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More money or better procedures? Evidence from an energy efficiency assistance program*

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Abstract

We contribute to the literature on how program design affects program performance among vulnerable groups by studying the effects of varying the subsidy level and program procedures in an energy efficiency assistance program targeting low-income households in Germany. Eligible households receive, upon enrolment, a voucher to subsidize refrigerator replacement. The voucher is redeemed against cash following replacement. Observing the decisions of 77,305 eligible households, our RDD design exploits two quasi-exogenous temporal discontinuities in voucher value and program procedures. We find that a switch from automatic to elective enrolment and more rigid voucher terms reduces the number of vouchers in circulation, but raises the replacement rate among eligible households, the key performance metric, by 4 to 10 percentage points, consistent with psychological theories of goal setting and time management. A subsidy increase of €50 raises replacement rates by 9 to 16 percentage points. The effect of procedural changes is equivalent to an additional €34 in subsidy. Back-of-the-envelope calculations highlight that low-cost changes in procedures that target the behavioral responses of low-income households represent plausible areas of unexploited economies in program design and merit systematic investigation. [184 words]

Keywords: Public behavioral economics, energy efficiency, low-income households, durable replacement, energy poverty, technology adoption.
JEL classification: C25, D15, H23, O33, Q20

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1 Introduction

A growing literature in behavioral public economics examines how program design affects program performance, in particular among vulnerable groups in society. “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]. This literature has begun to uncover how seemingly inconsequential design variations can lead to sizeable changes in program performance, highlighting the importance of psychological co-determinants of program success. Important examples range from procedural hassles in food stamp programs Bertrand et al. [2006] and information provision in school choice Hastings and Weinstein [2008] to variations in tax mailings Bhargava and Manoli [2015] and the local presence of Social Security field offices Deshpande and Li [2019]. To reach the goal of a “science of behaviorally informed program design” however, more work is required. So far, the range of economic decisions and the set of behavioral mechanisms targeted by policy-makers and studied by researchers remain limited. And crucially for coming to a decision on design, the policy-maker lacks as yet a metric for comparing options.

Against this background, we study the effects of varying subsidy levels and program procedures in a nation-wide energy efficiency assistance program targeting low-income households in Germany. The Refrigerator Replacement Program (RRP) subsidizes the modernization of household refrigeration appliances and has been operational in Germany since 2009. There, refrigerators are the consumer durable that accounts for the largest share (about 25 percent) of household electricity consumption [BDEW, 2019].[1] The RRP is embedded in a larger initiative called ”Energy-saving-check” (SSC) being funded by the German Federal 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 SSC home energy audit are used to screen for eligibility for the RRP. Three criteria determine eligibility: Being a recipient of at least

[1] This contrasts with the US experience where air conditioners are the most energy-intensive home durable accounting for 12 percent of total home energy expenditures in 2015 [EIA, 2015]. In Germany, AC units are yet relatively rare.

one of several federal income support schemes; the age of the refrigerator (> 10 years); and expected annual savings from refrigerator replacement of at least 200kWh.[2] In the first twelve years of the RRP's existence, the screening has identified 77,305 eligible households. These households are then 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. On average, 26 percent of eligible households take up the voucher-based subsidy to replace energy-inefficient refrigerators.[3] With average electricity prices of €0.289 in 2020 and average annual savings of 342 kWh, successful refrigerator replacement has led to annual savings in electricity bills of €99.

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 metric of the RRP, not least because of the considerable cost of each home energy audit to the program. Our study is able to examine a number of aspects that can enrich the literature on program design for low-income households. First, our study exploits the fact that after being scaled up to its present size in 2013, the RRP experienced two quasi-exogenous shocks that changed different dimensions of the program design unexpectedly and at short notice. These shocks mean that we observe the RRP in three distinct regimes, one until December 2017, a second from January 2018 to March 2019, and a third from April 2019 onwards. Proceeding conservatively and making use of the rolling nature of the program, we make the case that much of the change in replacement rates across the three regimes can be attributed to changes in program design. This attribution relies on a tailored regression discontinuity design (RDD) framework that takes into account interim periods in the RRP as well as seasonality effects

[2] This translate into minimum savings of approximately €70-99 per year at current retail electricity prices. For more details on the RRP, see section 2.

[3] To put this into perspective, take-up of financial incentives among low-income U.S. households for energy efficiency improvements such as building weatherization is minimal, even when the gains of doing so are high [Fowlie et al., 2015, 2018, Hancevic and Sandoval, 2022]. Comparable 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 led to 1.9 million appliance replacements, among them 1.7 million refrigerators. This corresponds to a take-up rate of around 17 percent [Davis et al., 2014]. A much shorter similar campaign in the US (duration between 1 and 91 weeks, 26 weeks on average) led to 1.8 million appliance replacements, among them 631,561 refrigerators, under much less stringent eligibility criteria [Houde and Aldy, 2017]. There is no estimated take-up rate reported.

and location-specific factors. The RRP therefore constitutes a particularly rich, but also statistically favorable setting to explore the comparative impact of design variations on program performance.

Second, our study exploits the fact that the design dimensions changed by each of the policy shocks were almost orthogonal. One shock changed the level of the cash subsidy that households receive upon replacing their appliance: Since the start of the RRP, the cash value of the voucher had always been set at €150, accounting for on average 37 percent of the purchase price of the new refrigerator. From April 1, 2019, the subsidy fell to €100, a reduction by one third. After the reduction the subsidy accounted for 24 percent of the purchase price. The paper can therefore speak to the effects of large relative changes in financial incentives on program performance among low-income households.[4] The other shock changed program procedures: Since the start of the RRP, enrolment had always been automatic. Every eligible households was enrolled and received the voucher by default. From January 2018, enrolment became elective: Eligible households had to actively enrol by requesting the voucher after the second visit from their local branch. At the same time, the voucher terms changed. Terms had always been flexible: The voucher was valid for three months at a time and repeatedly renewable. From January 2018, voucher terms became rigid: The voucher was valid for two months and not renewable. The paper can therefore speak to the effects of procedural changes on program performance among low-income households, furthering our understanding of how "psychological frictions" [Bhargava and Manoli, 2015] and "hassle" [Bertrand et al., 2006] affect program uptake. This includes new evidence on the effect of deadlines on program performance [Bertrand et al., 2010, Shu and Gneezy, 2010, Altmann et al., 2021], for which – to our knowledge – no specific evidence for low-income households has been available so far. Importantly, we are able to benchmark the effect of these procedural changes against the variation in cash subsidies, providing an intuitive metric of comparison.

Third, this paper extends the range of economic decisions taken by low-income household beyond the typical consumption or income support programs towards their investment decisions. In particular, it adds value to the scarce literature on investment decisions in

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

energy efficiency among low income households [Fowlie et al., 2015, 2018], by presenting the – to our knowledge – first evidence that can explicitly speak to the impact of program design variations on investments in energy efficient appliances. The investment decision at the heart of the RRP constitutes a particularly challenging problem that all owners of energy-intensive consumer durables who pay their own electricity bills have to solve [Rapson, 2014, Wang and Matsumoto, 2021]: Due to wear and tear in use, consumer 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 sophistication, leading to errors in decision-making [Calvet et al., 2009]. Low-income 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 problem and miss optimal replacement points in consumer durables. For German low-income households, mis-timing is particularly costly: At €0.36 per kWh Germany has some of the highest retail prices for electricity in the world,[5] and German low-income households tend to face higher retail prices for electricity than the average household.[6] Despite their exposure, low-income households invest less in energy-efficiency consumer durables [Ameli and Brandt, 2015, Schleich, 2019] and are less responsive to public energy-efficiency programs than the average household [Allcott, 2011, Gillingham and Tsvetanov, 2018]. A further aggravating factor for optimal replacement is the annual billing cycle by German electricity suppliers: Households learn about their electricity consumption only with significant delay and with little hope of being able to attribute the annual total to spe-

[5] Consumer electricity prices have doubled since 2002. In March 2022, wholesale prices peaked at a new all-time high. In consequence, some providers started to charge prices of more than 70 cents per kWh.

[6] Using household data for Germany, Frondel et al. [2019] show that the energy price elasticity for low-income households is low. Andor et al. [2021] report that low-income households are on average less efficient in their electricity use per square meter than wealthy households.

cific appliances, such as refrigerators, or consumption episodes, such as hot weather periods. Taken together, these particular challenges make appliance replacement decisions particularly interesting among the class of economic decisions for which public policies provide support to low-income households.

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 9 to 16 percentage points higher. We believe this is the first evidence on the "subsidy elasticity" of consumer durables replacement among low-income households, and the elasticity is substantial. The estimates underscore both the presence of an effect of economic incentives on RRP performance and its significant scale: Program performance is demonstrably a question of subsidy levels. The data also provide insights into the nature of the subsidy elasticity, which is important to researchers and program administrators. That nature is 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 in the RRP cause replacement rates to rise by 4 to 10 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 behavioral 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 are insufficient, however, for explaining 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 behavioral 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].[7] Jointly, they lead to an intensive-margin effect that more than compensates for the changes in the enrolment mechanism.

Our third result comes from comparing the effects of varying subsidies and varying procedures and using them to conduct back-of-the-envelope calculations of the merits of alternative program design. Such a comparison yields that procedural changes that added little to no cost to the program[8] generated an improvement in replacement rates that was equivalent to an estimated subsidy increase of €12 to €56 per replacing household. This estimate represents for social assistance programs the first estimate of the monetary equivalent of changes in program procedures, complementing similar estimates for loan marketing targeting the general population [Bertrand et al., 2010]. These estimates support our conservative assessment that implementing these procedural changes from 2013 rather than 2018 would have realized 1,900 additional replacements by low-income households at the same budgetary cost, leading to additional savings in electricity bills of €187,800.

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 estimate the effects of the alternative, untried regime. Section 8 concludes.

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[7] *Prima facie*, the impact 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.

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

2 The Refrigerator Replacement Program

Since 2009, the Refrigerator Replacement Program (RRP; German: *Kühlgeräte - Tauschprogramm*) has been offering cash vouchers to households on federal income support[9] 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 from which the RPP draws its population. 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 of program grants with a funding cycle of three years, subject to successful (re-)application by the implementing agencies. The RRP started on January 1, 2009 and was scaled up to its current size with the start of its second funding cycle of the SSC ("SSC plus") in April 2013. The fifth funding cycle started on April 1, 2022 and will last until 2025 ("SSC close-by", German: *Stromspar-Check in Ihrer Nähe*) (see Figure 1 for an overview of the funding cycles).

Recruitment of qualified households into the SSC's home energy audits takes place through a variety of channels. SCC 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 SCC also maintains a website where information is available about the RRP in eleven languages. Additionally, recruitment takes place directly through the local branches. The program has

[9] To qualify, the household needs to receive at least one type 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].

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 initiative 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 around three weeks. During the first visit, the "energy advisors" make an inventory of all electric devices and their usage in the household, assess the electricity consumption of refrigerators and freezers, and educate the household on electricity-saving behavior. The inventory and electricity consumption assessment are used 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 such as 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. Non-eligible households then exit the SSC initiative. For eligible households, the second visit contains an additional component in which they are specifically targeted for enrolment in the RRP through educational material and promotion.[10]

The rationale for enrolling households in the RRP is the large contribution, roughly 25 percent [BDEW, 2019], that refrigerators make to the electricity consumption of the average German household.[11] Differences in refrigerator efficiency can therefore impact significantly on domestic 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.[12] The expected savings are communicated to the household in writing during the second visit. Under the terms of the RRP, enrolled households can redeem their voucher for cash only

[10] Only households that completed the first visit of the home energy audit can become eligible for the RRP.

[11] We use "refrigerator" to refer to both refrigerators, freezers, and combination units within the program.

[12] 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 fulfills 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+++ in the classes B and C. Transitional arrangements are in place both in the retail sector and in the RRP.

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.[13] 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.

The RRP is the only federal voucher scheme for replacing refrigerators in low-income households. At the same time, complementary programs exist in at least four of the sixteen states (*Länder*) and in a number of municipalities.[14] This coexistence of programs is one feature of the policy landscape that requires an appropriate empirical strategy. Another feature of the policy landscape are expected and unexpected program changes at the federal level. Expected changes in the RRP occurred at the end and beginning of each of funding cycle: Vouchers are cycle-specific and do not carry over from one funding 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.

There were also two unexpected changes in the RRP, one on January 1, 2018 and one on April 1, 2019. The first change, within the third funding period of the SSC, simultaneously affected specific procedures of the program, nameley the enrolment mode of the RRP and the terms of the voucher. The enrolment mode switched from automatic enrolment until the end of 2017 to elective enrolment from 2018 onwards. Under automatic enrolment, all eligible households received the RRP voucher on the second visit. Under elective enrolment, eligible households have been receiving on the second visit an *invitation to claim* a voucher from the local branch before purchasing a new refrigerator. Enrolment hence requires households to take an active step. In addition, the terms of the voucher changed at the same time: Until

[13] 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.

[14] At the level of the federal states, Berlin offers 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 complements 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.

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 upon request. From 2018 onwards, the voucher has been valid for two months, without the option to renew. The reason for the change from a flexible three-month renewable to a rigid two-month non-renewable terms in January 2018 was the discovery in late 2017 that a 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. Taken together, the four funding cycles so far constitute a twelve-year history of experience with appliance replacement through a voucher-based subsidy scheme.

3 Data

Our data includes 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 a subsidized refrigerator replacement, the sample of interest for our analysis. About 20,000 households actually replaced their refrigerator. The share of eligible households that successfully participated in the replacement program 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 the state and ZIP code of residence. Documentation from the audit includes the date of the first and second visit, the local branch that administered the audit, the auditors who conducted the first and the second visit, the annual electricity consumption of the household and the price paid per kWh. For the refrigerator replacement program, status of eligibility, enrolment (i.e. voucher request) and voucher redemption after refrigerator replacement is available. Moreover, the dataset contains information on the old refrigerators in the household, such as age, measured kWh consumption and volume. Finally, the data contains information on the newly purchased refrigerator, including the purchasing price, volume and kWh consumption as specified by the manufacturer.

Table 1 presents descriptive statistics for household and old refrigerator characteristics on the sample of for refrigerator replacement eligible households. On average, households eligible for subsidized refrigerator replacement consist of 2.8 household members which live on 69 square meter.[15] Their refrigerators and freezers have an average age of 17.3 years, a capacity of 239 liters 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.

[15] An average German household consists of 2.03 members [Destatis, 2020] and lives on 93 square meters [Destatis, 2018].

Table 1: Descriptive statistics

	Observations	Mean	Median	Std. Dev.	Min	Max
RRP variables						
Total No. of eligbile households	77,305					
– Automatic enrolment (2009 - 2017)	49,182	0.99	1	0.04	0	1
– Elective enrolment (since 2018)	28,123	0.40	0	0.49	0	1
Voucher redemption	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 - March 2019)	14,945	0.32	0	0.47	0	1
– Regime EE-RIG/EUR100 (April 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 (2009 - March 2019)	17,428	0.37	0.34	0.16	0.09	1
– Subsidy rate (March 2019 - 2020)	2,481	0.24	0.21	0.10	0.07	1
Household variables						
Number of inhabitants	77,305	2.79	2	1.74	1	15
Electricity price per kWh	77,270	0.28	0.28	0.02	0.03	0.90
Living space in m^2	77,305	69.37	65	24.65	10	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	77,299	17.31	16	4.76	1	45
Volume in liters	77,299	239.27	238	76.87	37	733
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. Figure 8 in the Appendix shows the distribution of the subsidy rate summing up the federal and, if applicable, the respective complementary state subsidy.

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 another household composition. Close to all eligible households are on some type of federal income support. 75 percent receive unemployment benefits and 12 percent get a basic income.[16] 5 percent receive a housing allowance[17] and 4 percent profit from other public benefits. 3 percent of households in the sample are not on federal income support. The state with the highest population share within the country is prominently represented in the sample: 38 percent of households live in North Rhine-Westphalia. Another third of households live in the states Baden-Wuerttemberg, Hesse, Lower Saxony and Berlin, which are among the eight states with the highest population share in Germany.

The overall aim of the SSC programs is to reduce the financial burden of high energy bills for low-income households. Based on its own data, the average annual savings of households that successfully replaced their refrigerator between 2009-2020 amounted to 342 kWh.[18] Over the same period, the electricity price paid by the households audited in the program increased from an average of €0.205 in 2009 to €0.289 in 2020 (see Figure 27 in the Appendix), mirroring a general increasing trend in electricity prices in Germany. As a result, the savings in the average electricity bill of redeeming household increased from €70 in 2009 to €99 in 2020. 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 an average purchase price of €478 less the program grant of €100, the investment amortizes after about three years. As electricity prices are projected to keep rising, the significance of the potential

16 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.

17 Households with sufficiently low incomes qualify for a partial or total grant of their rent costs.

18 Old refrigerators consume on average 479 kWh. The new refrigerators that replace them consume on average 138 kWh. These figures remain broadly constant across the observed period (see Figure 15 in the Appendix). New efficient refrigerators grow in size over the sample period (see Figure 26 in the Appendix).

savings further increases for low-income households.

Figure 1: Program timeline and audit distribution

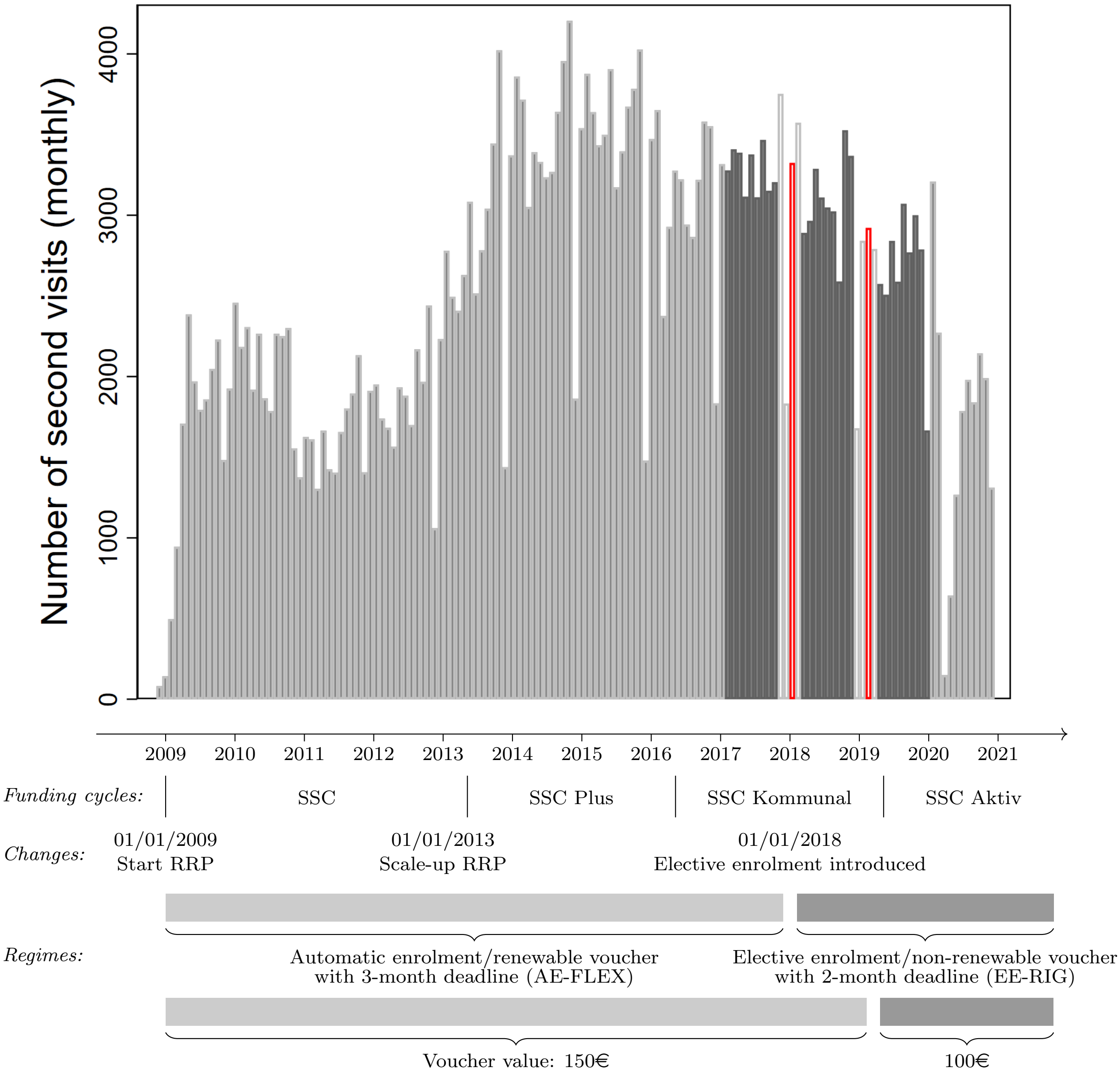


Figure 1 shows the distribution of audits in the program over time, each bar mapping one month from January 2009 to December 2020. The number of monthly audits increases up to 2015 and remains on the high level until it slightly decreases from 2018 on. The dip to zero during the second quarter of 2020 displays the repercussions of the first SARS-CoV-2 lockdown. During the rest of 2020, the number of monthly audits does not yet rebound back to the level of the pre-lockdown months. To estimate the effect of varying procedures and subsidy levels (see red-colored bars in Figure 1), in our main RDD specification we use data from February 2017 to December 2019 (see dark-colored bars) leaving out data in the interim periods directly before and after the program changes (see light-colored bars). Some cyclical fluctuations are visible over the course of each year. The seasonal pattern is particularly pronounced in December, due to the end-of-year and Christmas break at the SSC branches; the month marks the monthly minimum with about a thousand audits less than in the other months each year.

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, 2021] and we weight each index according to the share of each RRP category in all newly purchased durables within the program.[19]

4 Empirical strategy

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) in a Regression Discontinuity Design (RDD) in time. These program changes mean that over the sample period, we observe eligible low-income households making replacement decisions in three distinct regimes: A regime with automatic enrolment, flexible terms, and a subsidy of €150 up to December 2017, a regime with elective enrolment, rigid terms and a subsidy of €150 up to February 2019[20], and – finally – a regime with elective enrolment, rigid terms, and a subsidy of €100 from March 1, 2020 on.

RDD analysis relies on a minimum of two important assumptions about the empirical setting. The first is the absence of selection effects: Households need to have been quasi-randomly assigned to the three regimes of the program. The second is comparability: Re-

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

[20] 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. Therefore, we set the day for the regime change on February 1, 2019 in our analysis.

placement decisions that households took at different points in time and space need to be comparable. On the first, we have three reasons for assuming no evidence for selection bias in the way that households were sorted into the three regimes. 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. The second reason is empirical: To test formally for evidence that households strategically selected out of or into regimes around program changes, we test for bunching and discontinuities in household observables around the cutoff points. These tests reveal no visual clues for bunching around the thresholds (see Figures 15 and 16 in the Appendix), and based on a McCrary test, we cannot reject the hypothesis that there is no bunching around the thresholds (see Tables 9.1 and 9.1 in the Appendix). We also do not find any discontinuities in household observables (see Figures 17 and 18 in the Appendix). 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 detectably over time (see Figures 9 to 14 in the Appendix). This supports the view that there is no evidence for clear selection effects and that observations can be treated as independent.

The comparability assumption is under threat in our setting because the conditions within the program under which households take the replacement decision vary over time and space. To be able to compare replacement decisions, we account for a range of temporal and spatial factors that likely affect households' investment decisions. Such factors comprise changes in the economic environment outside of the RRP such as the persistent increase in German electricity prices during the sample period, the long-run decrease in refrigerator prices during the same period, but also cyclical effects such as seasonal variations in refrigerator prices, seasonally varying household liquidity, and annual adjustments for inflation in federal income support rates at the beginning of each year. We also account for the presence of complementary programs at the state and municipal level that coexist with the RRP and complement the federal subsidy. 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 Figure 19 in the Appendix).[21] Both observations suggest selection to be biased towards households with a high propensity to replace their refrigerator in the interim period.[22]

We ensure comparability of replacement decisions through three strategies that help us to jointly account for the dynamic economic environment that the program is embedded in. First, we employ a Donut RDD as proposed by Barreca et al. [2011]. When applying RDD to a setting which is prone to irregularities in the observations closely around the policy change, observations in this period should be excluded from the sample on each side of the threshold, creating a "Donut hole".[23] Our preferred Donut RDD excludes two months of observations on each side of the threshold (program change). This choice controls for the detected bias in the selection towards households with a high propensity to redeem the voucher during the

[21] 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 2,423 eligible households before the design change and 3,577 households after, and making up 63 percent of all households that fulfill 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 fulfill the eligibility criteria during this period).

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

[23] Examples for applications are Ost et al. [2018], Kim and Koh [2020], and Gillingham and Huang [2021].

interim periods.

Second, we apply an Augmented Local Linear design to control for seasonality and location effects, thereby increasing the power of estimation. In a two-step approach, we first regress the outcome of interest on time and 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 RDD estimation in a bandwidth of 6 to 11 months around the program change [Hausman and Rapson, 2018].[24] We apply Augmented Local Linear using a series of temporal and spatial indicators. We control for different practices at the local branches and changes at each branch over time by including branch and branch-by-year fixed effects, for audits by different advisors by including fixed effects for the advisors who conducted the first and second visit of the audit separately, and for complementary programs by states, municipalities and energy providers by including state and branch fixed effects. To control for seasonal variation in liquidity we include month fixed effects, for adjustments in the income support rates we include year-by-income support type fixed effects. To control more granularly for differences in the socio-economic environment we also include ZIP code fixed effects, and to control for other time trends we include month-by-year and year fixed effects.

Third, we add further explanatory variables to our econometric model to correct for potential differences in the household groups before and after each regime change.[25] 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. We also add a refrigerator price index as control for changes in refrigerator purchasing prices over time.

Our identification strategy uses between-household variation to estimate the effect of the changes in the subsidy level and the procedures on the replacement decision. We estimate

[24] Examples for applications are Li et al. [2020] and Gillingham and Huang [2021].

[25] Table 8 provides a comparison in means for relevant covariates before and after each program change (subsidy level and procedures). Small imbalances in some of the variables are due to changes of variables exogenous to the program, e.g. the refrigerator price index which varies seasonally, and the electricity price per kWh which on average increases over the sample period in Germany, in turn increasing the database estimate for savings after replacement.

the basic RDD equation as follows, separately for the subsidy and procedural variations:

$$Outcome_{it} = \beta_0 + \beta_1 Regime_t + \beta_2 DayCount_t + \beta_3 X_i + \varepsilon_{it} \tag{1}$$

Regime indicates the current regime as a binary treatment variable: 1 for a €150/0 for a €100 subsidy (automatic enrolment and flexible voucher terms in both regimes) or, alternatively, 0 for automatic enrolment and flexible voucher terms/1 for elective enrolment and rigid voucher terms (€150 subsidy in both regimes). *DayCount* is the running variable counting the number of days from the program change. X is the vector of controls. The subscripts t and i denote time in days and individual households.[26] We estimate the equation 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 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 our main specification, we apply the Donut RDD and the Augmented Local Linear as described above. We estimate equation (1) as linear probability model in a bandwidth of six to eleven months around each program change.[27] We bootstrap standard errors, using 50

[26] We choose the most basic linear RDD specification without allowing for a more flexible functional form as this is in line with both the empirical appearance of the data and economic reasoning, and as is practice in many empirical studies [Gelman and Imbens, 2019, Pei et al., 2021].

[27] We choose the minimum bandwidth at $+/-$ 6 months as precision of the estimates is low with a bandwidth below 6 months. The maximum bandwidth of $+/-$ 11 months is determined by data constraints: a longer bandwidth choice for both treatment effects would include observations located inside the interim period of the respective other program change and would bias the estimations.

repetitions. We run robustness checks that estimate the treatment effects for subsamples of only households in North Rhine-Westphalia (NRW) that receive a large amount of additional funding from the state government on top of the federal subsidy, and only non-NRW households. Additionally, we vary the size of the Donut or entirely omit the Donut design, skip the Augmented Local Linear, and estimate a binary probability model instead of a linear probability model.

5 Main Results

5.1 Subsidy variations

We first investigate to what extent replacement decisions among eligible households respond to a €50 variation in the voucher-based subsidy. This variation is large relative to the voucher values of €100 and €150, respectively. It also leads to sizeable variations in the subsidy share as a percentage of the retail price of new refrigerators (see Table 1), from around 37 percent of the price before to around 24 percent after the change. The effect size of the €50 variation, predicted to be significant, positive, and economically meaningful, also provides an intuitive benchmark for gauging the effects of procedural variations in the following section.

Figure 2 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 14 day interval, with larger bubbles signifying more observations. Observations marked in light gray lie in the interim period and are excluded by 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 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).

Figure 2: Subsidy variation, replacement rate: Discontinuity graph

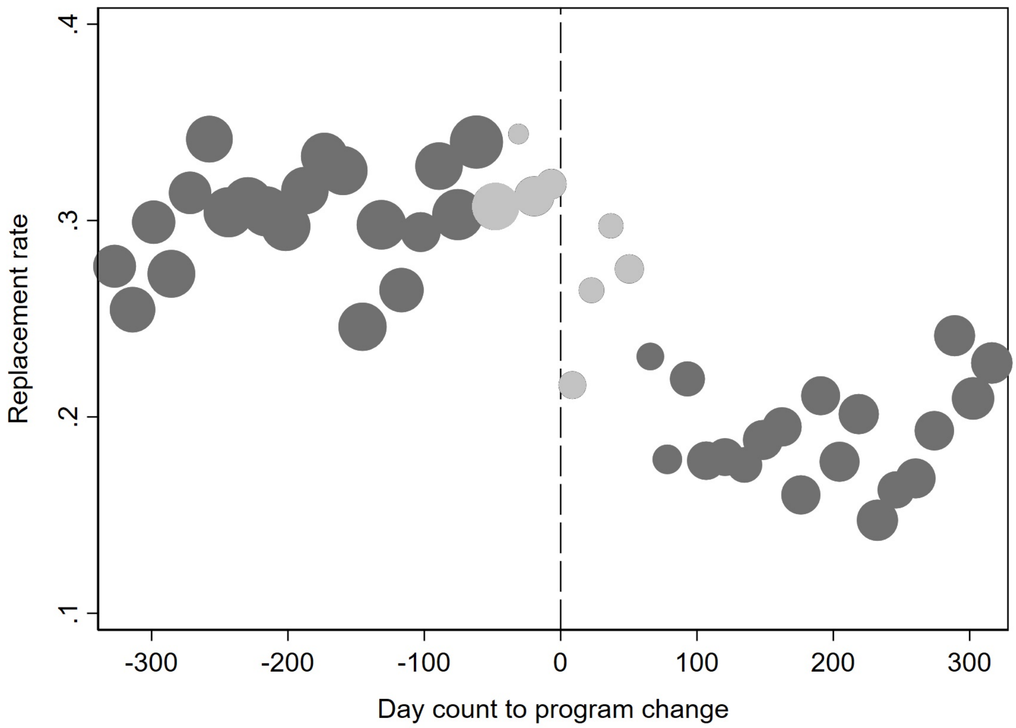


Table 2 provides our estimation results for a bandwidth of six and eleven months, with and without controls. All models indicate the treatment indicator of subsidy variation (= 1 for the subsidy of €150, 0 for €100) to be positive and significantly differ from zero (p<0.001),[28] confirming the visual impression of Figure 2 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 specifications (Columns II and IV) that account for the Donut design, the Augmented Local Linear approach and further control variables we estimate the replacement rate to be 8.7 to 15.8 percentage points higher for a voucher that has a €50 higher value.[29] In other words, a 33 percent percent lower subsidy level is associated with a likelihood of appliance replacement that is 9 to 16 percentage points lower.

[28] Appendix Table 9 provides robustness check results.

[29] Figure 20 in the Appendix shows how the treatment effect changes as function of the bandwidth.

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

	I	II	III	IV
Subsidy variation (€150 = 1)	0.096*** (0.016)	0.087*** (0.022)	0.154*** (0.009)	0.158*** (0.010)
Day count	yes	yes	yes	yes
Controls		yes		yes
Bandwidth in months	6	6	11	11
No. observations	7,222	6,739	16,434	15,401

Notes: Controls include the number of inhabitants, living space, type of federal income support received, kWh price paid, annual electricity consumption, old appliance age, appliance price index and estimated replacement savings. The Donut design excludes 2 months around the regime change. The Augmented Local Linear approach uses month, month-by-year, year, state, branch, branch-by-year, ZIP code and auditor controls. * p<0.05, ** p<0.01, *** p<0.001. Estimated on the sample of eligible households in a bandwidth around February 1, 2019.

5.2 Procedural variations

Against the background of the effect of a €50 variation in subsidy levels, we now turn to the effect of simultaneous procedural changes from automatic to elective enrolment and from flexible to rigid voucher terms.

Figure 3 shows the replacement rate around the procedural change. 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 14 day interval, with larger bubbles signifying more observations. Observations marked in light gray lie in the interim period and are excluded by the Donut design. By inspection, noise is strong inside the interim period. Outside, 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 household 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 results in an increase of 6 percentage points (from 0.26 to 0.32, see Table 1).

Figure 3: Procedural variation, replacement rate: Discontinuity graph

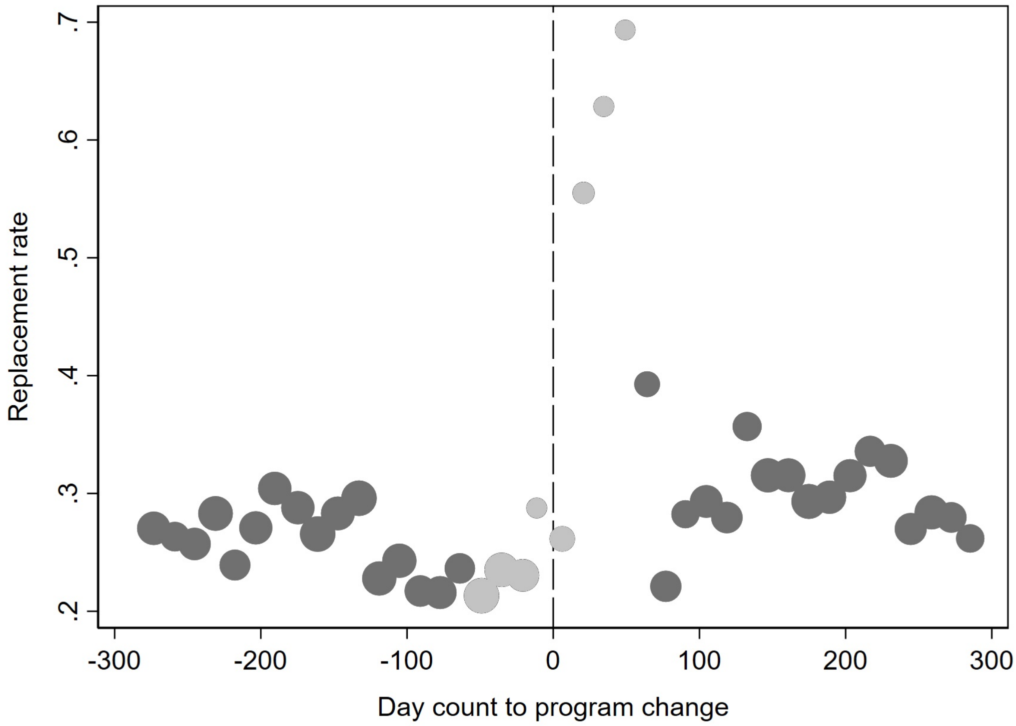


Table 3 provides our estimation results. The specifications are analogous to the estimation of the subsidy effect. We estimate a significant positive coefficient ($p<0.001$) in all four specifications, which confirms the visual impression and the difference in means.[30] Based on our preferred specifications II and IV, we estimate the replacement rate to be 3.9 to 9.7 percentage points higher under elective enrolment with rigid terms compared to automatic enrolment with flexible terms.[31] 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 these effects of varying procedures to those of a variation in a subsidy in a back-of-the envelope calculations stresses the merits of alternative program design. The procedural variations within the RRP appears to stimulate the adoption of energy-efficient appliance among low-income households and to deliver one half to two-thirds of an increase

[30] Appendix Table 12 provides robustness check results.

[31] Figure 23 in the Appendix shows how the treatment effect changes as function of the bandwidth.

that would require a €50 increase in the subsidy.

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

	I	II	III	IV
Procedural change (EE-RIG = 1)	0.095*** (0.016)	0.097*** (0.018)	0.044*** (0.009)	0.039*** (0.007)
Day count	yes	yes	yes	yes
Controls		yes		yes
Bandwidth in months	6	6	11	11
No. observations	9,102	8,539	20,532	19,174

Notes: Controls include the number of inhabitants, living space, type of federal income support received, kWh price paid, annual electricity consumption, old appliance age, appliance price index and estimated replacement savings. The Donut design excludes 2 months around the regime change. The Augmented Local Linear approach uses month, month-by-year, year, state, branch, branch-by-year, ZIP code and auditor controls. EE-RIG denotes the elective enrolment mode with rigid voucher terms. * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Estimated on the sample of eligible households in a bandwidth around January 1, 2018.

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.

Figure 4 shows a discontinuity graph similar to Figure 3 for the enrolment stage. 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 (light gray dots): 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.[32]

Figure 4: Subsidy variation, enrolment rate: Discontinuity graph

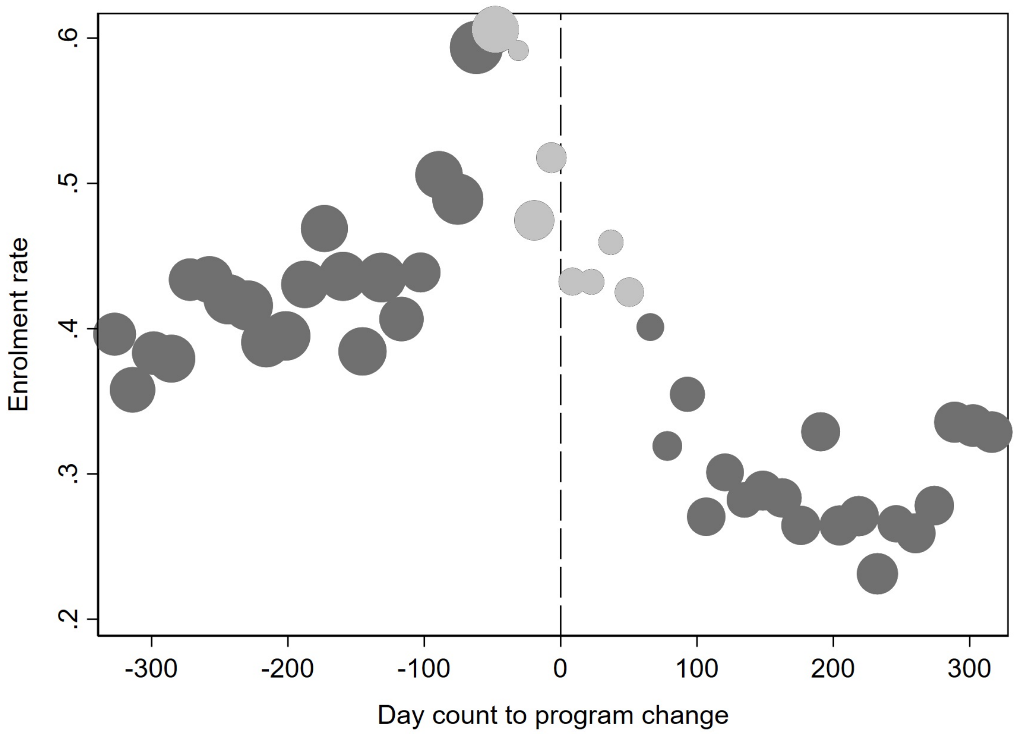


Table 4 provides estimation results, using the same specifications as for the replacement rate in section 5. All specifications show a positive significant coefficient (p<0.001), mirroring the results of our descriptive analysis.[33] In our preferred specifications II and IV, we estimate the enrolment rate to be 24.8 to 24.9 percentage points higher for a €50 higher voucher value.[34] That is, 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 Figure 5. The key difference to the previous analysis is the redemption rate as the dependent

[32] 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 Figure 19 in the Appendix and explanations in the empirical strategy section). This has the effect of decreasing the denominator of the enrolment rate, driving up the enrolment rate.

[33] Appendix Table 10 provides robustness check results.

[34] Figure 21 in the Appendix shows how the treatment effect changes as function of the bandwidth.

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

	I	II	III	IV
Subsidy variation (€ 150 = 1)	0.210*** (0.018)	0.248*** (0.025)	0.225*** (0.011)	0.249*** (0.010)
Day count	yes	yes	yes	yes
Controls		yes		yes
Bandwidth in months	6	6	11	11
No. observations	7,222	6,739	16,434	15,401

Notes: Controls include the number of inhabitants, living space, type of federal income support received, kWh price paid, annual electricity consumption, old appliance age, appliance price index and estimated replacement savings. The Donut design excludes 2 months around the regime change. The Augmented Local Linear approach uses month, month-by-year, year, state, branch, branch-by-year, ZIP code and auditor controls. * p<0.05, ** p<0.01, *** p<0.001. Estimated on the sample of eligible households in a bandwidth February 1, 2019.

variable, i.e. the share of enrolled households that redeem the voucher. Redemption rates are characterized by considerable variation, both before, around (light gray dots), and after the change in voucher value. By inspection, they lie in the range between 0.5 and 0.8 up to 300 days before the change and 0.5 to 0.66 up to 100 days before: One half to two thirds of enrolled household 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 household 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. Only the treatment coefficients in I and II are significant.[35] In our preferred specifications II and IV, we estimate the redemption rate to decrease by 3.1 to 16.5 percentage points for a € 50 higher subsidy level.[36] Intuitively, it could be expected that households holding a voucher worth € 150 rather than € 100 are more likely to replace successfully their refrigerator and redeem the voucher. Statistically, however, the evidence is weak.

[35] Appendix Table 11 provides robustness check results.
[36] Figure 22 in the Appendix shows how the treatment effect changes as function of the bandwidth.

Figure 5: Subsidy variation, redemption rate: Discontinuity graph

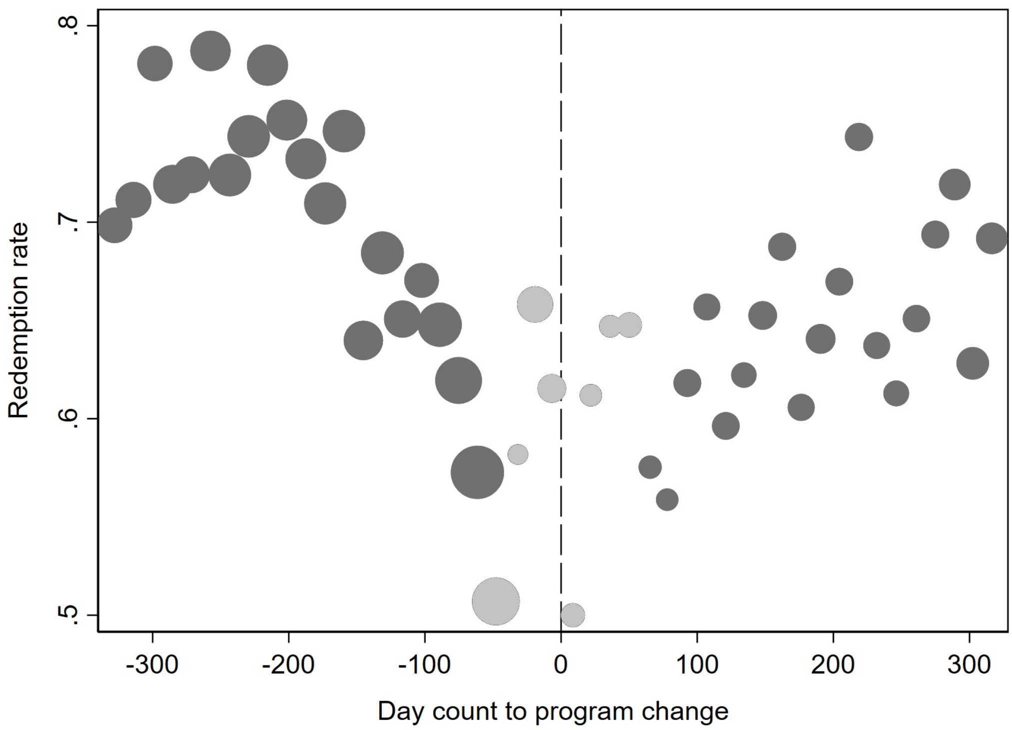


Table 5: Estimated effect of subsidy variation on the redemption rate

	I	II	III	IV
Subsidy variation (€150 = 1)	-0.093** (0.034)	-0.165*** (0.038)	0.008 (0.022)	-0.031 (0.022)
Day count	yes	yes	yes	yes
Controls		yes		yes
Bandwidth in months	6	6	11	11
No. observations	2,774	2,617	5,955	5,616

Notes: Controls include the number of inhabitants, living space, type of federal income support received, kWh price paid, annual electricity consumption, old appliance age, appliance price index and estimated replacement savings. The Donut design excludes 2 months around the regime change. The Augmented Local Linear approach uses month, month-by-year, year, state, branch, branch-by-year, ZIP code and auditor controls. * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Estimated on the sample of households that have requested a voucher in a bandwidth around February 1, 2019.

Combining these insights, our data suggests that out of the two candidate mechanisms, one at the enrolment and one at the redemption stage, only one is operational. This means that the effect of varying the subsidy estimated in section 5 is predominantly a recruitment effect at the enrolment stage. Reducing the value of the voucher from € 150 to € 100 results in a lower propensity among eligible households to elect enrolment by requesting the voucher. Once households hold the voucher, its cash value no longer reliably influences the chance that the household will actually replace the refrigerator. This finding demonstrates that the economic incentive did not succeed at every margin of decision-making.

6.2 Procedural variation: Behavioral 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 behavioral patterns before and after the procedural changes compare.

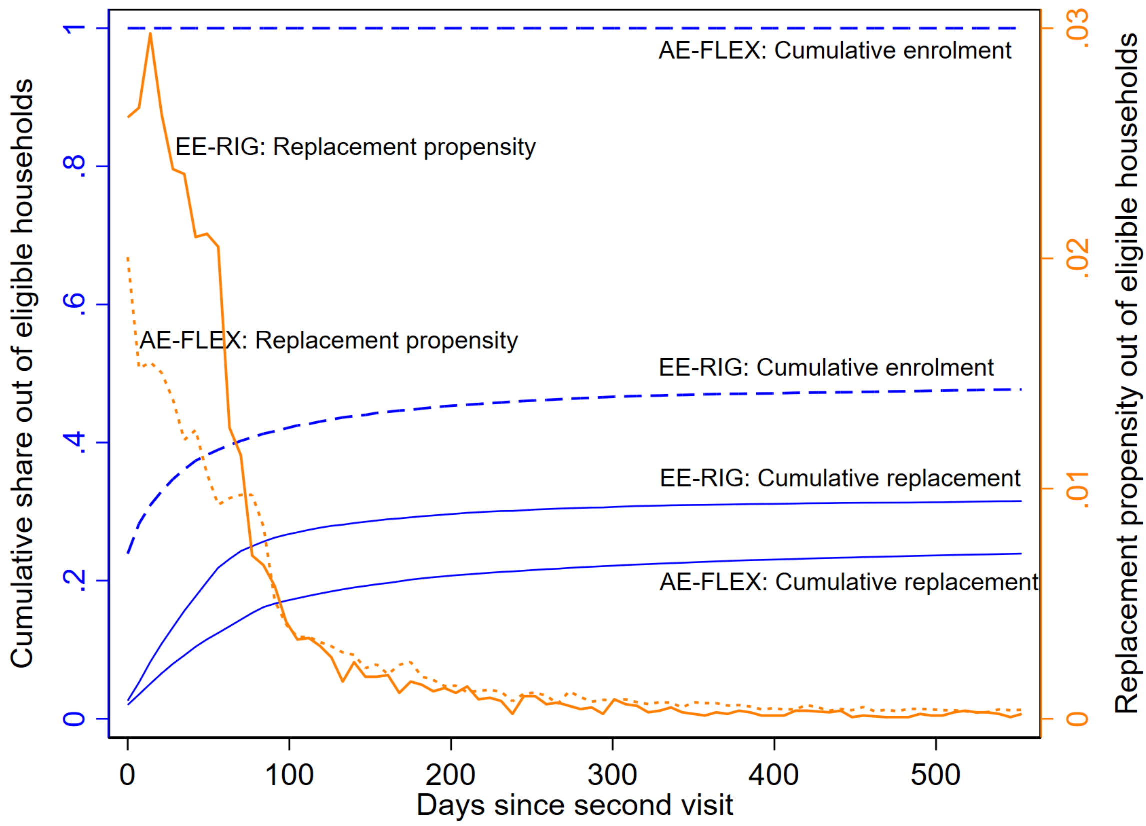
Figure 6 shows, as a function of days passed since the second home visit, three temporal patterns, two cumulative (in blue, left scale) and one intensive (in yellow, right scale), under two regimes, automatic enrolment and flexible terms (AE-FLEX), and elective enrolment and rigid terms (EE-RIG). The 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). As a result, 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 plausible be traced to 'hassle' costs of overcoming psychological frictions, 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 metric 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 could trivially 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. 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 expire. 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

Figure 6: 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.

below that of AE-FLEX and does not recover.

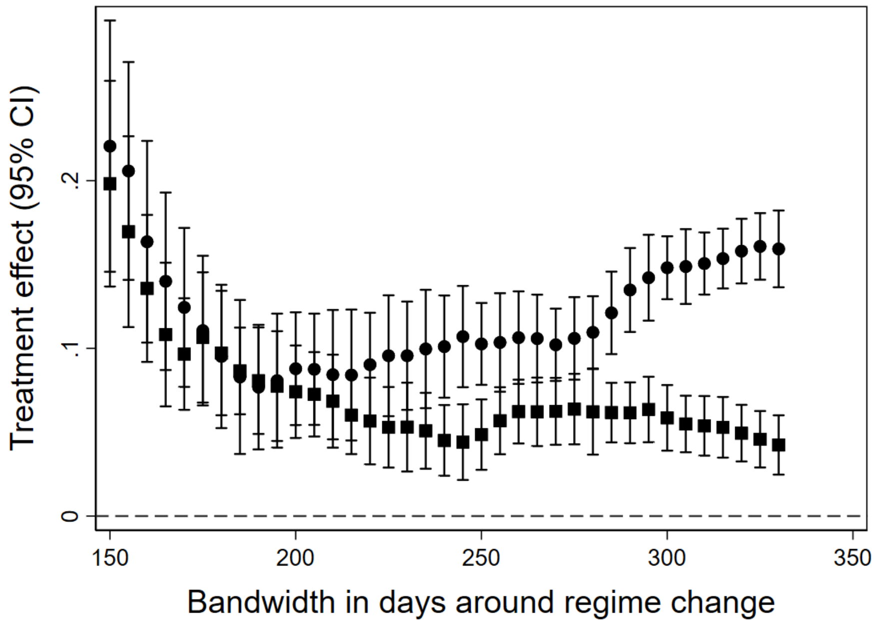
Comparing these patterns, it becomes clear that the differences in cumulative replacement rates stem from phenomena that arise at and right after the second visit. The typical electively enrolled households replace more vigorously and complete their planned replacement faster than their automatically enrolled counterparts. One candidate explanation advanced by psychologists relates such behavior 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 can also sharpen the implementation intention to support 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 to stray 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 Figure 24 in the Appendix).

These insights highlights the potential to use behaviorally informed procedural changes, such goal setting, in the future in an effort to target more narrowly the motivation effect detected here.

7 Policy assessment

In this section we discuss the economic magnitude of our estimates in a stylized back-of-the envelope calculation. To do so, we discuss the benefits of both the change in the subsidy levels and the procedures against the cost of implementation. As shown in Figure 7, a direct comparison of the treatment effects reveals the subsidy variation to be up to four times but at least as effective as the procedural variation to stimulate additional refrigerator replacement. The relative difference depends on the choice of bandwidth.

Figure 7: Comparison of subsidy and procedural variation effects on the replacement rate



Notes: This figure shows the estimate of the subsidy (dot) and the procedural effect (square) for different bandwidth choices. The estimates are based on specification IV in Tables 2

The direct comparison in size has to be evaluated against the background that the procedural variation is considerably less costly to implement. A change in the subsidy level from €100 to €150 increases the average replacement rate by 9 to 16 percentage points. The higher voucher value increases efficiency of each conducted home visit since the probability of replacement increases, so that the net benefit per home visit rises.[37] But implementation of the change in the subsidy increases the cost per replacement by 50 percent. In addition, as shown in the results section, a higher subsidy level predominantly affects uptake at the enrolment stage: More households request a voucher but the share of successfully redeemed vouchers does not increase which in turn leads to higher administrative costs per replacement. Efficiency of the subsidy variation would be higher if it affected households at the redemption stage.

In comparison, the procedural changes boost the replacement rate by "only" 4 to 10 percentage points. In contrast to the subsidy variation it comes with close to zero additional costs or even reduces the administrative cost of the program: Less vouchers have to be kept track of and kept on the balance sheet. The estimates of the procedural change (4 to 10 percentage points) and the subsidy variation (9 to 16 percentage points) can be used to conduct a back-of-the envelope calculation of the subsidy increase needed to generate an equivalent effect. This calculation yields that the subsidy would need to be increased by €12 to €56 per replacing household, with a best estimate of €34, in order to improve the replacement rate by the same amount as the procedural changes.

In addition to this comparison, we can use our estimates for a counterfactual program scenario. We ask to what extent energy efficiency programs for low-income households using voucher-based subsidies, which – in contrast to the SSC program – have not yet introduced elective enrollment and rigid terms, could have increased the number of replacements. Our point estimate for the EE-RIG implementation suggests at least 400 additional refrigerator replacements for every 10,000 invitations to claim a voucher with rigid terms for such programs. Applied to our observation period since RRP scale-up (2013 – 2017) and assuming a constant treatment effect over time (4 to 10 percentage points) [95% CI: 3.2 pp; 11.5 pp][38] we calculate elective enrollment and rigid terms to have led to at least 1,900 (= 0.04 x 48,615) [95% CI: 1,556; 5,591] additional refrigerator replacements. At an average electricity prices

37 We cannot precisely quantify the replacement program's cost (recording refrigerator information and reporting it in the database, generating the invitation letter, handing it to the household and explaining the details of the replacement process) as the share of the cost of home visits.

38 We provide the lower and upper bound of the 95% confidence interval of the low and high estimate respectively.

of €0.289 in 2020 and average annual savings of 342 kWh, this would have led to additional savings in electricity bills of €187,800.

8 Conclusion

A growing literature in behavioral public policy has lately been demonstrating how program design affects program performance, in particular for policies targeting low-income households. Our paper adds to this literature by studying – in the form of investments in energy-efficient appliances – a type of household decision that differs from the labor supply or consumption decisions typically examined. This study benefits from empirically favorable circumstances: Not only were the changes in program design quasi-exogenous, they also varied both subsidy levels and procedures separately. As a result, our paper cannot just speak to the impact of each variation on program performance individually, but also how variations along these two dimensions compare. To our knowledge, such evidence has so far not been available in the literature.

Over its lifetime so far, the national Refrigerator Replacement Program in Germany has amassed twelve years (2009 - 2020) of data from over 77,000 eligible low-income households making a replacement decision about the most energy-intensive home appliance through a voucher-based subsidy program. In combination with the changes in subsidies and procedures, these data offer a rare glimpse into the 'black box' of consumer durable replacement decisions among the poor under three different program design regimes. As a result, we have three main findings. One is the first evidence on the subsidy elasticity of replacement decisions: A 50 percent higher subsidy increases the likelihood of refrigerator replacement by 9 to 16 percentage points. We can attribute this effect to changes exclusively at the extensive margin of the program: More households enrol in the program when the subsidy is higher, but the same share of enrolled household replaces their refrigerator. The second is the evidence on how replacement rates are affected by procedural changes. These rates are 4 to 10 percentage points higher under elective enrolment and rigid terms than under automatic enrolment and flexible terms. This overall change consists of a drop at the enrolment stage from 100 percent to 40 percent of eligible households combined with an increase in redemption rates strong enough such that cumulative replacement rates after the changes outperform those before for every point in time following the second home visit. Additional observational evidence points to households entering the RRP more prepared and accelerating replacement as the fixed deadline approaches. Such patterns are consistent with a behavioral interpretation that the procedural changes facilitated goal setting by households and helped overcome time management problems.

Our third main finding is that, comparing the subsidy and the procedural variation, the accidental changes in how to enrol households and what voucher terms to set were equivalent – in terms of replacement rates – to raising the subsidy by between €12 and €56. 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 1,900 refrigerators that could have been replaced if the new procedures had been in place from 2013 onwards. 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.

In our mind, the novel evidence on the comparative impact of procedural changes on program performance has implications for future research for three reasons. One is that our results make it more likely that (re-)evaluations of existing programs will also uncover effects of procedural changes on program performance. Many small changes in procedures happen for reasons other than deliberate program optimization. The RRP is a case in point. There, unexpected budgetary considerations of the program sponsor and sudden realization of problematic implications of current procedures for budgeting were the main drivers. 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 greater understanding of how and why procedures matter for program success.

The second reason is that our evidence highlights the potential of the economics of program design benefiting from progress towards theoretically and empirically informed procedural changes. Changes that are accidental or driven by expediency should over time give way to deliberate changes. These 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 voucher 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 joint presence of accidental procedural changes delivering both unanticipated performance improvements and unanticipated cost savings leads us to believe that the economics of program design retain the potential to make significant contributions to behavioral public policy.

The third reason why the evidence presented here can inform future research is that it highlights an unexplored dimension of program design. This dimension is how to optimally integrate economic incentives and procedures for program design. When the subsidy and the procedural variations were introduced in the RRP, design optimization was not part of the agenda. 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.

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9 Appendix

9.1 Tables

Table 6: McCrary Test results: procedural variation cutoff

Procedural variation (EE-RIG = 1)	-1,392.44 (1,818.82)	-379.58 (597.64)	-1,003.81 (771.83)	-285.94 (171.30)	-153.20 (198.25)	-399.03 (266.33)	-319.24 (194.38)
Bin size	50	25	25	25	10	10	10
Bandwidth in days	150	150	100	50	150	100	50

Notes: We conduct the McCrary Test [McCrary, 2008] for different bin sizes and bandwidths around the cutoff on January 1, 2018 when the subsidy level changes.

Table 7: McCrary Test results: subsidy variation cutoff

Subsidy variation (€ 150 = 1)	901.097 (1,369.933)	527.033 (341.001)	236.981 (353.834)	463.678 (54.090)	183.923 (94.996)	60.653 (107.208)	136.028* (54.090)
Bin size	50	25	25	25	10	10	10
Bandwidth in days	150	150	100	50	150	100	50

Notes: We conduct the McCrary Test [McCrary, 2008] for different bin sizes and bandwidths around the cutoff on February 1, 2019 when the enrolment procedure and voucher terms change. EE-RIG denotes the elective enrolment mode with rigid voucher terms.

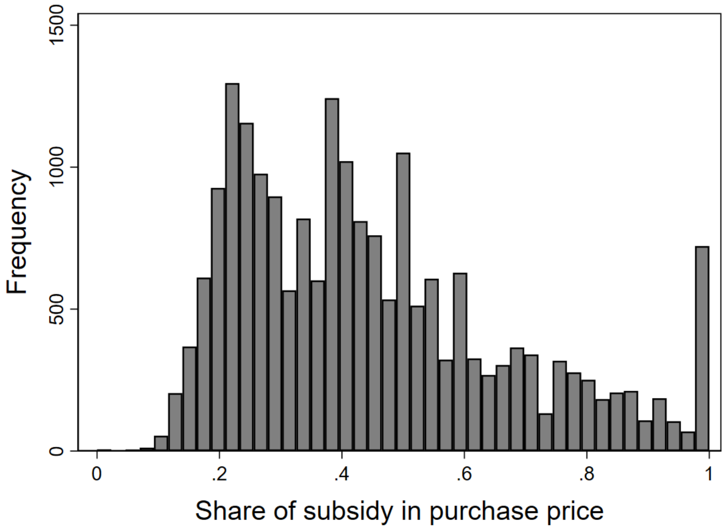
Table 8: Mean comparison of covariates before and after regime changes

	Procedural variation		
	Mean before Jan 2017 - Dec 2017	Mean after Jan 2018 - Dec 2018	Difference
Household variables			
No. inhabitants	2.886	2.967	-0.083***
Living space in m^2	69.830	70.557	-0.727*
Electricity price per kWh	0.276	0.276	-0.0001
Annual electricity consumption in kWh	3,053.508	3,069.962	-16.454
Old refrigerator variables			
Age in years	17.624	18.214	-0.590***
Volume in liters	239.618	245.750	-6.132***
Estimated savings from replacement	329.040	341.715	-12.675***
Price index cooling appliances	95.826	95.370	0.456***

	Subsidy variation		
	Mean before Feb 2018 - Jan 2019	Mean after Feb 2019 - Jan 2020	Difference
Household variables			
No. inhabitants	2.975	3.014	-0.039
Living space in m^2	70.662	70.662	-0.0004
Electricity price per kWh	0.276	0.279	-0.003***
Annual electricity consumption in kWh	3,068.515	3,030.006	38.509
Old refrigerator variables			
Age in years	18.241	17.209	1.032***
Volume in liters	245.945	254.001	-8.056***
Estimated savings from replacement	341.438	330.333	11.105***
Price index cooling appliances	95.375	96.321	-0.947***

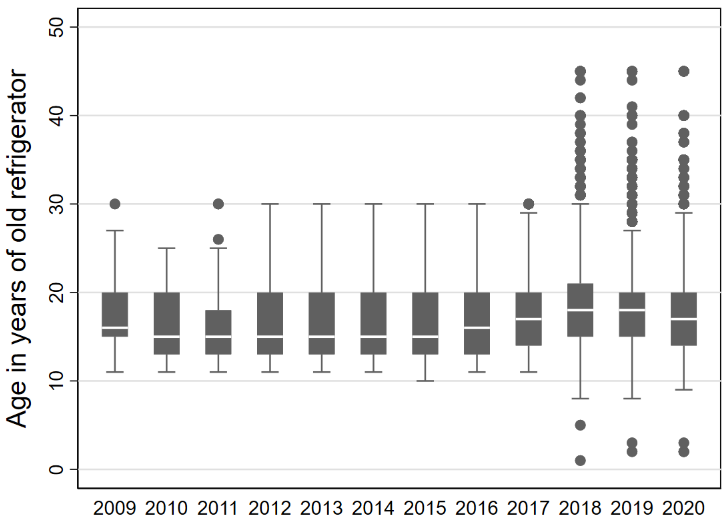
9.2 Figures

Figure 8: Share of subsidy in purchase price of new refrigerator



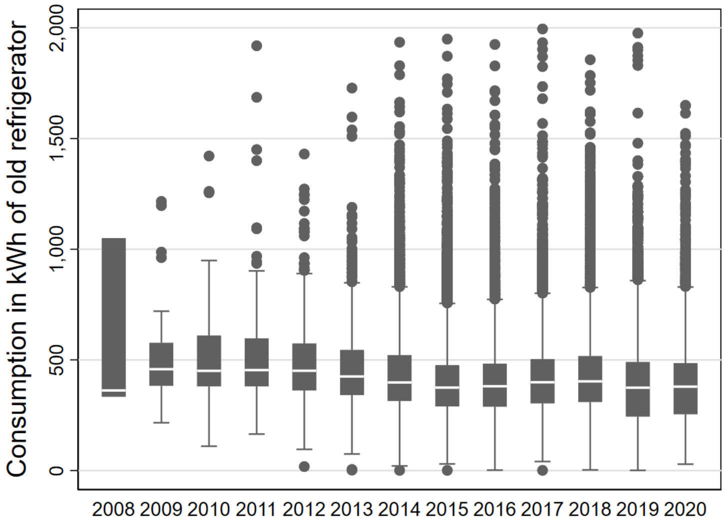
Notes: This figure shows the share that the replacement subsidy covers of the total purchase price of the new refrigerator. The subsidies considered here include the federal subsidy of €150 up to 2017 and €100 as of 2018 respectively as well as the complementary programs by four state governments as listed in section 2.

Figure 9: Age in years of old refrigerators



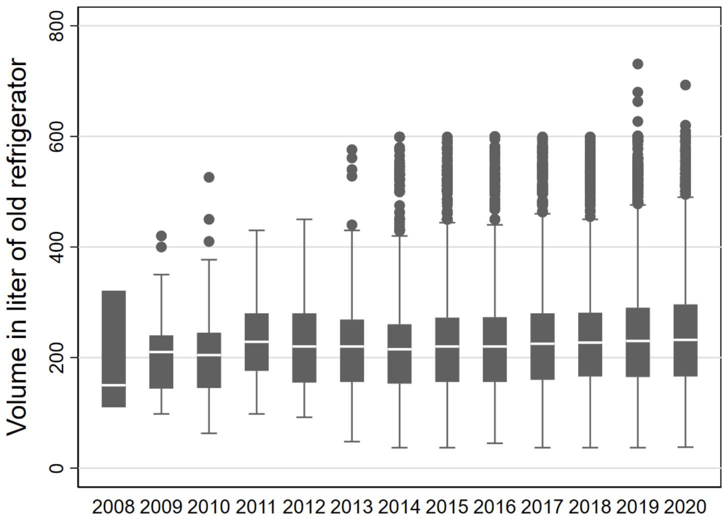
Notes: This figure shows the age distribution of old refrigerators for each year in the sample period separately. The upper end of the distribution is truncated at 30 years up to 2017, and at 45 years after. Note that in the years 2018-2020, 13 refrigerators were marked for replacement although they were younger than 10 years. The figure was created with the sample of for replacement eligible households.

Figure 10: KWh consumption of old refrigerators



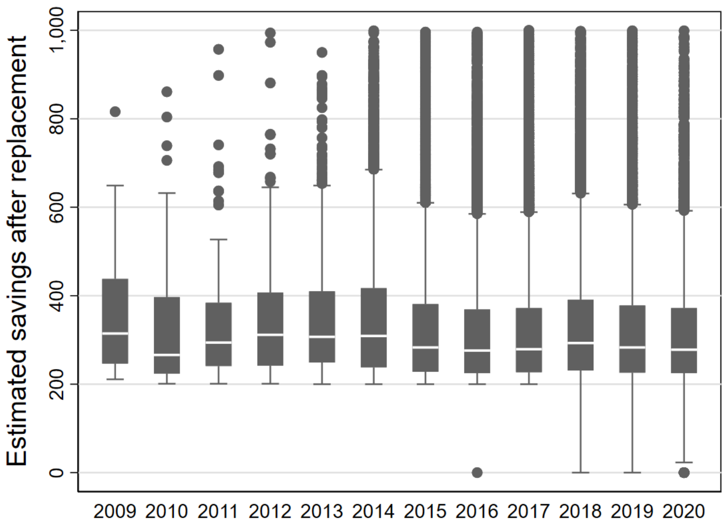
Notes: This figure shows the consumption distribution of old refrigerators in kWh for each year in the sample period separately. Note that a few outliers lie above 2,000 kWh which we omit in the figure. The figure was created with the sample of for replacement eligible households.

Figure 11: Volume in liters of old refrigerators



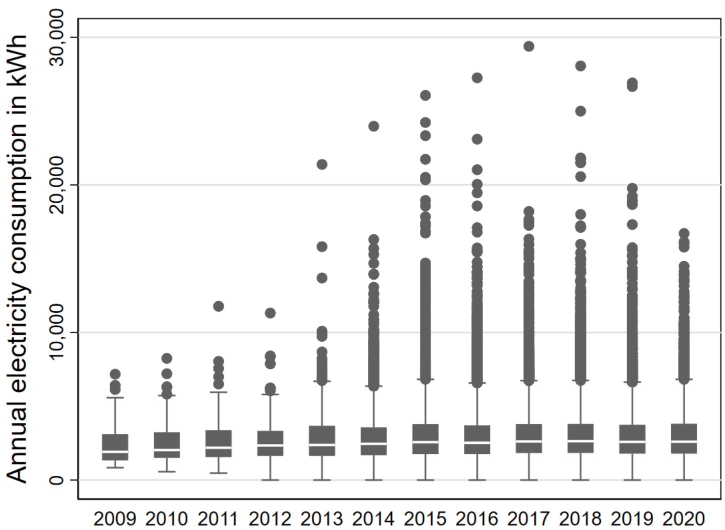
Notes: This figure shows the volume distribution of old refrigerators in liter for each year in the sample period separately. The figure was created with the sample of for replacement eligible households.

Figure 12: Estimated savings after replacement



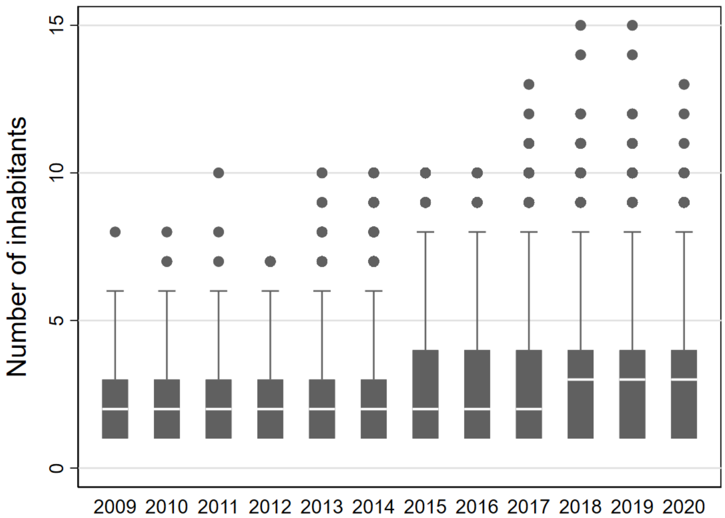
Notes: This figure shows the distribution of estimated savings after replacement for each year in the sample period separately. Note that a few outliers lie above 1,000 kWh which we omit in the figure, and that in the years 2016-2020, 19 refrigerators were marked for replacement although their replacement would have saved these household less than 200 kWh annually according to the estimate. The figure was created with the sample of for replacement eligible households.

Figure 13: Annual electricity consumption of households



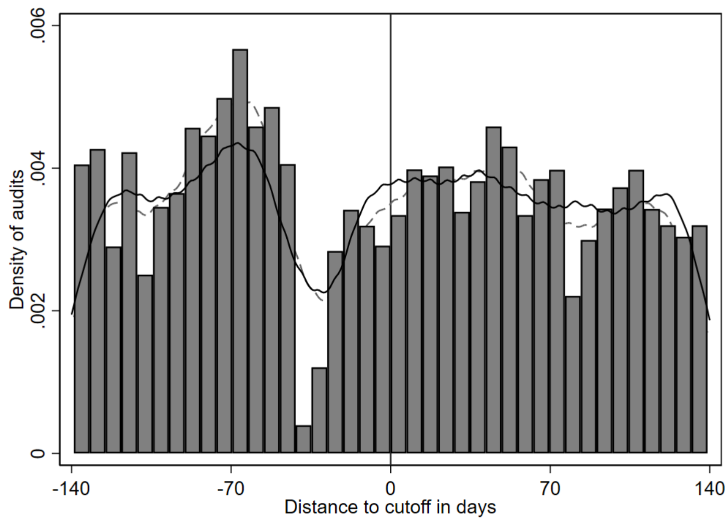
Notes: This figure shows the distribution of the annual electricity consumption of households for each year in the sample period separately. The figure was created with the sample of for replacement eligible households.

Figure 14: Household structure



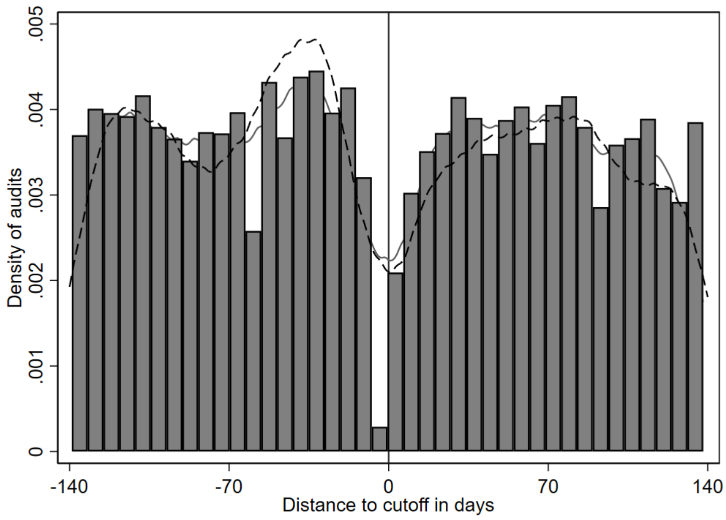
Notes: This figure shows the distribution of the number of inhabitants for each year in the sample period separately. The upper end of the distribution is truncated at 10 inhabitants up to 2016, and at 15 in the years after. The figure was created with the sample of for replacement eligible households.

Figure 15: Audit density around the change in the subsidy level



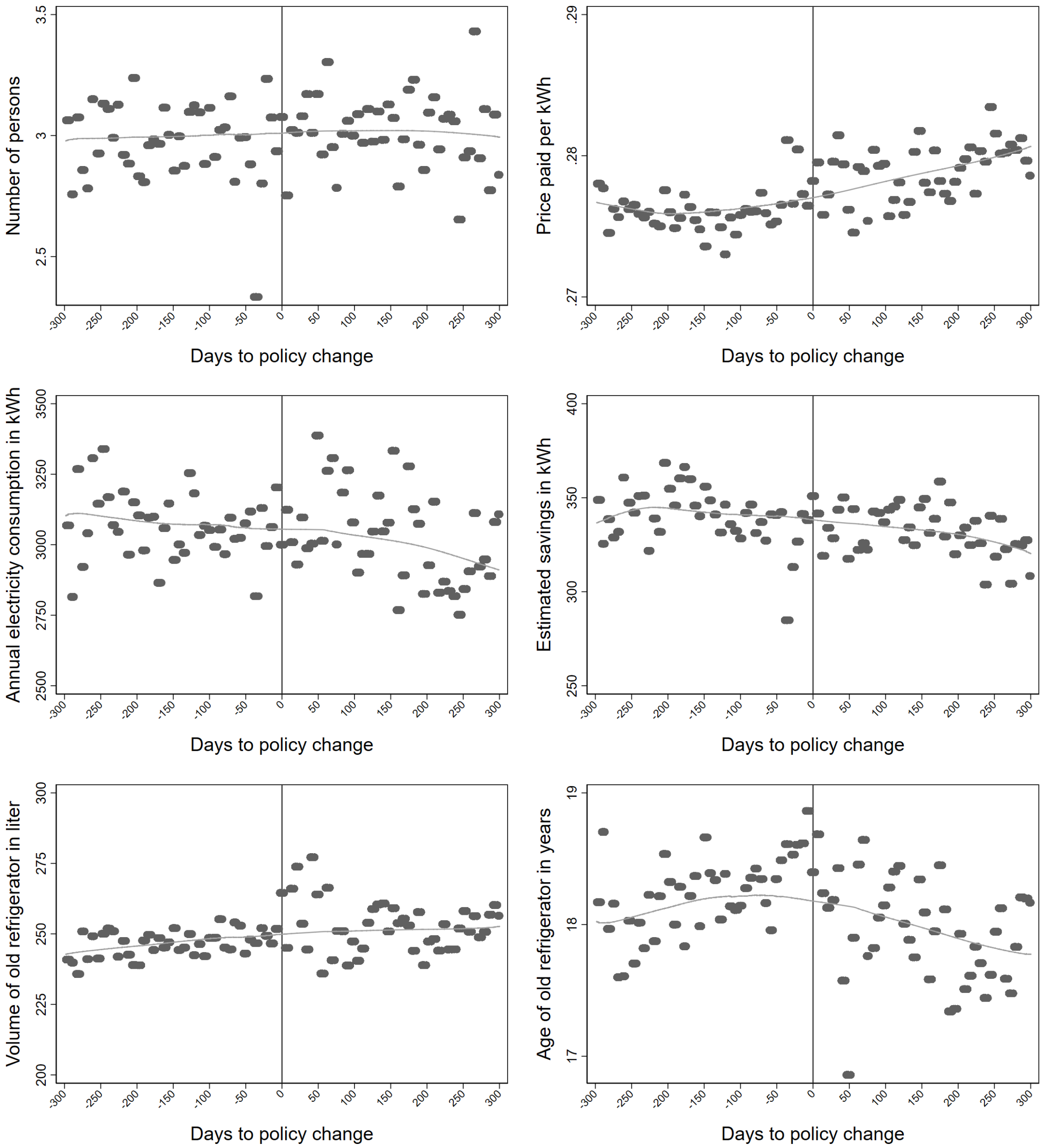
Notes: This figure shows the density (bars) and Kernel density (dashed line) of audits (second home visits) in a bandwidth of 20 weeks around the regime change. No bunching is apparent on either side of the cutoff (we would expect bunching to occur on the left side if households wanted to sort themselves into the regime with the higher subsidy level). A sharp drop in the audit density appears 6 to 5 weeks before the regime change which coincides with the Christmas and end-of-year break when most local branches close for one to two weeks. To demonstrate that this pattern is usual we also provide the Kernel density of audits in the year before (2018) during the same season (solid line). Both Kernel densities are almost perfectly aligned.

Figure 16: Audit density around the procedural change



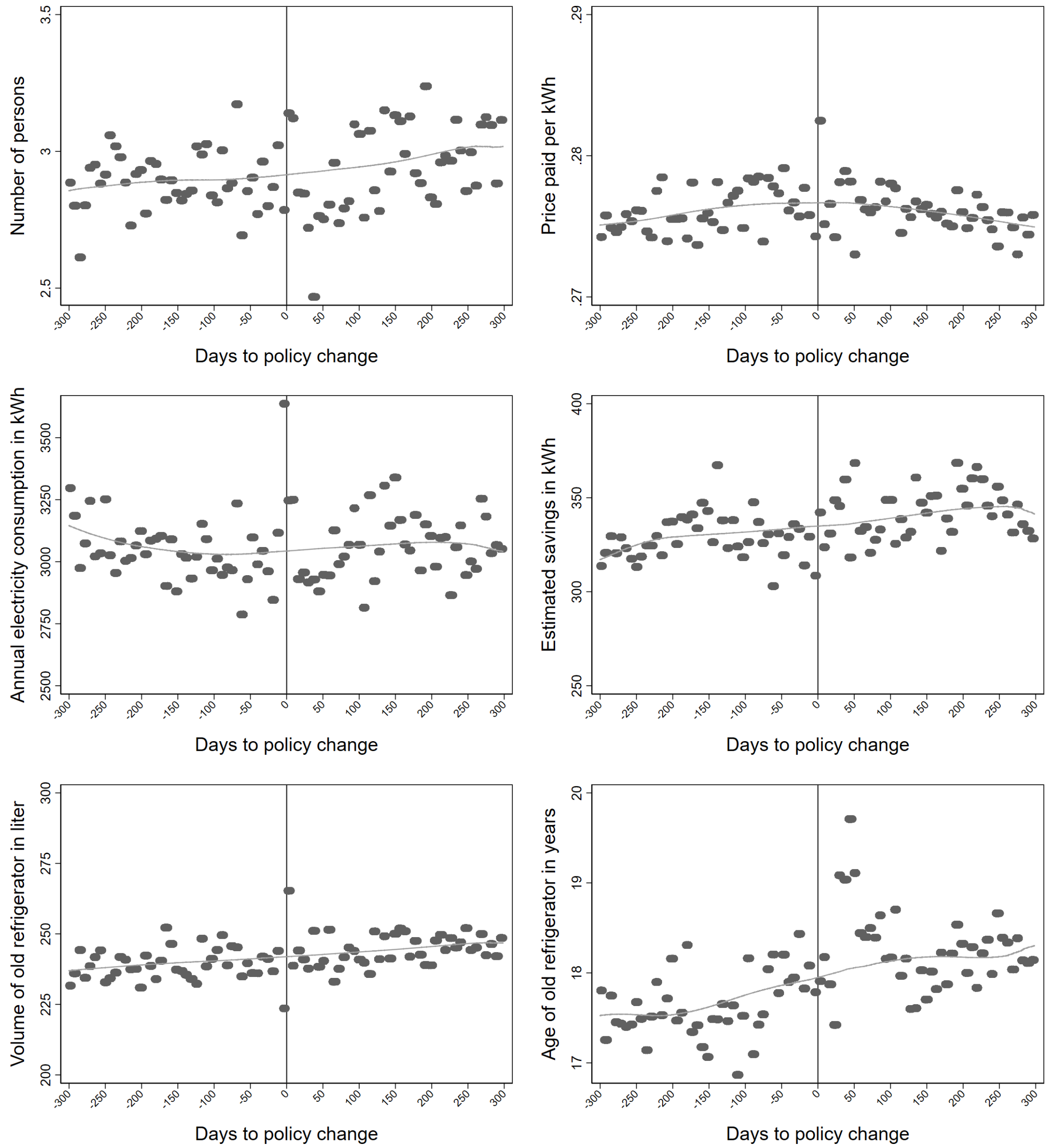
Notes: This figure shows the density (bars) and Kernel density (solid line) of audits (second home visits) in a bandwidth of 20 weeks around the regime change. A sharp drop in density appears directly before the regime change which coincides with the Christmas and end-of-year break when most local branches close for one to two weeks.We do not expect bunching to occur; the more attractive renewable vouchers had a definite deadline set on the day the regime changed to vouchers with a strict deadline so that no additional incentive was present on either side of the cutoff. To demonstrate that this pattern is usual we also provide the Kernel density of audits in the year after (2019) during the same season (dashed line). Both Kernel densities are almost perfectly aligned.

Figure 17: Discontinuity check of covariates at change in subsidy level



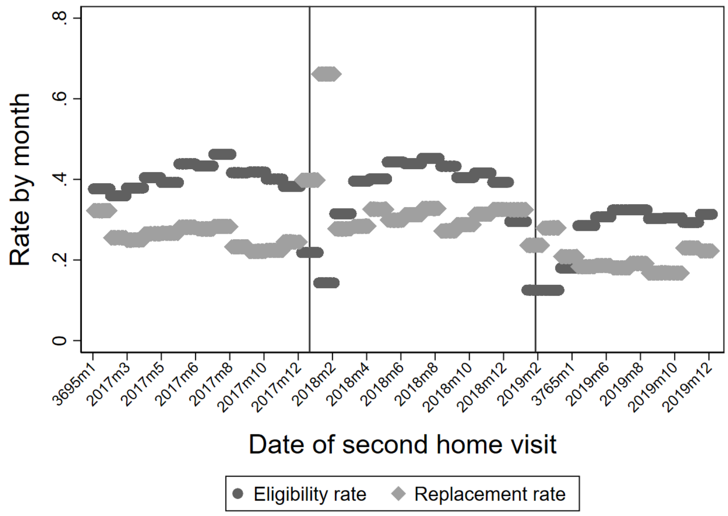
Notes: The figures show weekly averages of household variables in a bandwidth of 300 days around the change in the subsidy level, and a locally weighted regression through the individual data points. There is no evidence for a systematic discontinuity at the point in time when the program design changes.

Figure 18: Discontinuity check of covariates at change in program procedures



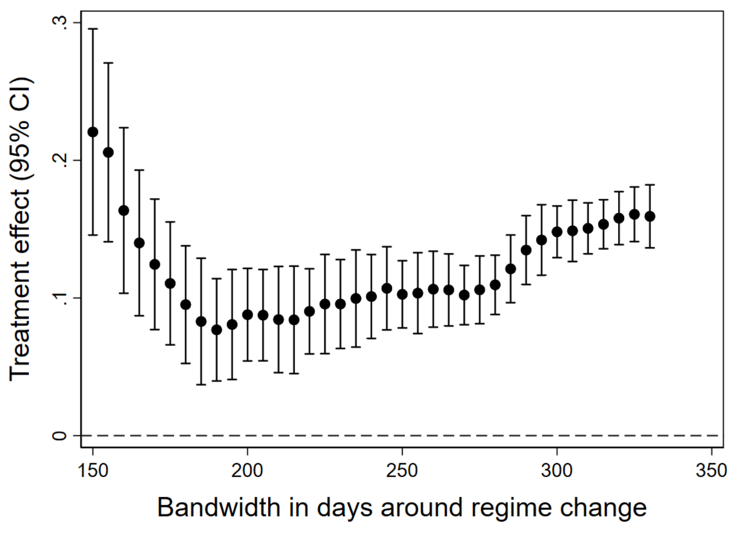
Notes: The figures show weekly averages of household variables in a bandwidth of 300 days around the change in program procedures (enrolment mode and voucher terms), and a locally weighted regression through the individual data points. There is no evidence for a systematic discontinuity at the point in time when the program design changes.

Figure 19: Eligibility ratio around the program changes



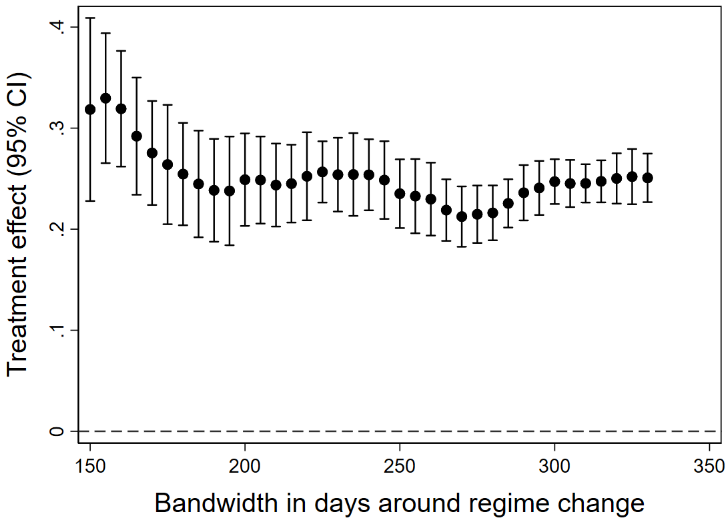
Notes: This figure shows the monthly ratio of households that are found eligible for replacement and receive an information letter out of all audited households. Around both regime changes (procedural change and change in the subsidy level), the eligibility ratio drops considerably. In the data, we see that this is not due to fewer households whose refrigerators fulfill the criteria for replacement (older than 10 years, annual savings of at least 200 kWh). Instead we observe that not all households that fulfill the criteria receive an information letter or voucher which enables them to join the program. This pattern may origin in irregularities in the program process due to the introduction of the information letter at the first regime change and due to the end and start of a new funding phase at the second regime change.

Figure 20: Effect of subsidy variation (replacement rate) as function of bandwidth



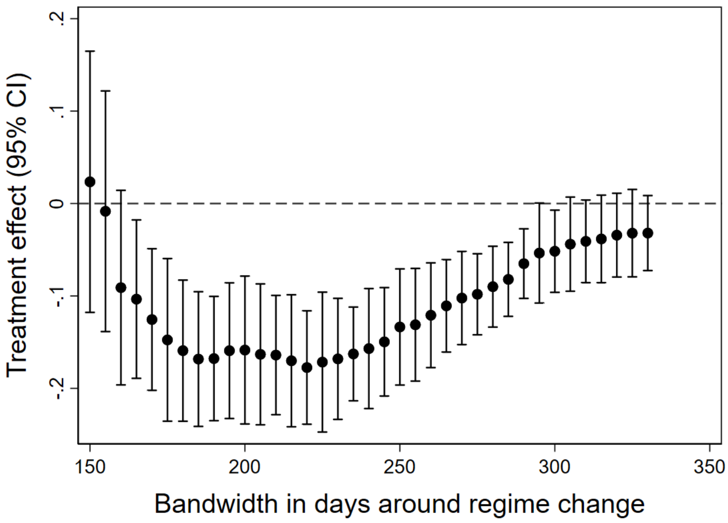
Notes: This figure shows the effect of subsidy variation (+€ 50, specification IV) on the replacement rate for different bandwidth choices.

Figure 21: Effect of subsidy variation (enrolment rate) as function of bandwidth



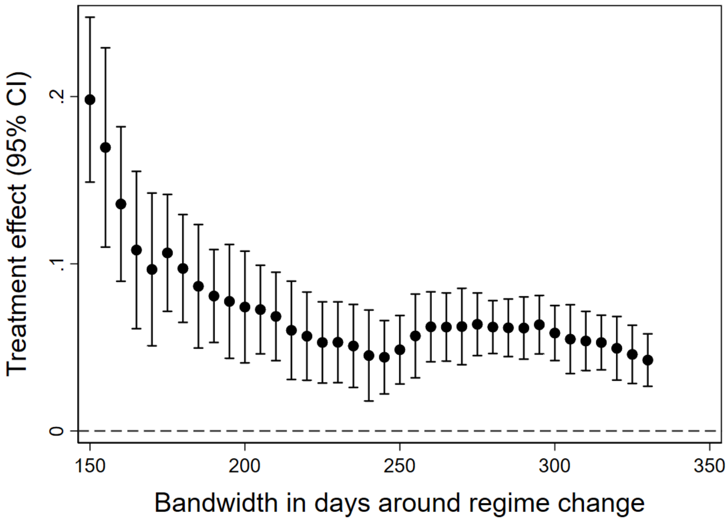
Notes: This figure shows the effect of subsidy variation (+€ 50, specification IV) on the enrolment rate for different bandwidth choices.

Figure 22: Effect of subsidy variation (redemption rate) as function of bandwidth



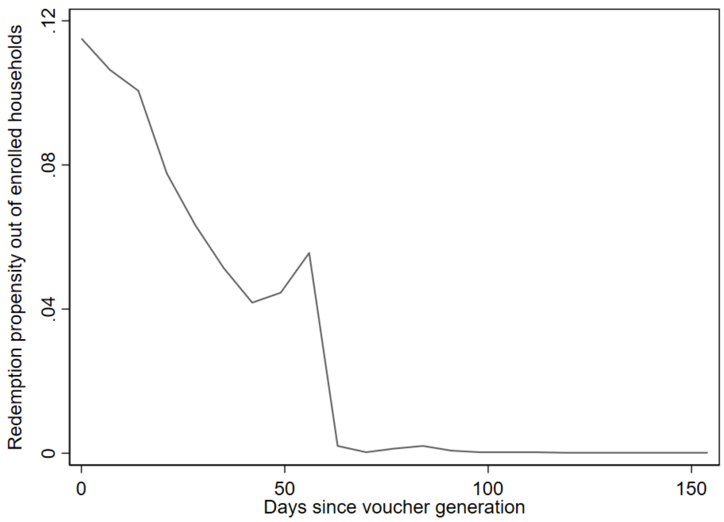
Notes: This figure shows the effect of subsidy variation (+€ 50, specification IV) on the redemption rate for different bandwidth choices.

Figure 23: Effect of procedural variation (replacement rate) as function of bandwidth



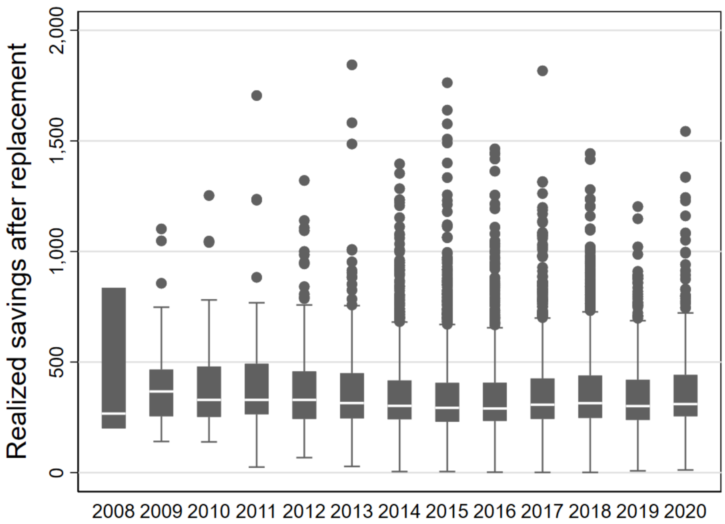
Notes: This figure shows the effect of procedural variation (introduction of elective enrolment and rigid voucher terms, specification IV) on the replacement rate for different bandwidth choices.

Figure 24: Redemption propensity of enrolled households in EE-RIG



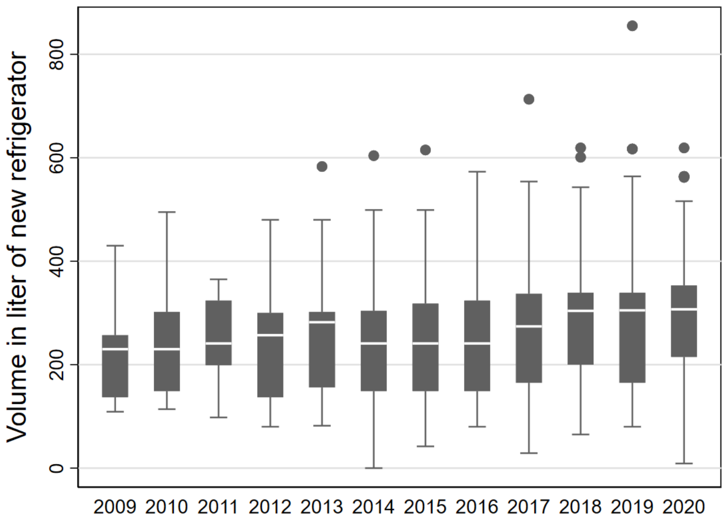
Notes: This figure shows the propensity of enrolled households to redeem the voucher as function of the days passed since the voucher was generated for the sample of enrolled households in the period January 2018 to January 2019.

Figure 25: Realized savings after replacement



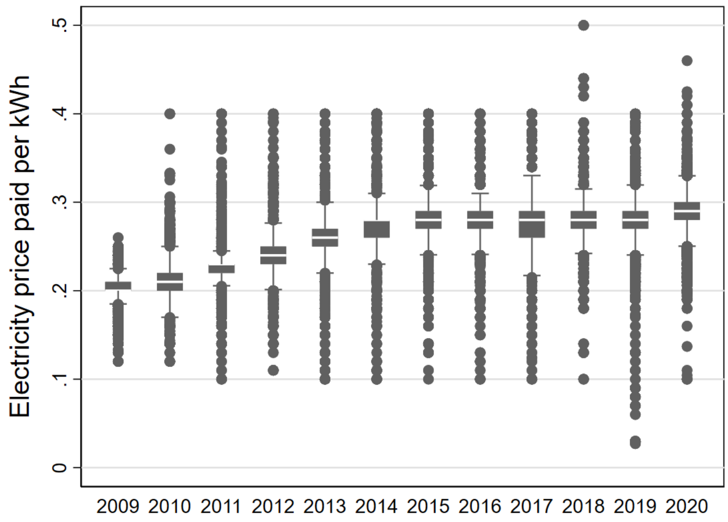
Notes: This figure shows the distribution of realized savings after replacement (different from estimated savings *before* replacement) for each year in the sample period separately. The figure was created with the sample of households that replaced their refrigerator.

Figure 26: Volume of new refrigerator



Notes: This figure shows the distribution of the volume in liters of the new refrigerators that households purchase as replacement for each year in the sample period separately.

Figure 27: Electricity price paid per kWh



Notes: This figure shows the distribution of the price per kWh paid for electricity for each year in the sample period separately. The median increases significantly over time mirroring a general rise in electricity prices in Germany during the sample period. The figure was created with the sample of all audited households.

9.3 Robustness checks

Table 9: Robustness checks for the effect of subsidy variation on the replacement rate

	V	VI	VII	VIII	IX	X	XI	XII	XIII	XIV	XV	XVI	XVII	XVIII	XIX	XX
Subsidy variation (€ 150 = 1)	0.058 (0.031)	0.105*** (0.012)	0.119*** (0.028)	0.212*** (0.010)	0.100*** (0.018)	0.152*** (0.009)	0.108*** (0.011)	0.146*** (0.008)	0.081* (0.039)	0.124*** (0.032)	0.086 (0.076)	0.136** (0.048)	0.267* (0.114)	0.397*** (0.101)	0.318* (0.124)	0.385*** (0.103)
Daycount	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Bandwidth	6	11	6	11	6	11	6	11	6	11	6	11	6	11	6	11
Donut (months)	2	2	2	2	1	1	0	0	2	2	2	2	2	2	2	2
Augmented Local Linear	yes	yes	yes	yes	yes	yes	yes	yes								
Model/Estimation	LPM	LPM	LPM	LPM	LPM	LPM	LPM	LPM	LPM	LPM	LPM	LPM	BPM	BPM	BPM	BPM
No. observations	3,562	8,122	3,562	7,279	7,804	16,466	8,645	17,307	7,628	17,478	5,774	14,270	7,628	17,478	7,539	17,416
Full sample					yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Non-NRW only	yes	yes														
NRW only			yes	yes												

Note: Controls include the number of inhabitants, living space, type of federal income support received, kWh price paid, annual electricity consumption, old appliance age, appliance price index and estimated replacement savings. The Augmented Local Linear approach uses month, month-by-year, year, state, branch, branch-by-year, ZIP code and auditor controls. XV-XVI include state, branch, ZIP code, and auditor FE. XIX-XX include state and branch FE. The binary probability model (BPM) is estimated as probit. Standard errors are bootstrapped for V-XII and clustered by branch for XIII-XX. * p<0.05, ** p<0.01, *** p<0.001. Estimated on the sample of eligible households around February 1, 2019.

Table 10: Robustness checks for the pecuniary effect on the enrolment rate

	V	VI	VII	VIII	IX	X	XI	XII	XIII	XIV	XV	XVI	XVII	XVIII	XIX	XX
Subsidy variation (€ 150 = 1)	0.235*** (0.039)	0.217*** (0.016)	0.262*** (0.025)	0.281*** (0.015)	0.357*** (0.018)	0.303*** (0.011)	0.258*** (0.017)	0.271*** (0.008)	0.268*** (0.054)	0.244*** (0.038)	0.243** (0.087)	0.217*** (0.048)	0.700*** (0.139)	0.653*** (0.100)	0.761*** (0.142)	0.675*** (0.101)
Daycount	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Bandwidth	6	11	6	11	6	11	6	11	6	11	6	11	6	11	6	11
Donut (months)	2	2	2	2	1	1	0	0	2	2	2	2	2	2	2	2
Augmented Local Linear	yes	yes	yes	yes	yes	yes	yes	yes								
Model/Estimation	LPM	LPM	LPM	LPM	LPM	LPM	LPM	LPM	LPM	LPM	LPM	LPM	BPM	BPM	BPM	BPM
No. observations	3,562	8,122	3,177	7,279	7,804	16,466	8,645	17,307	7,628	17,478	5,774	14,270	7,628	17,478	7,511	17,384
Full sample					yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Non-NRW only	yes	yes														
NRW only			yes	yes												

Note: Controls include the number of inhabitants, living space, type of federal income support received, kWh price paid, annual electricity consumption, old appliance age, appliance price index and estimated replacement savings. The Augmented Local Linear approach uses month, month-by-year, year, state, branch, branch-by-year, ZIP code and auditor controls. XV-XVI include state, branch, ZIP code, and auditor FE. XIX-XX include state and branch FE. The binary probability model (BPM) is estimated as probit. Standard errors are bootstrapped for V-XII and clustered by branch for XIII-XX. * p<0.05, ** p<0.01, *** p<0.001. Estimated on the sample of eligible households around February 1, 2019.

Table 11: Robustness checks for the pecuniary effect on the redemption rate

	V	VI	VII	VIII	IX	X	XI	XII	XIII	XIV	XV	XVI	XVII	XVIII	XIX	XX
Subsidy variation (€150 = 1)	-0.181** (0.054)	-0.093** (0.030)	-0.142** (0.042)	0.008 (0.026)	-0.261*** (0.034)	-0.126*** (0.020)	-0.121*** (0.026)	-0.087*** (0.016)	-0.200* (0.085)	-0.107 (0.058)	-0.039 (0.173)	-0.023 (0.127)	-0.568* (0.233)	-0.311 (0.164)	-0.444 (0.238)	-0.280 (0.161)
Daycount	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Bandwidth	6	11	6	11	6	11	6	11	6	11	6	11	6	11	6	11
Donut (months)	2	2	2	2	1	1	0	0	2	2	2	2	2	2	2	2
Augmented Local Linear	yes	yes	yes	yes	yes	yes	yes	yes								
Model/Estimation	LPM	LPM	LPM	LPM	LPM	LPM	LPM	LPM	LPM	LPM	LPM	LPM	BPM	BPM	BPM	BPM
No. observations	1,288	2,724	1,329	2,892	3,212	6,211	3,593	6,592	3,087	6,636	1,660	4,402	3,087	6,636	3,011	6,561
Full sample					yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Non-NRW only	yes	yes														
NRW only			yes	yes												

Note: Controls include the number of inhabitants, living space, type of federal income support received, kWh price paid, annual electricity consumption, old appliance age, appliance price index and estimated replacement savings. The Augmented Local Linear approach uses month, month-by-year, year, state, branch, branch-by-year, ZIP code and auditor controls. XV-XVI include state, branch, ZIP code, and auditor FE. XIX-XX include state and branch FE. The binary probability model (BPM) is estimated as probit. Standard errors are bootstrapped for V-XII and clustered by branch for XIII-XX. * p<0.05, ** p<0.01, *** p<0.001. Estimated on the sample of households that have requested a voucher around February 1, 2019.

Table 12: Robustness checks for effect of the procedural variations on the replacement rate

	V	VI	VII	VIII	IX	X	XI	XII	XIII	XIV	XV	XVI	XVII	XVIII	XIX	XX
Procedural change (EE-RIG = 1)	0.083**	0.033**	0.111***	0.040**	0.265***	0.128***	0.225***	0.136***	0.095*	0.043*	0.126*	0.048	0.289*	0.130*	0.331*	0.155**
	(0.027)	(0.011)	(0.024)	(0.012)	(0.015)	(0.008)	(0.010)	(0.008)	(0.039)	(0.018)	(0.057)	(0.025)	(0.120)	(0.055)	(0.122)	(0.059)
Daycount	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Bandwidth	6	11	6	11	6	11	6	11	6	11	6	11	6	11	6	11
Donut (months)	2	2	2	2	1	1	0	0	2	2	2	2	2	2	2	2
Augmented Local Linear	yes	yes	yes	yes	yes	yes	yes	yes								
Model/Estimation	LPM	LPM	LPM	LPM	LPM	LPM	LPM	LPM	LPM	LPM	LPM	LPM	BPM	BPM	BPM	BPM
No. observations	4,632	10,285	3,907	8,889	10,071	20,706	11,363	21,998	9,824	22,003	7,484	18,012	9,824	22,003	9,726	21,913
Full sample					yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Non-NRW only	yes	yes														
NRW only			yes	yes												

Note: Controls include the number of inhabitants, living space, type of federal income support received, kWh price paid, annual electricity consumption, old appliance age, appliance price index and estimated replacement savings. The Augmented Local Linear approach uses month, month-by-year, year, state, branch, branch-by-year, ZIP code and auditor controls. XV-XVI include state, branch, ZIP code, and auditor FE. XIX-XX include state and branch FE. The binary probability model (BPM) is estimated as probit. Standard errors are bootstrapped for V-XII and clustered by branch for XIII-XX. * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Estimated on the sample of eligible households around January 1, 2018.