Cleaner Nudges? Policy Labels and Investment Decision-making

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Abstract

Recent evidence suggests that labeling of unconditional cash transfer leads recipients to spend more on the labeled good. In this paper we show that the Winter Fuel Payment has distortionary effects on the market for goods related to the labeled product, renewable technologies. Using the sharp eligibility criteria of the transfer at age 60 in a Regression Discontinuity Design with age as a running variable, this analysis finds a robust reduction in the propensity to install renewable energy technologies of 1.2 percentage points. Falsification tests support the labeling hypothesis. As a result, households use too much energy from sources which generate pollution and too little from relatively cleaner technologies.

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Key words: Winter Fuel Payment; Regression Discontinuity; Renewable energy

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1 Introduction

Many governments have started to incorporate the lessons of behavioral economics in their policies. These behavioral interventions (or "nudges") are characterized by their non-pecuniary nature, including appeals to social norms, information provision, default options, and cash transfer labels (e.g., Schultz et al., 2007; Homonoff, 2013; Allcott, 2011; Allcott and Mullainathan, 2010; Ferraro and Price, 2013). The attractiveness of these interventions lies in the fact that they are simple and often inexpensive to implement, but at the same time produce considerable changes in behavior. Nudges have been found to be successful in a variety of settings, improving healthy and pro-social behaviors (e.g., Giné et al., 2010; Breman, 2011; Schultz et al., 2008), adoption of better technologies (Duflo et al., 2011), saving rates (e.g., Madrian and Shea, 2001; Thaler and Benartzi, 2004; Chetty et al., 2009; Chetty et al., 2012) and energy efficiency and use (e.g., Allcott and Rogers, 2012; Ayres et al., 2013; Jessoe and Rapson, 2014; Reiss and White, 2008; Brown et al., 2013).

Among these interventions, labeling manipulations have attracted the attention of social scientists and economists in recent years (see, e.g., Newell and Siikamäki, 2013; Swartz et al., 2011; Mathios, 2000; Fischer, 2008; Kallbekken et al., 2013). Labels are often attached to cash transfers that, although unconditional to any specific use, are given a suggestive name with the intention to nudge recipients into socially desirable behaviors. Example of these types are child benefits or food stamps , which transfer cash (or cash-equivalent vouchers) that may be spent on any good. [1] The literature typically studies the effectiveness of the label in promoting desired behaviors and stress that standard economics would predict unconditional labeled cash transfers to be equivalent to an unconditional unlabeled cash transfers. However, recent evidence suggests that labeled transfers seem to be spent more than proportionally on the items suggested by the label

[1]Assuming the recipient is not close to a boundary condition which would restrict their ability to shift income to different expenditure categories.

(e.g., Beatty and Tuttle, 2015; Kooreman, 2000; Beatty et al., 2014; Blow et al., 2012).

This paper is different in that it asks whether labels alter decisions on products related to the labeled good. The literature cited above generally classifies the labeling effect as encouraging behavior that policymarkers would like to occur. Should the effect of the label ”spillover” to decision on other goods, it becomes less clear that this altered behaviors are the decisions policymakers would like to encourage.

The UK Winter Fuel Payment (WFP) is an unconditional cash transfer designed to combat the excess elderly winter mortality and morbidity associated with cold indoor climates. It provides households, which have a member 60 years of age or older (in the qualifying week of a given year), with a lump sum annual payment. The WFP is not means tested nor is it mandated that the payment be spent on fuel. Though the WFP transfers cash that could be utilized for any expenditure, the label of the transfer induces households to use a larger portion of it to pay their energy bills than a non-labeled transfer (Beatty et al., 2014). The rationale for this behavior is based on the framework of mental accounting (Thaler, 1990). Households assign their income to categories of expenditure, thus when income is received that is labeled, it is disproportionately assigned into the labeled category. We interpret this as implying that households treat the WFP like a reduction in the price of energy. This affects directly the amount of money spent for fuel and can have indirect effects on substitute goods too. For instance, perceived lower price of energy might induce households to substitute away from more energy efficient technologies. Renewables are clean technologies with the potential to achieve the same goal set by the WFP, i.e., keeping elderly warm in winter, while reducing the negative externalities from emissions. Our analysis shows that the WFP has the unintended consequence of reducing the propensity to install renewable technologies.[2]

The identification strategy is based on the sharp eligibility criteria of the WFP which

[2]Other notable examples of unintended consequences of nudges are found in Costa and Kahn (2013) and for counterproductive labels, see, e.g., Cialdini (2003).

allows for an estimation of the casual impact of the WFP on the propensity to install renewable energy with a regression discontinuity design (RDD). [3] Valid RDD estimation requires that other potential explanatory variables that affect the outcome are continuous around the treatment discontinuity point (see, e.g., Hahn et al., 2001 and Lee and Lemieux, 2010). Since WFP eligibility occurs at the same age as pension eligibility for females, there is the potential for a discontinuity in retirement for females to confound the effect of the WFP on propensity to install renewables.[4] Additionally, the decision-making process concerning renewable technologies may not rest with the older members of the household if they rent their home (instead of owing) and/or contain more than two adults (e.g., older person living with their own children). To ensure that the results obtained from the RDD estimation identify the effect of the WFP, and not one of the issues discussed above, we restrict the sample to homeowners, living in a household composed by maximum two members in which the oldest is a male (whose pension eligibility age is 65). Outside of these identification concerns, RDD estimates are sensitive to the choice of bandwidth size (the window on either side of the cut off) and functional form. For this reason, we present estimates from various combinations between different bandwidths (6, 8 and 10) and functional forms (linear, quadratic and cubic) in a parametric estimation and different bandwiths (6, 3, 2) in a non-parametric estimation.

Results consistently find a negative effect of the WFP on the propensity to install renewables. Parametric models with optimal functional forms, as established by Akaike Information Criterion (AIC), show that WFP recipients are 1.2 percentage points less likely to install renewable energy technologies. This drop corresponds to 69% of households substituting away from renewable investments after receiving the payment. Given the universality of the WFP this is a considerable distortion. Non-parametric models and

[3]For recent reviews of the RDD in economics and social sciences see Imbens and Wooldridge (2008); DiNardo and Lee (2011); Van der Klaauw (2008).

[4]Indeed, tests of discontinuity in employment for females show a large and statistically significant decrease in employment at 60 years of age.

parametric models with those of age 60 removed, known as the "donut hole" model, find a negative and statistically significant drop in renewable installation also. Additionally, placebo WFP eligibility ages of 55 and 65 generally do not find statistically significant changes in the propensity to install renewables. Other falsification tests show that the WFP has no effect on the probability to invest in one's home through other large items, such as remodeling their kitchen, and that extra income that is not labeled does not effect the probability of installing renewables.

This analysis is the first to estimate the indirect effects of a labeled cash transfer payment by looking at the potential distortionary effects on related goods. These indirect effects are especially important in energy issues, in which negative externalities are pervasive and policies that seems at first effective, may ultimately lead to socially inefficient outcomes. We found that households are *nudged away* from sources which generate relatively cleaner energy. The impact of the WFP label on renewable energy investment is particularly concerning given current UK energy policy. The UK Committee on Climate Change (CCC) has outlined ambitious goals for improved household energy efficiency and uptake of renewable energy technologies. The scenario envisioned by the CCC for the UK to meet their carbon budgets requires substantial savings from the building sector. As a result of these climate change-driven energy goals, increased concern over the security of energy supplies and competitiveness of the UK economy, a number of high profile energy saving policies have been implemented in the last 5 years. Many target the residential sector, such as the Green Deal and Feed-in Tariff Scheme. These policies are designed to make it easier for citizens to recognize the future benefits of energy efficient choices and reduce the upfront cost of installing energy efficient and/or renewable technologies. The research here reveals that the WFP payment is in conflict with the goals of UK energy policy.

The remainder of the paper is structured as follows. The next section provides a conceptual framework on the relationship between the WFP and household's installation of renewable energy. Section three describes the data, while Section four details the empirical strategy. Sections five discusses the results and associated robustness checks, and Section six concludes the study.

2 Background

The WFP was initiated in 1997 by the UK government as a means to reduce excess winter morbidity and mortality in the elderly. At the time, the UK had one of the highest rates of winter mortality in Europe. Initially the payment was £20 per household, but in 2001 it increased to £200, and it has stayed at that level since then, although some years included extra one-time payments. Households who have a member who is 60 or older at the beginning of the qualifying week are eligible to receive the WFP.[5] Households who have not previously registered with the Department of Work and Pensions (DWP), the agency that manages the WFP, have to fill out a form to receive the payment. Those that have previously registered will automatically receive the payment. Once a household is in receipt of the WFP, it continues to be paid until the DWP is notified of a change in circumstance that makes the household no longer eligible for the payment. The placement of the qualifying week has changed over time, however during the years in our data the qualifying week came in September. The payment is generally direct deposited into the eligible person's checking account in November and a letter is sent to them beforehand which states that they will be recieveing the WFP. [6] Important for this analysis is that the WFP is not means tested and all households which contain a member 60 or above at the

[5]Additionally, the UK Government provides the Cold Weather Payment of £25 to low income households if the temperature in their area of residence is subzero for seven consecutive days. Our analysis does not include this payment. Given the small amount, our use of survey year dummies, and different eligibility criteria this will not confound our analysis.

[6]To the best of our knowledge, no further information or suggestions are given about how a household should spend the money.

qualifying week receive the payment.[7]

A simple model where the household produces energy services (e.g., heating) through the use of energy (e.g., electricity) and capital (e.g., renewable technologies) is utilized to show how the WFP could affect household decisions around renewable energy technologies. It is assumed that the household maximizes the production of energy services subject to a budget constraint.[8] The household's production of energy services is assumed to follow a Cobb-Douglas production function and can be modeled using isoquant and isocost curves, which show the household's ability to purchase energy or capital constrained by total expenditure.[9] In this setting, higher levels of capital imply lower levels of energy used for a given level of energy services. Standard economic theory assumes that income and cash transfers are always fungible: any unit of money can be substituted for another and that the source does not matter for rational consumers. A direct consequence of this is that the labeling of an income sources alone (cash or cash-equivalents such as vouchers) should not yield any sizable and statistically significant effect on spending choices. In other words, standard economic theory would predict that the WFP is seen as income. When WFP is treated as income, the WFP leads to a rightward shift of the isocost curve as households can increase the use of both capital and energy to produce more energy services. This is shown in Figure 1.

However, recent literature shows that cash transfers with a label attached is treated like a price subsidy to the labeled good. Conceptually, this is a violation of the fungibility assumption and can be explained by the mental accounting framework proposed by Thaler in several works (e.g., Thaler, 1990, 2004). In this framework, individuals are thought to use simple heuristics to make financial and consumption decisions. In particular, individuals have mental budgets for different expenditure categories (food, clothes, and energy)

[7] This aspect of the WFP has proved quite controversial as many fuel poverty and austerity groups argue that the WFP should be altered to help the fuel poor exclusively.

[8] The household has a budget for all other goods which are abstained from here. The budget constraint for energy services is a part of overall budget constraint for all goods the household consumes.

[9] An isocost curve here can be considered as a budget line for energy services.

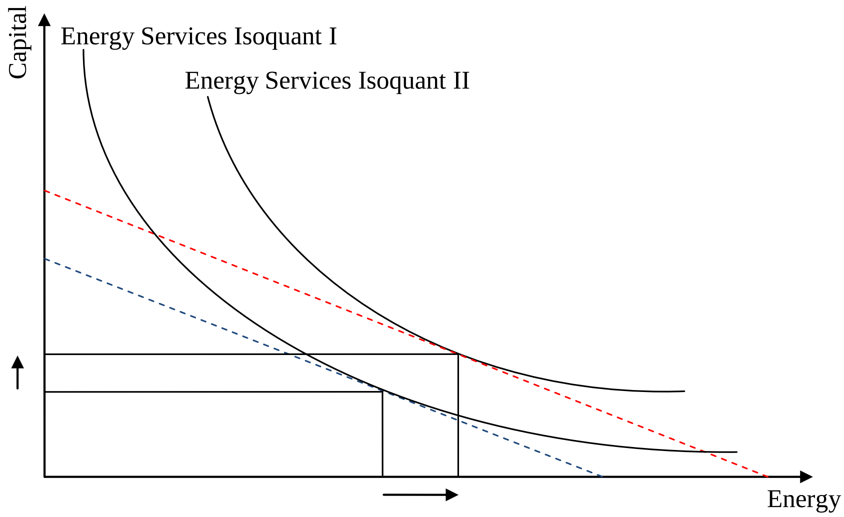

Figure 1: Impact of the WFP as income on use of energy and capital

that they treat separately. So when in receipt of labeled cash transfers, the money is used disproportionately more to purchase goods suggested by the label. Mental accounting would pivot out the isocost curve to allow more energy to be used as in Figure 2. This result is in line with the findings of Beatty et al. (2014). In this case, the sign of the effect of the WFP on capital (i.e. renewable technologies) depends on the relative strength of the substitution effect and the output effect. If the substitution effect (towards energy and away from capital) dominates the output effect, less capital is used and vice versa.[10] To summarize, our simple model predicts that households will reduce their investment in renewable energy only if the WFP is seen as a price subsidy to energy (and the substitution effect is stronger than the output effect). This refutable implication is taken to the data to determine if it has empirical validity.

A number of examples across a number of fields of economics have found evidence

[10]To reflect the ambiguity of the sign of an energy price subsidy on the level of capital, Figure 2 shows no change in the level of capital used.

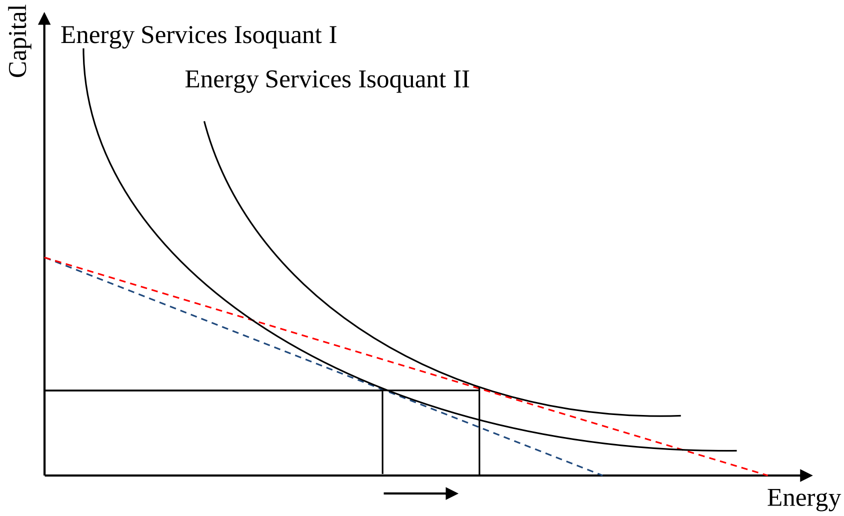

Figure 2: Impact of the WFP as a price subsidy to energy on use of energy and capital

of mental accounting. Abeler and Marklein (2008) show that individuals change consumption according to the suggestion of the label in a field experiment conducted in a restaurant. Food stamps, a cash-equivalent benefit that can be exchanged for food, have also being studied extensively. The results are mixed with observational studies showing that the fungibility assumption is usually violated, while experimental evidence would suggest that agents act rationally. A recent paper by Beatty and Tuttle (2015) shows that an exogenous large increase in food stamp benefits caused households to increase food-at-home expenditure as well as increase households' share of total expenditure allocated towards food-at-home expenditure. Recent work found that the cash incentives to education that are labeled, but not conditional on school attendance, performs as well as more expensive conditional cash transfers in Morocco (Benhassine et al., 2013). Beatty et al. (2014) estimate the effect of the WFP on share of total expenditure spent on fuel, holding total expenditure constant. They find that non-labeled transfers generally lead to a 3 percent increase in energy expenditures while the WFP has led to between a 13 and 60 percent increase. No other expenditure category was significantly affected by receiving the WFP.

The prediction of our model when households use mental accounting implies that the WFP label has indirect effects on the renewables market. Should the WFP lead to less renewable energy investment, it would imply that the label of the WFP leads households to see a lower price of energy and thus substitute away from renewable energy and towards more energy that makes pollution. In this scenario, the WFP would lead (indirectly) to a socially inefficient outcome, namely an equilibrium in which a given indoor temperature is obtained with too much pollution. This outcome is also of concern because indoor temperatures can be kept at comfortable levels by employing different strategies (or combination of those), some of which are more socially optimal than just switching the heater on. Some of these alternative strategies include improving energy efficiency and/or installing renewable technologies at home.

3 Empirical Approach

The eligibility criterion based on age allows for an estimation of the causal effects of the WFP on renewable energy installations using a sharp RDD. In other words, assignment to the treatment is determined exogenously by the age of the oldest member in the qualifying week in September. Thus, households will be either treated by the WFP if eligible or not treated if not eligible. The empirical specification will then compare households who are immediately above and below the eligibility age with the identifying assumption that these households with similar observed and unobserved characteristics would have behaved similarly with respect to renewable energy installation in the absence of the WFP. In other words, this assumption ensures that households on the left-hand side of the cutoff represent a valid counterfactual and that the WFP is as “good as randomly assigned” near the discontinuity point (i.e., local randomization assumption). Now, let ρ denote the causal effect of WFP on the probability of renewable energy installment; for small $\epsilon > 0$ a formal representation of the causal effect can be given by the following equation:

$$\rho = \lim_{\epsilon \to 0} \mathrm{E}(y|x = x_0 + \epsilon) - \mathrm{E}(y|x = x_0 - \epsilon), \tag{1}$$

where y is a dummy variable indicating whether the household has installed renewable technologies at home, x is the age of the oldest member – the assignment variable and x_0 is the cut off age of 60 in the qualifying week. Equation 1 states that any jump in the propensity of renewable energy installment at the threshold can be interpreted as having been caused by the discontinuity in the WFP, under some specific conditions. The most important condition in our case is that nothing, other than eligibility to WFP, changes discontinuously around the threshold age. For households where females are the oldest member, there is likely to be a discontinuous change in employment status as the pension eligibility age for females is also 60 years of age. Thus, we exclude these households from our sample. Additional identification concerns are that households which do not own their own home are unlikely to be the ones making decisions regarding renewable energy investments, as they require some alteration to the home's structure, and that households with three or more adults may have a decision-making process that is less likely to be impacted by the receipt of the WFP (a parent living with their children's family). To ensure that these issues do not confound the estimation, our sample does not include households which rent their home and those with three or more adult members. Further, in order to check for the validity of our design, we will be testing for the presence of discontinuities in observed covariates, in this case income, employment status, educational attainment, and year of the survey. The absence of any significant discontinuity will be taken as further reassurance that local randomization is an appropriate assumption.

Finally, the last conditions that allows ρ being interpreted as the average treatment effect (ATE) near the threshold pertains to the econometric specification and bandwidth size. Formally, we can write our econometric model as follows:

$$y = \alpha + \beta_1 \widetilde{x} + \cdots + \beta_k \widetilde{x}^k + \delta_1 D\widetilde{x} + \cdots + \delta_k D\widetilde{x}^k + \rho D + \theta T + \lambda Z + \eta, \quad (2)$$

where D is the treatment indicator that takes the value of 1 if the household receives the WFP and 0 otherwise, and $\widetilde{x} = x - x_0$ is the normalized age (i.e., centered around the cutoff) of the older member of the household. To allow for different functional forms on either side of the cutoff, our model includes interaction terms between the treatment indicator D and $\widetilde{x}$ and its k polynomial orders.[11] T is a vector of time dummies that control the survey fixed effects, and Z is a vector of controls which include (log of) household income, employment status and educational attainment dummies.

The order of the polynomial of $\widetilde{x}$ represents the shape of the preferences for installing renewable energy as age changes. While the assumption is that the preferences are smooth, this does not provide guidance as to the correct order of polynomial. The optimal polynomial order for the functional form is chosen using the AIC across different bandwidths.

Equation 2 can be estimated using different windows around the cut off age, i.e., bandwidth sizes. Note that as the bandwidth becomes larger, more data is considered, however households at either end of the spectrum are less likely to have similar observed and unobserved characteristics. Therefore, much wider bandwidths may give biased results of a causal effect. Narrower bandwidths, on the other hand, may reduce the precision of the regression model. For this reason, we employ the cross validation method of optimal bandwidth selection, suggested by Imbens and Lemieux (2008), which balances between bias and precision. To ensure that the parametric form is not biasing our results, we also estimate non-parametric locally weighted linear regressions using a triangular and rectangular kernel with narrower bandwidths selected using the method suggested by

[11]The normalized age, $\widetilde{x} = x - x_0$, gives a guarantee that the coefficient on D is still a causal effect even after these interactions (Angrist and Pischke, 2009).

Imbens and Kalyanaraman (2012).[12]

Having established ways of selecting bandwidths and specifications is helpful, but following the best practices, we do not rely on one particular specification or bandwidth, because a range of estimations that are stable across different alternatives are more reliable than single sets of estimations. Each table reports the estimated coefficient of interest under three bandwidths and parametric models use three polynomials (linear, quadratic and cubic).[13]

4 Data

This analysis utilizes household level micro-datasets of a representative sample of the UK population. The first dataset is the British Household Panel Survey (BHPS) Wave 18. The BHPS is a longitudinal survey covering on average 12,000 individuals and more than 5,000 households from 1991 to 2009, providing both individual and household-level information on a large variety of variables. Wave 18 of the BHPS asked households about the presence of renewable technologies at the home in 2008 and 2009. The second dataset is the Understanding Society Survey (USS), which replaced the BHPS. We use the first wave of the USS, which was collected in 2010 and 2011. While these are both panel datasets, the two samples do not overlap as the BHPS sample is brought into the USS in its second wave. The USS samples more households than the BHPS did and asks some additional questions, but they are otherwise very similar.

Both waves of the BHPS and USS ask each household ”Have you installed or are you seriously considering installing...” solar photovoltaic (PV) panels, solar water heaters or a micro wind turbine.[14] Our outcome variable y equals one if any of the three renewable

[12]Triangular kernel assigns more weight to observations around the threshold age. The sensitivity of these local linear regressions was also assessed by re-estimating at double and half the optimal bandwidths.

[13]Higher order polynomials might mislead the interpretation of results and are not used in the paper, see Gelman and Imbens (2014).

[14]Other waves of the BHPS and USS do not contain these questions, thus we do not know the exact date

technologies have been installed and is zero otherwise.[15]. Solar PV systems are mounted on the roofs to produce electricity that is either used by the household or exported to the transmission grid. The generation that is used by the household reduces its expenditure on energy. According to the Energy Savings Trust, a typical solar PV system will generate up to 75 percent of a household's electricity needs. Any excess may be sold back to the grid. Similar arguments hold for micro-wind turbines, which can generate up to three times the average household's electricity consumption, and solar water heaters, which save around £70 a year.[16]

Given the eligibility requirement of the WFP discussed above, a sharp RDD requires the assignment variable x be observable. Here, x is the age of the oldest member of the household during the month of September in the year of the survey. In other words, not every household in which the oldest male member is 60 is *treated*. The data provides the month and year of birth as well as the month and year of the survey. This enables us to compute the age of the oldest member of the household with extreme precision, i.e., removing any potential measurement error in x, especially at 60.

Using this data, we construct x in the following way,

$$x = \begin{cases} SY - BY & \text{if } 1 \leq BM < 9 \text{ and } 10 \leq SM \leq 12 \\ SY - BY - 1 & \text{if } 1 \leq BM < 9 \text{ and } 1 \leq SM < 9 \\ SY - BY - 1 & \text{if } 10 \leq BM \leq 12 \text{ and } 1 \leq SM \leq 12, \end{cases}$$

where SY and BY denote survey year and birth year respectively, and SM and BM

of installation for these renewables. The most popular installed renewable in our sample was solar PV and by far the biggest increase in generation of solar PV came from the years in our sample. According to data from the Department of Energy and Climate Change, the amount of solar PV generation in the year before our data (2007) was 1.2 thousand tons of oil equivalent (toe) while generation in the last year of our sample (2011) was 21 thousand toe.

[15] $Pr(y = 1|x)$ is therefore the propensity to invest in renewables.

[16] There are no subsidy schemes that the authors are aware of that restrict eligibility to 60 and over. The microrenewable Feed-In Tariffs introduced in 2010 are not based on age, however the analysis controls for year effects.

denote survey month and birth month respectively. We assign $1, 2, 3, \ldots, 12$, to both SM and BM, where 1 means January and 12 means December. Thus, in the first case, $x = SY - BY$ if the oldest member of a household was born from January to August and surveyed from October to December.[17] For other combinations of BM and SM, we subtract 1 from $SY - BY$. In the first case, the oldest members aged 60 are considered as 60, i.e., *treated*, but in the second and third cases, they are considered as 59 because they are not eligible for the WFP. The assignment variable, x, is then used to create a discontinuity dummy, D, which is equal to one if the oldest member of a household is 60 or older (and thus eligible for the WFP) and is zero otherwise (e.g. $D = 1\{x \geq 60\}$). As the take up of the WFP is above 95% according to Beatty et al. (2014), we consider D as a treatment dummy too where 1 implies that a household receives the WFP and 0 otherwise. In this way, we consider the sharp RDD where the probability of receiving the WFP, $Pr(D = 1|x)$, is sharply discontinuous at 60.[18]

For descriptive purposes, Table 1 shows the number of households and their average propensity of renewables installment (mean of y) by age (of the oldest member) x, for each year of the survey. The regression analyses are based on a bandwidth of 10 or narrower. It is clear that the majority of observations come from 2009 and 2010 with many fewer households in 2011. As age increases, the number of observations slightly declines in each year of the sample, suggesting an increase in the mortality rate with age. In general, the mean of y is small in every age-year cell, however the total column reveals that the overall mean of y increases with age up to 59, and then declines before increasing again after 65. This pattern indicates that as age increases, households increasingly consider renewable energy installment. After receiving the WFP, the propensity to install

[17]The eligibility criterion for the WFP is that the oldest member of a household turns into 60 before a given date in September. As the data has no information about day or week of birth, we do not know the eligibility of households with the oldest members born in September. We drop those households.

[18]A special release of the 2010 version of the English Housing Survey did include whether the household was in receipt of the WFP. The correlation of receipt of the WFP and the specification of our discontinuity dummy D (using age of the oldest member in the qualifying week) was above 98%.

Table 1: Probability of renewable energy installment by age-year of the survey cell

x	2008		2009		2010		2011		Total	
	y	Obs.	y	Obs.	y	Obs.	y	Obs.	y	Obs.
50	0	27	0	37	0	31	0	5	0	100
51	0	14	0	40	0	32	0	3	0	89
52	0	19	0	43	0.025	40	0	2	0.01	104
53	0	23	0	58	0.053	38	0	4	0.016	123
54	0	25	0	54	0	53	0	3	0	135
55	0.028	36	0	56	0	45	0	4	0.007	141
56	0	37	0	57	0.023	44	0	6	0.007	144
57	0	27	0.015	66	0	61	0	3	0.006	157
58	0	23	0	52	0.018	56	0.25	4	0.015	135
59	0.029	35	0.015	68	0.036	56	0	6	0.024	165
60	0	51	0.03	66	0.016	64	0	8	0.016	189
61	0	52	0	102	0.023	86	0	4	0.008	244
62	0.022	46	0.011	88	0	91	0	2	0.009	227
63	0.029	34	0	72	0	99	0	6	0.005	211
64	0.023	43	0.02	100	0	71	0	3	0.014	217
65	0	47	0	101	0.01	96	0	7	0.004	251
66	0.056	36	0.025	79	0.042	71	0	9	0.036	195
67	0	44	0.032	94	0.011	95	0	5	0.017	238
68	0.021	47	0	88	0.016	61	0	2	0.01	198
69	0.025	40	0.037	82	0.027	73	0	7	0.03	202
70	0	42	0.029	70	0.053	75	0	4	0.031	191

Note: This table reports the average propensity of renewables installment (mean of y) and the number of households (Obs.) by age of the oldest member (x) for each survey year (2008-2011). Data is from wave 18 of the British Household Panel Survey (BHPS) which covers the year 2008 and 2009, and wave 1 of Understanding Society Survey (USS) for 2010 and 2011. The sample includes home owners whose household size is two or lower and the oldest member is male.

renewable energy falls initially and then increases from 66 and on. This provides first evidence that the propensity to install renewables might be discontinuous at the cut off age due to the WFP.

To improve sampling variability, some models include the following covariates: whether the respondent is employed, the log of annual gross household income, household size and a set of educational attainment dummies: whether the respondent has obtained higher education, an academic degree, high school advanced qualifications (called

A-levels in UK), standard high school qualifications (called O-levels in UK) and no qualifications. Summary statistics of these variables are available in Table 2 for both recipients (*treated*) and non-recipients.[19]

Table 2: Summary Statistics (bandwidth=10)

	Total		Non Recipients		Recipients	
Variable	Mean	N	Mean	N	Mean	N
Renewable energy installment	0.013	3656	0.009	1293	0.016	2363
Employment (1=yes, 0=no)	0.064	3656	0.821	1293	0.333	2363
Household size	1.798	3656	1.735	1293	1.833	2363
Log of annual household income	8.187	3656	8.366	1293	8.089	2363
Higher education (1=yes, 0=no)	0.086	3656	0.106	1293	0.075	2363
Degree (1=yes, 0=no)	0.128	3656	0.148	1293	0.117	2363
Advanced qualification (1=yes, 0=no)	0.17	3656	0.196	1293	0.157	2363
Qualification (1=yes, 0=no)	0.25	3656	0.277	1293	0.235	2363
No qualifications (1=yes, 0=no)	0.366	3656	0.274	1293	0.416	2363

Note: This table reports summary statistics of the variables used to estimate the effect of the WFP on the propensity of renewable energy installment and compare WFP recipients and non-recipients. All the variables are from wave 18 of the British Household Panel Survey (BHPS) which covers the year 2008 and 2009, and wave 1 of Understanding Society Survey (USS) for 2010 and 2011. The sample includes home owners whose household size is two or lower and the oldest member is male with age between 50 and 70 (i.e., bandwidth size of 10).

5 Results

5.1 Main Results

Figure 3 provides a graphical representation of the estimated effects using a bandwidth of 10. Each dot represents the propensity of installing renewable energy technology, mean of y for a particular age-year of the survey cell (i.e., they are not single observations). The lines represent linear, quadratic and cubic fit.[20] Every specification has a discontinuous

[19]To test the validity of our identification strategy, we will check for discontinuity of these covariates in the next section, among other things.

[20]These correspond to the models without controls reported in the first three columns in Table 3.

jump down at the threshold age. This provides first evidence that households who are in receipt of the WFP are less likely to install renewable technologies at home. This is in accordance with the prediction of our model under the mental accounting framework. The WFP is seen as energy price subsidy, not as cash income (and substitution effect dominates output effect, see Figure 2).

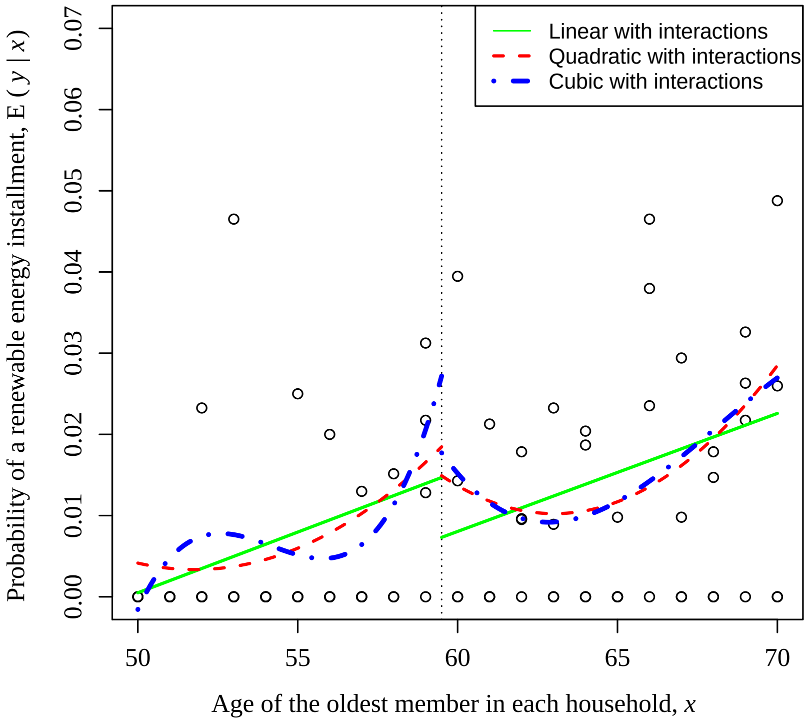

Figure 3: Discontinuity in renewable energy installment from estimated model without controls in Table 3

Table 3 shows the estimated values of ρ from estimated equation (2) under three different bandwidths (6, 8 and 10), three orders of polynomials (linear, quadratic and cubic) and with and without control variables.[21] The control variables utilized are year of the survey dummies, log of household income, education qualification dummies and an em-

[21]The optimal polynomial order identified using the AIC is denoted by the subscript letter a. Table A.1 in Appendix reports the values of AIC for each specification.

ployment dummy. All models interact the polynomial of age with the treatment variable to allow for different functional forms on either side of the discontinuity. According to the Imbens and Lemieux (2008) cross validation method, the optimal bandwidth is 10 (for details, see Figure A.1 in Appendix).

Standard errors are clustered at age level and corrected for the bias arising from small clusters as shown by Brewer et al. (2013).[22] However, for robustness purposes, Table A.2 in Appendix reports p-values using the wild cluster bootstrapped t-procedure, with imposition of the null hypothesis for each coefficient, which Cameron et al. (2008) shown to greatly improve inference with very few clusters.[23] The significance levels reported using these two approaches are identical. Thus in every Table that we report only the bias-corrected clustered standard errors because they are far less computationally demanding.

The discontinuity parameters are all negative with estimates that range from 1 to 3.5 percentage points, indicating that the WFP reduces the likelihood of investing in renewables at home. The majority of these parameters are statistically significant with improved precision when controls are added. The estimates in Table 3 use a linear probability model. Table A.3 runs the same model with a logit specification and finds similar sign and significance.

As specified above, the basic underlying assumption of the RDD is local random assignment around the cutoff age of 60 (in the qualifying week). One way to check the validity of the above results is to examine whether the covariates are discontinuous around that threshold. To test the local randomization, we check discontinuities in the covariates

[22] These bias-corrected standard errors are simply obtained by using the `cluster` option in Stata after the `regress` command. This simple option computes a t-statistic with clustered robust standard errors that uses residuals scaled by $\sqrt{\frac{G(N-1)}{(G-1)(N-K)}} \approx \sqrt{\frac{G}{(G-1)}}$, and critical values from a t distribution with $(G-1)$ degrees of freedom, where G is the number of clusters, N is the total number of observations, K is the number of coefficients to be estimated. See Brewer et al. (2013) for more details.

[23] p-values from bootstrapped t-statistics were obtained by using the Stata command `bootwildct` by Mansi and Scott (2015) and available at http://www.ifs.org.uk/publications/6231. The program was downloaded in June 2015.

Table 3: The effect of the WFP on renewable energy installment

Bandwidth	Without controls			With controls		
	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
10	-0.012**	-0.013*	-0.028***	-0.012*	-0.014*	-0.030***
	[0.006]	[0.007]	[0.004]	[0.006]	[0.007]	[0.004]
	N=3656	N=3656	N=3656	N=3656	N=3656	N=3656
8	-0.009	-0.023***	-0.023***	-0.009	-0.024***	-0.025***
	[0.006]	[0.005]	[0.006]	[0.007]	[0.006]	[0.006]
	N=3074	N=3074	N=3074	N=3074	N=3074	N=3074
6	-0.018**	-0.015***	-0.035***	-0.018**	-0.016***	-0.036***
	[0.006]	[0.004]	[0.005]	[0.007]	[0.004]	[0.005]
	N=2411	N=2411	N=2411	N=2411	N=2411	N=2411

Note: This table reports the estimated coefficients from sharp RDDs of the propensity to install renewable technology on an indicator variable for whether the household received the WFP using different polynomials (linear, quadratic and cubic) and bandwidths (6, 8 and 10). Each regression includes year of survey fixed effects and a series of interactions between the treatment variable and normalized age. The last three columns include also log of household income, employment and education qualification dummies. See equation 2 for more detail. The estimation sample includes only home owners whose household size is two or lower and the oldest member is male. Standard errors in brackets are adjusted for clustering at age level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The subscript letter ^{a} denotes optimal polynomial orders according to the AIC statistics (see Table **??**). The optimal bandwidth is equal to 10 according to the cross validation method suggested by Imbens and Lemieux (2008).

(Imbens and Lemieux, 2008). One may argue that at the WFP eligibility age other things change that could be related to the outcome of interest, for example employment status.[24] Indeed, changes in pension or other benefit eligibility may alter labor supply decisions. [25] In what follows, we check for discontinuity in the following set of variables: employment status, household size, (log of) annual household income and a set of education indicators. Every one of these variable is regressed on the treatment indicator, D, nor-

[24] Another issue might be whether people have a higher propensity to change homes around the same age. The dataset provide information concerning the age at which the household moved into their current home. People are most likely to move into their home at the age of 35 and the propensity falls smoothly as age increases. A visual inspection of this data reveals no jump in propensity to move around the discontinuity. Results are not shown but are available upon request.

[25] In addition to the checks for discontinuity in employment, Blundell et al. (2011) find no evidence of a discontinuity in male labor supply at the intensive or extensive margin at the cutoff age of 60.

Table 4: Discontinuities in observed covariates (bandwidth=10)

	Discontinuity	Standard error
Employment (1=yes, 0=no)	-0.008	[0.24]
Log of annual household income	-0.042	[0.05]
Higher education (1=yes, 0=no)	-0.013	[0.11]
Degree (1=yes, 0=no)	0.008	[0.01]
Advanced qualifications (1=yes, 0=no)	-0.005	[0.01]
Qualifications (1=yes, 0=no)	0.033	[0.02]
No qualifications (1=yes, 0=no)	-0.023	[0.02]

Note: This table reports the estimated coefficients from seemingly unrelated regressions (SUR) of sharp RDDs of each reported variable on an indicator for whether the household received the WFP using a bandwidth of 10 and optimal polynomials. Each regression includes the optimal polynomial order of normalized age ($\widetilde{x}$). This varies with each regression. Every model includes year of survey fixed effects and a series of interactions between the treatment variable and normalized age ($\widetilde{x}$). The estimation sample includes only home owners whose household size is two or lower and the oldest member is male. Standard errors in brackets are adjusted for clustering at age level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

malized age ($\widetilde{x}$), their interactions ($D\widetilde{x}$) and interactions with optimal polynomials under the optimal bandwidth of 10. Optimal polynomial order varies across different equations. Each regression includes survey year dummies. As the number of covariates increases, some discontinuities might be statistically significant by random chance. As suggested by Lee and Lemieux (2010), regression of each covariate is run as seemingly unrelated regression (SUR) to perform the test of joint discontinuities. Table 4 shows the coefficient of the discontinuity for every covariate. All covariates are not statistically significantly discontinuous at the cutoff (See Figure A.2 to A.8 in Appendix for graphical analysis of these discontinuities using a bandwidth of 10). We conclude that this discontinuity is not a concern for our identification.

5.2 Robustness

One may be concerned that households anticipate the receipt of the WFP and alter their behavior before turning 60. This may cause a ”bunching” around the discontinuity which manifests itself as a lack of installation of renewable technologies. This could potentially bias our estimates. Given that a RDD compares the mean renewable technology installation outcome as one approaches the discontinuity from either side, dropping the discontinuous point should not significantly alter the estimate of the effect of the discontinuity (Barreca et al., 2011). This is known as the “doughnut-hole” estimation and the results are given in Table 5. All estimates are negative and most are statistically significant. These estimates lead us to conclude that anticipation of the WFP is not a concern.

Table 5: The effect of the WFP on renewable energy installment excluding age 60

Bandwidth	Without controls			With controls		
	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
10	-0.016***	-0.018**	-0.035***	-0.016**	-0.019**	-0.037***
	[0.005]	[0.008]	[0.008]	[0.006]	[0.009]	[0.008]
	N=3467	N=3467	N=3467	N=3467	N=3467	N=3467
8	-0.012*	-0.031***	-0.015	-0.012*	-0.032***	-0.017
	[0.006]	[0.009]	[0.011]	[0.007]	[0.009]	[0.013]
	N=2885	N=2885	N=2885	N=2885	N=2885	N=2885
6	-0.024***	-0.011	-0.058***	-0.025***	-0.012	-0.061***
	[0.007]	[0.008]	[0.013]	[0.008]	[0.009]	[0.012]
	N=2222	N=2222	N=2222	N=2222	N=2222	N=2222

Note: This table reports the estimated coefficients from sharp RDDs of the propensity to install renewable technology on an indicator variable for whether the household received the WFP using different polynomials (linear, quadratic and cubic) and bandwidths (6, 8 and 10). Each regression includes year of survey fixed effects and a series of interactions between the treatment variable and age. The last last three columns include also log of household income, employment and education qualification dummies. See equation 2 for more detail. The estimation sample includes only home owners which household’s size is two or lower and the oldest member is male. Standard errors in brackets are adjusted for clustering at age level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The estimated causal effects shown so far are all from parametric RDDs: linear, quadratic or cubic. Technically, the linear specification in 3 is (non-parametric) local linear regression with rectangular kernel, i.e., a function which gives uniform weight to all observations. Alternatively, one could use triangular kernel, a weighting function which gives more "importance" to observations near the cut off. Further, Imbens and Kalyanaraman (2012) provide a formula for the optimal bandwidth that is suggested to be used in the case of local linear regressions. The method yields an optimal bandwidth of 1.6 (which for simplicity is rounded to 2) and Table 6 shows local linear regressions with and without covariates using rectangular and triangular kernel with different bandwidths (the optimal 2, 3 and 4) for robustness purposes. Every estimated coefficient is statistically significant at 1% level and adding covariates does not make any difference.

Table 6: Local linear regressions with triangular and rectangular kernels

Bandwidth	Without controls		With controls	
	Triangular	Rectangular	Triangular	Rectangular
4	-0.012***	-0.009***	-0.021***	-0.016***
	[0.00]	[0.00]	[0.00]	[0.00]
3	-0.012***	-0.012***	-0.023***	-0.020***
	[0.00]	[0.00]	[0.00]	[0.00]
2	-0.002***	-0.011***	-0.011***	-0.022***
	[0.00]	[0.00]	[0.00]	[0.00]

Note: This table reports the estimated coefficients from local linear RDDs of the propensity to install renewable technology on an indicator variable for whether the household received the WFP using triangular and rectangular kernels and different bandwidths (2, 3 and 4; where 2 is the optimal bandwidth according to an alternative method by Imbens and Kalyanaraman, 2012). The first two columns do not include any control variable, while the third and fourth one includes log of household income, employment and education qualification dummies. The estimation sample includes only home owners which household's size is two or lower and the oldest member is male. Standard errors in brackets are adjusted for clustering at age level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.3 Heterogeneity

Table 7 show estimates from equation 2 for households above and below median income. The impact of the WFP is similar in magnitude across the two groups but consistently statistically significant for the above median households. To our knowledge there is little evidence of differential effects of mental accounting across income groups. It seems that below median households are less impacted by the WFP label. Perhaps below median income households are unlikely to install renewables regardless of receipt of the WFP and thus no change is made once the household receives the WFP.

Table 7: The effect of the WFP on renewable energy installment by income groups

Bandwidth	Below Median			Above Median		
	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
10	-0.002	-0.006	-0.038***	-0.022***	-0.021***	-0.027***
	[0.01]	[0.02]	[0.01]	[0.01]	[0.01]	[0.01]
8	0.003	-0.024**	-0.027***	-0.019***	-0.027***	-0.025***
	[0.01]	[0.01]	[0.01]	[0.00]	[0.00]	[0.01]
6	-0.011	-0.016	-0.053***	-0.027***	-0.019***	-0.022*
	[0.01]	[0.01]	[0.01]	[0.01]	[0.00]	[0.01]

Note: This table reports the estimated coefficients from sharp RDDs of the propensity to install renewable technology on an indicator variable for whether the household received the WFP using different polynomials (linear, quadratic and cubic) and bandwidths (6, 8 and 10). Each regression includes year of survey fixed effects and a series of interactions between the treatment variable and age, log of household income, employment and education qualification dummies. The estimation sample includes only home owners which household's size is two or lower and the oldest member is male. The first three columns are for household with below median income while the second three columns are for households above median income. See equation 2 for more detail. The number of observations for models with below median income is 1874, 1542 and 1181 for bandwidths 10, 8 and 6, respectively, while is 1798, 1546 and 1239 for models with above median income. Standard errors in brackets are adjusted for clustering at age level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.4 Falsification Tests

If the mechanism which drives our results of a reduced propensity to install renewable energy technologies is the WFP, and in particular its suggestive label, than the propensity to make other investments in durable goods on one's home should not vary by whether the household receives the WFP. This proposition is tested in this section. The tests examines whether receipt of the WFP leads to a change in the propensity to invest in non-energy related goods, which costs are similar to the renewable energy investments considered above. Data from the English Housing Survey for the years 2006-2010 is used to create falsification outcomes which takes the value of one if the household has remodeled their kitchen (replaced units, worktops, and sinks), installed a burglar alarm, or replaced the gutters in the last 12 months and zero otherwise. If the WFP leads households to alter their decisions around energy investments only, the coefficient on receipt of WFP should not statistically alter the propensity to undertake one of the outcomes listed above. Table shows the estimation results for equation (2) with first three columns showing the kitchen remodeling estimation, the second three columns showing the installation of a burglar alarm estimation, and the third three columns showing gutter replacement estimation.[26] The estimated effect of the WFP in Table 8 is rarely statistically significant and moves from positive to negative across the different bandwiths and polynomial orders.

Another way to test whether the WFP label is the mechanism behind the reduction in the probability to install renewable energy is to determine whether there are any significant discontinuities in the probability of renewable energy installments at other age levels where receipt of the WFP does not change. If the WFP label is the mechanism, there should not be a discontinuity at other ages. Equation (2) is re-estimated with a treatment variable, D that equals one if the age of the oldest member of the household is (i)

[26]The English Housing Survey (EHS) does not provide the month of birth so the assignment variable is based on age of the oldest household member at the date of interview. As a result, households whose oldest member is 59 and interviewed before September and households whose oldest member is 60 and interviewed after September are removed from the analysis.

Table 8: Falsification Tests of the Effect of WFP on non-energy goods

Bandwidth	Kitchen Remodelling			Installing a Burglar Alarm			Replacing Gutters		
	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
10	0.015	-0.017	-0.030	-0.001	0.004	-0.001	-0.008	-0.022	-0.032
	[0.02]	[0.02]	[0.04]	[0.01]	[0.01]	[0.01]	[0.01]	[0.02]	[0.03]
8	0.008	-0.031	0.011	0.001	0.001	-0.007	-0.010	-0.025	-0.055**
	[0.02]	[0.03]	[0.05]	[0.01]	[0.01]	[0.02]	[0.01]	[0.02]	[0.02]
6	-0.005	-0.032	0.075	-0.002	0.003	0.019**	-0.016	-0.033	-0.107***
	[0.02]	[0.04]	[0.08]	[0.01]	[0.01]	[0.01]	[0.01]	[0.02]	[0.01]

Note: This table reports the estimated coefficients from sharp RDDs of the propensity to install the home upgrade given in each panel on an indicator variable for whether the household received the WFP using different polynomials (linear, quadratic and cubic) and bandwidths (6, 8 and 10). Each regression includes the indicated polynomial interactions between the treatment variable and age, log of household income, employment, education qualification dummies, and year of survey fixed effect. See equation 2 for more detail. The estimation sample includes only home owners which household's size is two or lower and the oldest member is male. The number of observations across all outcomes are 3298, 2779, and 2185 for bandwidths 10, 8 and 6, respectively. Standard errors in brackets are adjusted for clustering at age level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

55 and older or (ii) 65 and older. This specification will reveal whether a discontinuity in the propensity to install renewable energy exists at age 55 or 65, where households' eligibility of receiving WFP does not change. Table 9 shows that most estimates of the discontinuity at 55 or 65 are statistically insignificant and those estimates at the optimal bandwith are always statistically insignificant. This result is consistent with WFP leading to a change in propensity to invest in renewable energy, as false cutoffs do not find as strong of a discontinuity as the actual WFP cutoff.

Another test of the labeling mechanism is to determine whether non-labeled changes in income affect the probability of installing renewables. Ideally this non-labeled income would be about the same magnitude as the WFP. The BHPS and USS, the data used to estimate the impact of the WFP on the probability of installing renewables, ask questions related to extra income, generally described as income not part of a households usual pay (which both surveys ask about). The BHPS is more specific about breaking apart these extra income into categories like lottery winnings or bequests but the USS does not

Table 9: Discontinuities in the probability of renewable energy installment at two different cutoff ages 55 and 65

	Cutoff Age=55			Cutoff Age=65		
Bandwidth	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
10	-0.004	-0.011	-0.012	-0.010	-0.012	-0.008
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
8	-0.010	-0.008	-0.016*	-0.009	-0.016*	-0.007*
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.00]
6	-0.014*	-0.008	-0.010***	-0.014**	0.003	-0.002
	[0.01]	[0.01]	[0.00]	[0.00]	[0.00]	[0.01]

Note: This table reports the estimated coefficients from sharp RDDs of the propensity to install renewable technology on an indicator variable for whether the oldest member of the household is either above 55 (first three columns) or above 65 (second three columns) using different polynomials (linear, quadratic and cubic) and bandwidths (6, 8 and 10). Each regression includes year of survey fixed effects, the indicated polynomial interactions between the treatment variable and age, log of household income, employment and education qualification dummies. See equation 2 for more detail. The estimation sample includes only home owners which household's size is two or lower and the oldest member is male. The number of observations for models with a cutoff age of 55 is 3072, 2448, and 1813 for bandwidths 10, 8 and 6, respectively, while is 3947, 3339, and 2694 for models with a cutoff age of 65. Standard errors in brackets are adjusted for clustering at age level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

break them apart. The amount of this extra income is summed across each household and an estimation is run separately to determine whether the presence of extra income or the amount of extra income affects the probability of installing renewables. The median amount of extra income in the sample is £184. The results are given in Table 10. All estimates are statistically indistinguishable from zero.

Taken together, these three tests support the claim that the mechanism behind the change in the propensity to install renewable technologies found in Table 3 is due to the WFP and not a result of income effects or a change in age across the two groups. Specifically, this constitutes further evidence that the WFP is seen as price subsidy for energy.

Other possible threats to our identification seem unlikely to compromise the results.

Table 10: Effect of Non-labeled income changes on renewable energy installment

	Whole Sample		Homeowners Aged 50-70	
Variable	OLS	Logit	OLS	Logit
Presence of Extra Income	0.001	0.001	-2.16e-04	-1.08e-4
	[0.001]	[0.01]	[0.001]	[0.002]
Amount of Extra Income	1.82e-09	-2.98e-09	-1.04e-08	-3.92e-08
	[2.47e-08]	[2.60e-08]	[2.43e-08]	[6.13e-08]

Note: This table reports the coefficients from an OLS and the marginal effects from a logit model of the propensity to install renewable technology using two samples. Each regression includes year of survey fixed effects, age of oldest member, log of household income, and tenure. The number of observations are 37,213 for the whole sample and 13,455 for the homeowners aged 50 to 70. Standard errors in brackets are adjusted for clustering at age level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The price of solar PV systems generally do not vary based on age of homeowner and have been coming down over time (Feldman et al., 2012). The data utilized come from a large government survey where interviewers visit the home and which asks about numerous issues other than energy/environmental issues. As a result, any framing or reporting concerns seem unlikely. Browning et al. (2015) find that durable good consumption is flat or rising with age using the same dataset as this analysis and our falsification test show that other home investments are unaffected by this age cut-off, thus the drop in renewable energy investment is likely not due to a pure ”age effect. There is evidence of that solar panels are capitalized into housing prices, but no evidence that the value is different by age of homeowner (Dastrup et al., 2012). The data show no evidence that households are disproportionately likely to move when a member reaches the age of 60 thus anticipation of a change of homes are unlikely driving the results. Previous research finds that receipt of government transfers alters household behavior rather than anticipation of the transfer (Parker et al., 2013 and Attanasio et al., 2012) and the ”doughnut hole” estimation given in Table 5 supports this assertion. Finally, the Beatty et al. (2014) analysis show that a number of outcomes, such as changes in expenditures on other household items, are not impacted by reciept of the WFP and that no change in expenditures are found at other cutoff ages than 60. The falsification tests which support their analysis also support ours.

6 Conclusions

When cash transfers are labeled, does the labeling affect household decisions on goods related to the labeled one? While there is growing evidence building that the label of a cash transfer alters recipients decisions on purchases of the labeled good, the analysis here is the first to answer the question above. The answer has broad implications for nearly every policy. Many of the most common transfers have labels which suggest a use for the transfer, such as food stamps and child benefit.

This paper tests whether households substitute away from renewable energy technologies, which are more energy efficient, when receiving a cash transfer, the WFP, which primes them to purchase fuel. Using a simple model of household production of energy services which can be met by fuel or more efficient capital, it is shown that when households receive a cash transfer labeled with the word fuel it can lead to an increase in the amount of fuel used Beatty et al. (2014) and a substitution away from more efficient capital.

This theoretical result is confirmed when taken to data. Identification of the WFP treatment is based on the sharp eligibility criteria of the WFP, confirmation that other explanatory variables are continuous around the discontinuity, and numerous falsification tests. In other words, the effect of the WFP is for households to choose energy sources which pollute more. Results find that WFP recipients are 1.2 percentage points less likely to install renewable energy technologies. This is the middle point of a range of values that go from 0.05 to 3.5 percentage points. The results are not only statistically significant, but also economically relevant. Considering the universality of the transfer, this is a considerable number. Our models predict that between 69% of households whose oldest member turns 60 would have invested in renewable energy but refrain to do so after receiving the WFP.

Given that renewable technologies are one way to ensure that a household can afford to heat its home, these results imply that the label of the transfer nudges households towards a less socially efficient outcome in which a desired amount of heating is achieved with more pollution at the expense of cleaner renewable energy installments. Ultimately, the transfer is counterproductive to the ultimate goal of the policy as it moves households away from one way to achieve the goal itself. Additionally, concerns over greenhouse gas emissions, energy security, and the competitiveness of the UK economy, have led to the recent implementation of a number of renewable energy policies. The evidence given here suggests that the effectiveness of renewable policies is being hampered by the WFP label. This issue may be straightforward to remedy; rename the transfer to something that primes the household to think about energy efficiency or renewables, such as the Winter Renewable Energy Payment.

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Appendix A

Table A.1: Optimal polynomial order selection using the Akaike Information Criterion (AIC)

Bandwidth	Without controls			With controls		
	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
10	-5438.88	-5437.30	-5435.09	-5443.14	-5441.36	-5439.45
8	-5750.59	-5748.85	-5748.11	-4891.44	-4890.16	-4891.94
6	-4889.58	-4888.13	-4887.79	-4891.44	-4890.16	-4891.94

Note : This table reports the AIC statistics computed for each model presented in Table 3. The optimal polynomial order is the one with minimum AIC value.

Table A.2: The effect of the WFP on renewable energy installment using wild cluster-bootstrap (Cameron et al., 2008)

Bandwidth	Without controls			With controls		
	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
10	-0.012**	-0.013*	-0.028***	-0.012*	-0.014*	-0.030***
	(0.04)	(0.10)	(0.00)	(0.04)	(0.09)	(0.00)
	N=3656	N=3656	N=3656	N=3656	N=3656	N=3656
8	-0.009	-0.023***	-0.023***	-0.009	-0.024***	-0.025***
	(0.24)	(0.00)	(0.00)	(0.21)	(0.00)	(0.00)
	N=3074	N=3074	N=3074	N=3074	N=3074	N=3074
6	-0.018**	-0.015***	-0.035***	-0.018**	-0.016***	-0.036***
	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
	N=2411	N=2411	N=2411	N=2411	N=2411	N=2411

Note: This table estimates equation 2 in table 3 using wild cluster bootstrap percentile t-procedure, imposing the null hypothesis for each coefficient, as shown in (Cameron et al., 2008). *P*-values obtained from bootstrapped t-stats are shown in parenthesis.

Table A.3: The effect of WFP on energy renewable instalments – Logit regressions

Bandwidth	Without controls			With controls		
	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
10	-0.015***	-0.014*	-0.032***	-0.015***	-0.016**	-0.034***
	[0.005]	[0.007]	[0.008]	[0.005]	[0.008]	[0.008]
	N=3656	N=3656	N=3656	N=3656	N=3656	N=3656
8	-0.009	-0.021***	-0.017**	-0.010	-0.022***	-0.019**
	[0.006]	[0.007]	[0.008]	[0.006]	[0.007]	[0.008]
	N=3074	N=3074	N=3074	N=3074	N=3074	N=3074
6	-0.019***	-0.009**	-0.029***	-0.020**	-0.011***	-0.033***
	[0.007]	[0.004]	[0.010]	[0.008]	[0.004]	[0.008]
	N=2411	N=2411	N=2411	N=2411	N=2411	N=2411

Note: This table reports the marginal effects from sharp RDDs of the propensity to install renewable technology on an indicator variable for whether the household received the WFP using different polynomials (linear, quadratic and cubic) and bandwidths (6, 8 and 10) estimated using logit regressions. Each regression includes year of survey fixed effects and a series of interactions between the treatment variable and normalized age. The last three columns include also log of household income, employment and education qualification dummies. See equation 2 for more detail. The estimation sample includes only home owners whose household size is two or lower and the oldest member is male. Standard errors in brackets are adjusted for clustering at age level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

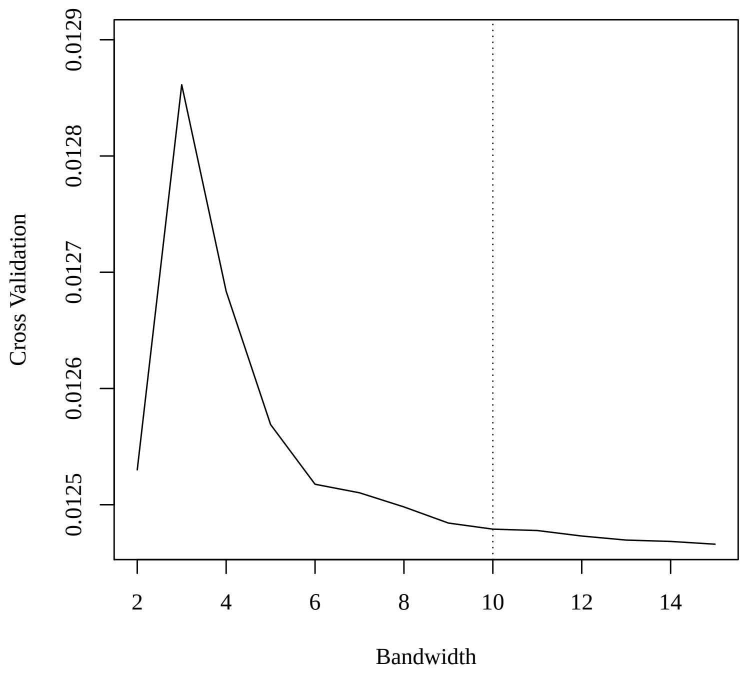

Figure A.1: Plotting cross validation against bandwidth for choosing the optimal bandwidth in Table 3

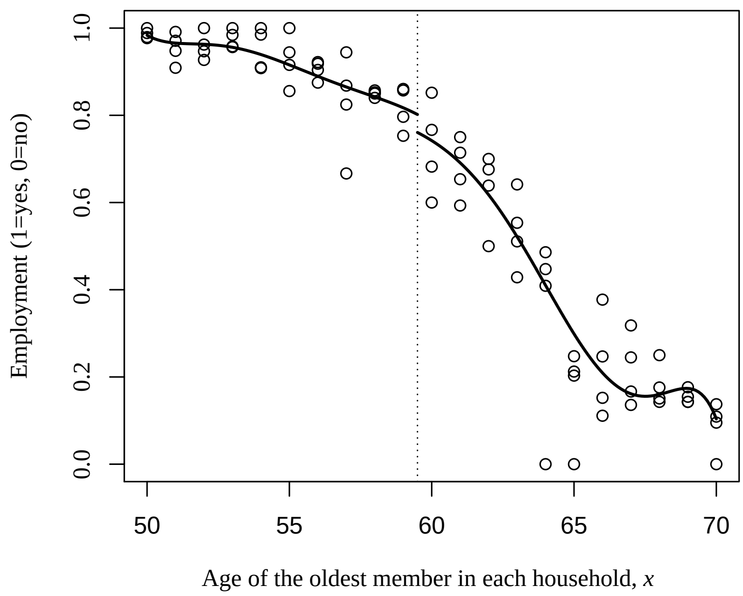

Figure A.2: Discontinuity in employment of the oldest member

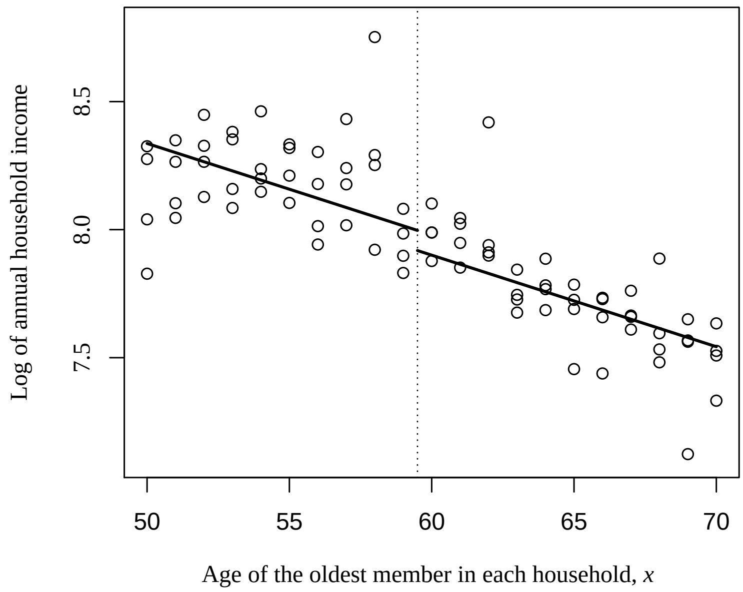

Figure A.3: Discontinuity in log of income

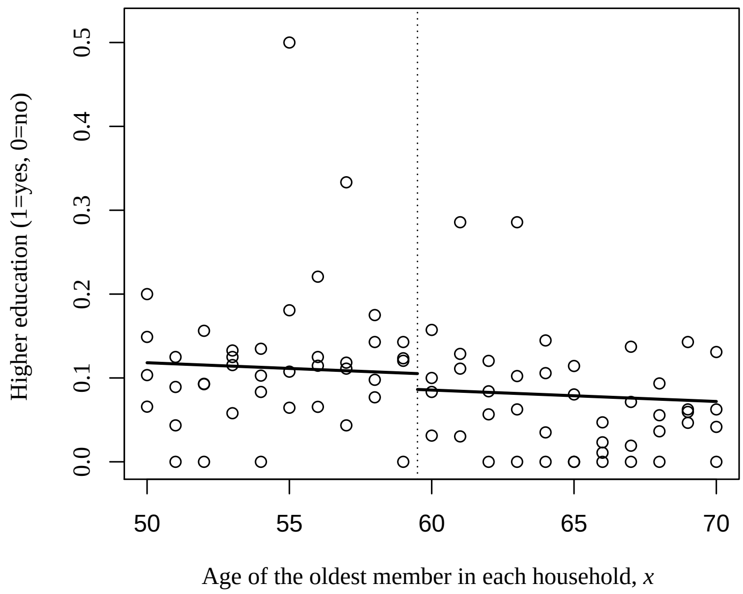

Figure A.4: Discontinuity in obtaining higher education

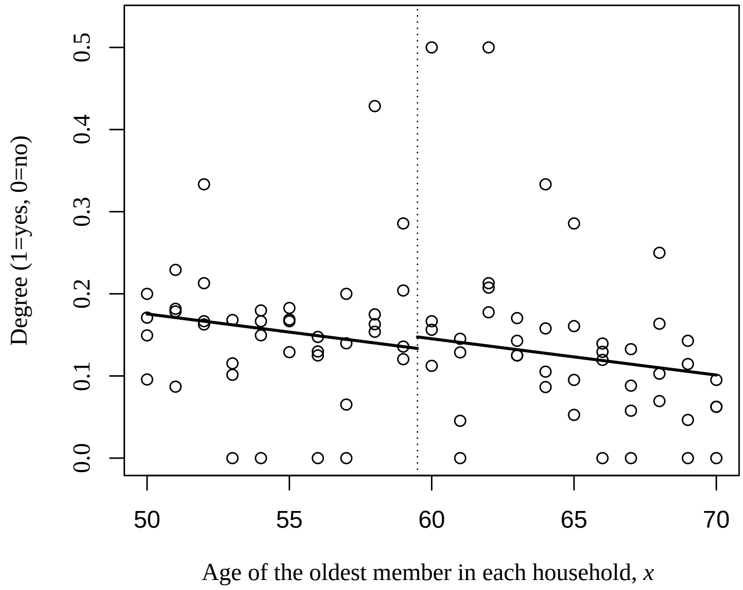

Figure A.5: Discontinuity in obtaining a degree

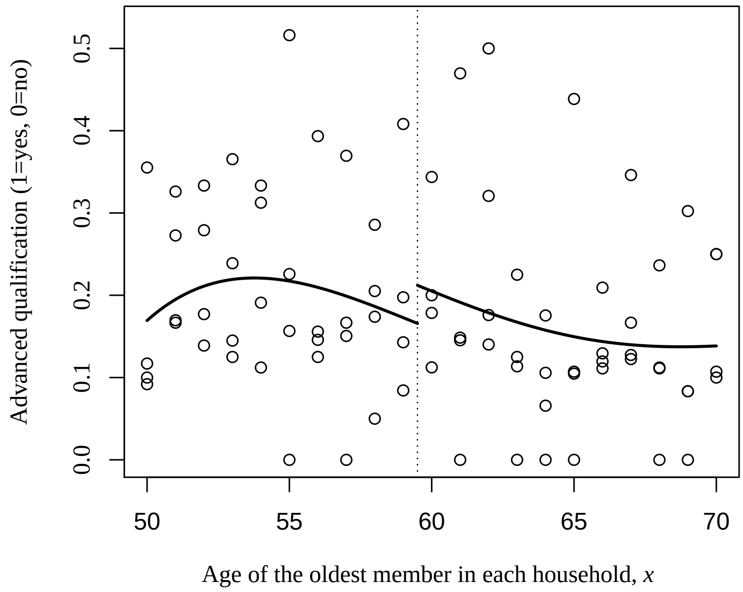

Figure A.6: Discontinuity in obtaining advanced qualifications

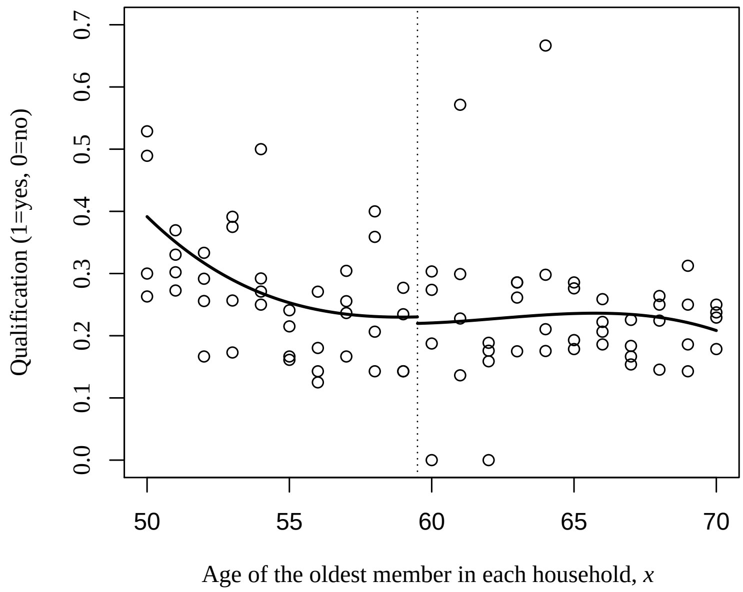

Figure A.7: Discontinuity in obtaining qualifications

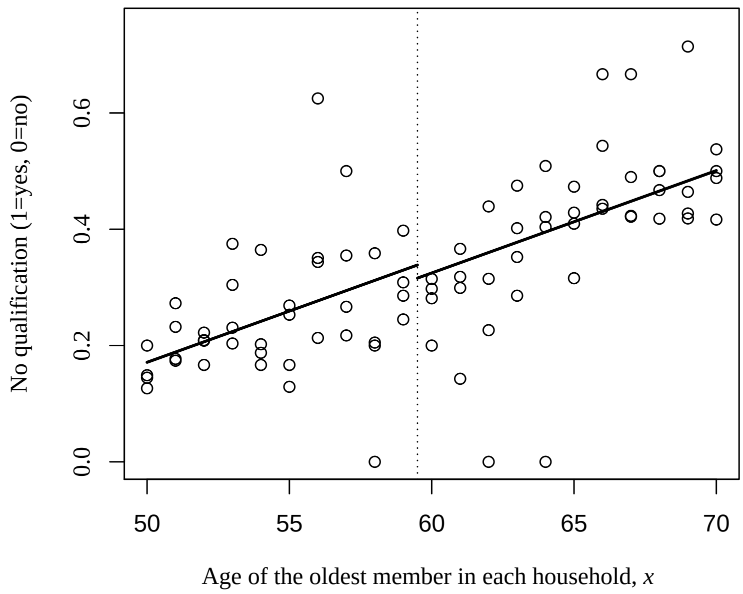

Figure A.8: Discontinuity in having no qualifications