150 = 1)	0.101 (0.032)	0.094 (0.029)	0.088 (0.025)
Day count	Yes	Yes	
Day count×Subsidy		Yes	Yes
Location fixed effects	Yes	Yes	
Time fixed effects	Yes		
Controls	Yes		
ALL			Yes
Donut			Yes
No. observations	70,426	16,832	13,959

Notes: Standard errors in parentheses, clustered by branch or bootstrapped (ALL). Location fixed effects include energy advisor ID and local branch. Time fixed effects include month and 2-year indicators. Augmented Local Linear includes advisor IDs and branch indicators. The Donut design excludes 2 months around the program change. Column 1 uses the sample over the sample period 2009–2021. RDD estimates in columns 2 and 3 use the sample of eligible households in a bandwidth of 9 months around February 1, 2019.

Fig. 5 shows a discontinuity graph for the enrolment stage similar to Fig. 4 for the replacement rate. The key difference is the enrolment rate as the outcome variable, i.e. the share of households that enrol in the program out of all eligible households. By inspection, enrolment rates are around 0.4 before the subsidy change and the interim period (blue-shaded area): Around 40 percent of eligible households elect to enrol in the RRP for a subsidy of €150. After the change in the subsidy and the interim period, the enrolment rate settles around 0.3: Roughly 30 percent of eligible households elect to enrol for a subsidy of €100. During the interim period, enrolment rates are elevated.[45]

Table 4 provides estimation results, using the same specifications as for the replacement rate in Section 5. All specifications show a positive significant coefficient ($p = 0.002$, $p = 0.002$ and $p = 0.003$ respectively), mirroring the results of our descriptive analysis.[46] In our preferred specification in column 3, we estimate the enrolment rate to be 8.8 percentage points higher for a €50 higher voucher value. The other two models produce slightly larger estimates at 9.4 and 10.1 percentage points. In Figure B.19, we show how the treatment effect changes as function of the bandwidth. For a higher subsidy, we observe significantly more households electing to enrol in the program.

The redemption stage of the replacement process is captured in the discontinuity graph of Fig. 6. The key difference to the previous analysis is the redemption rate as the dependent variable, i.e. the share of enrolled households that redeem the voucher.

[45] An important factor in the elevated levels are irregularities in the issuance of the invitation letters to households during the interim period: Despite fulfilling the eligibility criteria, there is evidence of invitation letters being withheld (see the eligibility ratio in Appendix Figure B.14 and explanations in Section 4). This has the effect of decreasing the denominator of the enrolment rate, driving up the enrolment rate.

[46] Appendix Table C.4 provides robustness check results in a specification chart.

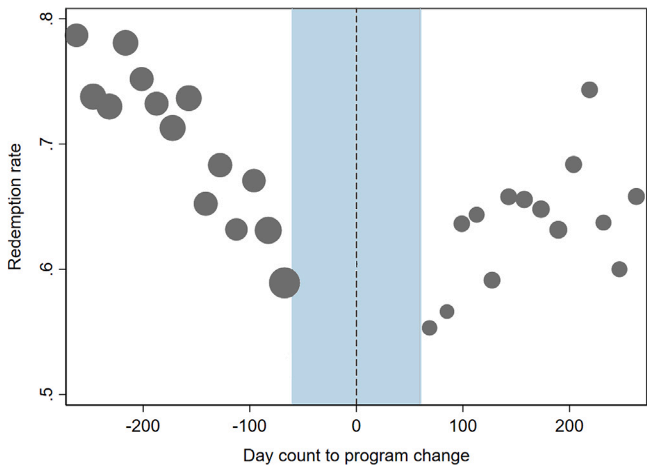

Fig. 6. Subsidy variation, redemption rate: Discontinuity.
Notes: This figure shows the rate of households that successfully replace their refrigerator out of all households that have requested a voucher and enroled in the program over time around the reduction of the voucher value by €50 on April 1, 2019. Replacement rates are binned and averaged over 15 days in a bandwidth of 270 days around the program change. The blue-shaded area marks the interim period of 2 months around the change. We exclude data points that fall in this period from the analysis in a RD Donut Design (see Figure B.18 in the Appendix for the raw data plot).

Table 5
Estimated effect of subsidy variation on the redemption rate.

	1	2	3
Subsidy (€150 = 1)	0.022 (0.034)	−0.021 (0.067)	−0.045 (0.044)
Day count		Yes	Yes
Day count×Subsidy		Yes	Yes
Location fixed effects	Yes	Yes	
Time fixed effects	Yes		
Controls	Yes		
ALL			Yes
Donut			Yes
No. observations	54,434	5,356	18,406

Notes: Standard errors in parentheses, clustered by branch or bootstrapped (ALL). Location fixed effects include energy advisor ID and local branch. Time fixed effects include month and 2-year indicators. Augmented Local Linear includes advisor IDs and branch indicators. The Donut design excludes 2 months around the program change. Column 1 uses the sample over the sample period 2009–2021. RDD estimates in columns 2 and 3 use the sample of households that have requested a voucher in a bandwidth of 9 months around February 1, 2019.

Redemption rates are characterized by considerable variation, both before, around, and after the change in voucher value. By inspection, they lie in the range between 0.5 and 0.8 up to 270 days before the change and 0.5 to 0.66 up to 100 days before: One half to two thirds of enrolled households redeem their voucher for €150 in cash after replacing their refrigerator. After the change, the redemption rates are between 0.50 and 0.75: One half to three quarters of enrolled households redeem their €100 voucher. As a result, there is no clear effect visible at the redemption stage.

Table 5 reports the formal estimation results, using the same specifications as in the previous models. The simple OLS model produces a small insignificant positive coefficient of 2.2 percentage points ($p = 0.529$), while the two RDD specifications produce small negative coefficients of −2.1 and −4.5 percentage points ($p = 0.757$ and $p = 0.297$ respectively) that are insignificant as well.[47] In Figure B.22, we show how the treatment effect changes as function of the bandwidth. For both specifications (columns 2 and 3), the effect remains insignificant across all bandwidths. We find a clear null effect for a higher subsidy value in the second-stage decision, conditional on voucher request. The intuition that households holding a voucher worth €150 rather than €100 are more likely to replace their refrigerator and redeem the voucher has therefore little empirical support.

Combining these insights, the effect of varying the subsidy estimated in Section 5 can be ascribed exclusively to a recruitment effect at the enrolment stage. This finding is relevant from a program management perspective, as we discuss in Section 7.

[47] Appendix Table C.5 provides robustness check results in a specification chart.

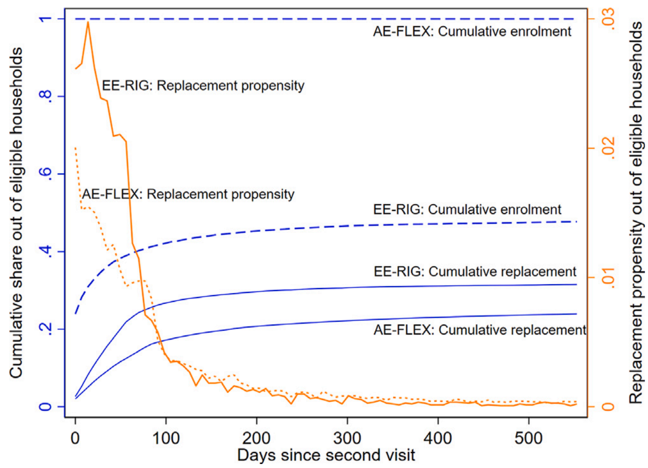

Fig. 7. Behavioural patterns of cumulative replacement and replacement propensities by procedural regime.
Notes: This figure shows the cumulative enrolment and replacement rates on the left-hand y-axis and replacement propensity on the right-hand y-axis for the automatic enrolment mode with flexible voucher terms (AE-FLEX) and the elective enrolment mode with rigid voucher terms (EE-RIG) respectively as a function of days passed since the second home visit. The data for AE-FLEX and EE-RIG cover the periods January 2009 to December 2017 and January 2018 to January 2019 respectively.

6.2. *Procedural variation: Behavioural effects*

To understand more about the mechanisms behind the effect of procedural variation on the success rate of the RRP, we take a closer look at how the behavioural patterns before and after the procedural changes compare.

Fig. 7 shows, as a function of days passed since the second home visit, three temporal patterns, two cumulative (in blue, left scale) and one intensive (in yellow, right scale), under the regimes AE-FLEX/EUR150 and EE-RIG/EUR150. The first cumulative dynamic is the share of enrolled households among all eligible households, the second the cumulative replacement rate among all eligible households. The intensities over time are the replacement propensities among eligible households.

Enrolment before the change is automatic (AE-FLEX): Cumulative enrolment of eligible households (blue, left scale) mechanically jumps to 100 percent on the day of the second visit. After the change, enrolment is elective (EE-RIG): Cumulative enrolment starts at around 20 percent of eligible households that enrol on the day of the second visit and grows at a slowing rate to top out at 44 percent. 90 percent of elective enrolment occurs within 90 days following the second visit. The differences in enrolment patterns mean that under elective enrolment, more than half of eligible households never request the voucher that they would have automatically received under the previous scheme. This removes thousands of households for whom replacement has been determined to be economically advantageous from the pool of potentially replacing households. The sizeable drop in cumulative enrolment can plausibly be traced to selection effects driven by ‘hassle’, time and effort costs when enrolment is elective. Despite their small size relative to the gains from replacement, such costs have been shown to effectively deter households from enrolling in social assistance programs (Bertrand et al., 2006; Bhargava and Manoli, 2015). At the same time, the drop in cumulative enrolment provides important information to the manager of the program, in particular if vouchers are costly to issue and require managers to set aside funds.

The key performance indicator of the RRP is not the enrolment, but the replacement rate. As expected, these rates start at zero for both regimes and grow more slowly than enrolment. Despite the lower cumulative enrolment, the cumulative replacement rate reaches 32 percent of eligible households when enrolment is elective and voucher terms are rigid (EE-RIG). This is consistently higher than under automatic enrolment and flexible terms. There, 24 percent of eligible households replace their refrigerator up to 550 days after the second home visit, most within the 90-day validity period of their first voucher. The reasons for the difference in performance between the two procedural regimes are not obvious. While selection effects are an obvious factor and can explain why cumulative replacement under EE-RIG is *not lower* than under AE-FLEX, additional mechanisms must be at play in order to explain why it is higher.

To dig deeper, we examine the temporal patterns of replacement propensity between the two regimes. Under AE-FLEX, about 2 percent of eligible households replace immediately after the second visit. This points to households having advance notice of their eligibility and awaiting voucher receipt on the second visit for final implementation. Replacement intensity then falls off, before increasing again to 1 percent as the first voucher approaches the end of its 90-day validity period. After that, the decline is fairly rapid, but some replacement activity still takes place long after the second visit. Progressively smaller peaks of replacement activity are detectable after 180 and 270 days, when the second and third voucher deadline approaches. Under EE-RIG, replacement intensity starts at a considerably higher level, indicating more preparedness among households ready to enrol than under AE-FLEX, and first increases, peaking at about 3 percent roughly a month after the second visit. It then falls off, with a shoulder at around 60 days.

This could indicate the expiry of those vouchers that were requested immediately on or following the second visit. After 80 days, replacement intensity under EE-RIG falls below that of AE-FLEX and does not recover.

Comparing these patterns, it becomes clear that the differences in cumulative replacement rates stem from phenomena that arise at and right after the second visit. The typical electively enrolled households replace more vigorously and complete their planned replacement faster than their automatically enrolled counterparts. One candidate explanation advanced by psychologists relates such behaviour to the extensive and intensive margins of goal setting (Locke and Latham, 1990) implicit in the voucher terms. Rigid terms commit the enrolling household receiving the voucher to meeting a two-month replacement goal. Such terms have been referred to as a 'pseudo 'self-set' goal' (Burdina et al., 2017) because the terms are set by an outside agency, but voluntarily adopted by a subset of households wishing to receive the subsidy. Rigid terms have little impact on the median household, but affect the tail end of the distribution. At the extensive margin, such goals lead to a demotivation effect: Individuals who consider the goals set by the outside agency as unattainable do not adopt the goal (Burdina et al., 2017). In the RRP, the change to rigid terms could therefore demotivate those eligible households that consider themselves unable to undertake – within two months – the not insignificant efforts required from themselves to complete all the steps of the RRP. At the intensive margin, there is a counteracting motivation effect: Challenging, but attainable goals lead to a higher likelihood of task completion (Harding and Hsiaw, 2014; Burdina et al., 2017). Related to this argument, voucher terms could be thought of as strengthening the implementation intention by supporting the realization of goal intentions by specifying "when, where, and how goal-directed responses should be initiated" (Achtziger et al., 2008, p.381). This in turn does not only facilitate the starting process but also prevents households from straying from the intended path. In the RRP, some households that would not have completed the replacement within 90 days under the flexible regime could therefore adopt the goal and be more motivated to redeem the voucher within its term limits. This positive effect on the implementation decision can therefore explain the sharper increase in cumulative replacement rates in EE-RIG compared to AE-FLEX within the first 60 days. In addition, we observe a deadline effect in EE-RIG: Approaching the 60 days under the rigid regime leads again to a spike in the redemption probability (see Appendix Figure B.23). These insights highlight the potential to use behaviourally informed procedural changes, such as goal setting, in the future in an effort to target more narrowly the motivation effect detected here.

7. Policy assessment

A key finding of our empirical analysis is that the procedural changes had a similar magnitude of impact on program performance as a €50 subsidy change.[48] This is subject to the qualification that the empirical setting only allows us to measure the impact of the subsidy change after the procedural change has been introduced. A conservative back-of-the envelope calculation of the subsidy increase needed to generate an effect equivalent to the procedural change suggests an additional €35 per household, using the estimate from the least favourable bandwidth choice.

To be useful for policy-makers and program managers, a comparison of effect sizes needs to be extended to considering not only their relative benefits, but also their costs or savings. An exhaustive assessment requires information often not available to the researcher.[49] As an indication, however, consider that lifting the average replacement rate by 5 to 7 percentage points by raising the voucher value from €100 to €150 not only means a higher productivity of each costly home visit conducted, but also raises the cost per replacement by 50 percent. One reason for the limited productivity is the lack of impacts at the redemption stage, as seen in the previous section. The procedural changes, on the other hand, not only boost the replacement rate by 4 to 15 percentage points, but do so at negligible and arguably even negative costs since fewer vouchers have to be issued and kept on the balance sheet.

The estimated effect sizes can also be used for counterfactual program scenarios. One scenario of interest is an alternative setting in which elective enrolment and rigid terms would have been introduced in 2013, right when the RRP was scaled up to its current size. Our point estimates in Section 5 suggest at least 420 additional refrigerator replacements for every 10,000 invitations letters issued to eligible households. Between 2013 and 2017, 48,615 households were found eligible for replacement. Extrapolating the Local Average Treatment Effect from the RD estimation of our main specification while assuming a constant effect over time (4.2 percentage points, 95% CI: [3.9 pp; 4.5 pp]), we conjecture that bringing the procedural change forward to 2013 would have led to at least 2,042 (= 0.042 × 48,615) [95% CI: 1,896; 2,188] additional refrigerator replacements and additional aggregated savings of €201,800 per year.[50]

8. Conclusion

Our paper shows in the context of investment subsidies to low-income households for energy-efficient appliances that even seemingly small and arguably cost-saving procedural changes can substantially substitute for monetary inducements. In this, it adds to a growing literature in behavioural public policy that demonstrates how program design affects program performance. As a novel element, the empirical opportunity of the setting allows to express the impact of these procedural changes in a money metric.

[48] The relative effect size depends on the choice of bandwidth and is smallest at 0.7 with 185 days of bandwidth and largest at 2.5 with 225 days (see Figure B.24).

[49] As an illustration, we were not granted access to detailed information about important cost components of the RRP, such as salaries, measurement costs and database management costs

[50] This calculation uses the average electricity price of €0.289 in 2020 and average annual savings of 342 kWh. This would have led to average additional annual savings of €99 in electricity bills for replacing households, or aggregated annual savings of €201,800.

The rich data made available by RRP management offer a rare glimpse into the 'black box' of consumer durable replacement decisions among the poor. Their analysis allows us to report three main findings. One is the subsidy elasticity of replacement decisions: A 50 percent higher subsidy increases the likelihood of refrigerator replacement by 5 to 7 percentage points, attributable to more households enrolling in the RRP. The second is how replacement rates are affected by procedural changes. These rates are 4 to 15 percentage points higher under elective enrolment and rigid terms than under automatic enrolment and flexible terms, with patterns that are consistent with self-selection and a behavioural mechanisms such as goal setting and time management by households. Our third main finding is that conservatively comparing the subsidy and the procedural variation, the arguably accidental changes in procedures were equivalent – in terms of replacement rates – to raising the subsidy by €35. These numbers give an intuitive metric to the potential of procedural changes to affect program performance. They are also at the basis of our conservative estimate of an additional 2,000 refrigerators that could have been replaced if the new procedures had been in place from 2013 onward. We believe that this finding in particular should be of interest to researchers investigating how best to deliver energy efficiency improvements to low-income households.

Future research can build on these findings in three ways. One is to (re-)evaluate existing programs with a view to uncovering more effects of procedural changes on program performance. Many small changes happen for reasons other than deliberate program optimization. The RRP is a case in point. Such changes may be easily treated as an empirical nuisance in ex-post evaluations of programs or simply be overlooked as seemingly irrelevant. A wider effort to identify procedural changes and to estimate their effects on program success is likely to contribute to a richer understanding of how and why procedures matter for program success.

The second way is to make progress towards theoretically and empirically informed procedural changes. Rather than accidental or driven by expediency, deliberate changes will be progressively informed by evidence that was generated through purposeful experimentation. This evidence should be complemented by careful studies of how changes in procedures affect program costs. For example, in the RRP there was a perception that having fewer vouchers in circulation simplified administrative procedures, reduced workload fluctuation, and required less budget to be set aside to cover possible late redemption. If correct, these changes therefore came at negative cost.

The third way is to explore the optimal integration of economic incentives and procedures for program design. Design optimization was not part of the agenda in RRP. On the basis of results in the marketing literature, however, the conjecture that combining economic and procedural elements in a single program re-design could help boost program performance further appears promising but will need to await future empirical opportunities in order to be tested.

CRediT authorship contribution statement

Bettina Chlond: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Timo Goeschl:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Martin Kesternich:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

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

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jeem.2024.103080.

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