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Ian Lange

Mirko Moro

Mohammad Mahbubur Rahman

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Policy Labels and Investment Decision-making

Ian Lange*[a], Mirko Moro[b], and Mohammad Mahbubur Rahman[b]

[a]*Division of Economics & Business, Colorado School of Mines, USA*
[b]*Division of Economics, University of Stirling, Scotland, UK*

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Abstract

Much attention in recent years has turned to the potential of behavioural insights to improve the performance of government policy. One behavioural concept of interest is the effect of a cash transfer label on how the transfer is spent. The Winter Fuel Payment (WFP) is a labelled cash transfer to offset the costs of keeping older households warm in the winter. Previous research has shown that households spend a higher proportion of the WFP on energy expenditures due to its label (Beatty et al., 2011). If households interpret the WFP as money for their energy bills, it may reduce their willingness to undertake investments which help achieving the same goal, such as the adoption of renewable energy technologies. In this paper we show that the WFP has distortionary effects on the renewable technology market. Using the sharp eligibility criteria of the WFP in a Regression Discontinuity Design, this analysis finds a reduction in the propensity to install renewable energy technologies of around 2.7 percentage points due to the WFP. This is a considerable number. It implies that 62% of households (whose oldest member turns 60) would have invested in renewable energy but refrain to do so after receiving the WFP. This analysis suggests that the labelling effect spreads to products related to the labelled good. In this case, households use too much energy from sources which generate pollution and too little from relatively cleaner technologies.

JEL Classification: C31, Q42, Q48

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

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. Behavioral approaches include appeals to social norms (Allcott, 2011; Ferraro and Price, 2013), commitment devices, information provision, small price changes (Homonoff, 2013), default options and cash transfer labels (Beatty and Tuttle, 2012). The attractiveness of these interventions lies in the fact that they are simple and inexpensive to implement, but at the same time produce considerable changes in behaviour. Nudges have been found to be successful in a variety of settings, improving healthy and pro-social behaviors (Giné et al., 2010), adoption of better technologies (Duflo et al., 2011) and saving rates (Thaler and Benartzi, 2004).

The labelling of cash transfers has attracted the attention of economists in recent years. Labelled cash transfers are unconditional to specific uses, but have been given a suggestive name which may nudge recipients into socially desirable behaviors. Example of these types of transfers are child benefits or food stamps (e.g., Kooreman, 2000; Blow et al., 2012). The literature typically studies the effectiveness of the label in promoting desired behaviors and stress the theoretical implications from an economic point of view. Standard economics would predict unconditional labelled cash transfer to be equivalent to a unlabelled cash transfer. However, some evidence exists showing that labelled transfers seem to be spent more than proportionally on the items suggested by the label (e.g., Beatty and Tuttle, 2012; Kooreman, 2000).

One such unconditional cash transfer policy is the UK Winter Fuel Payment (WFP). The WFP was initiated to combat the excess elderly winter mortality and morbidity associated with cold indoor climates. It provides households, which have a member 60 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 utilised 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-labelled transfer (Beatty et al., 2011). The rationale for this behaviour 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 labelled, it is assigned into the labelled category.

This paper builds upon Beatty et al. (2011) and relates to the literature of unconditional cash transfers. However, it is not concerned with the direct effect of the label on the good suggested, but asks whether labels alter decisions on products related to the good suggested. We investigate the effect of the WFP on the renewables market. 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. The motivation for the WFP to alter renewable energy investments suggested here is that households become less sensitive to energy expenditures, they feel that the energy mental account is satisfied and options to reduce this expenditure would not be considered.

Our analysis shows that the WFP has an unintended consequence of reducing the propensity to install renewable technologies. The sharp eligibility criteria of the WFP allows for an estimation of the casual impact of the WFP on the propensity to install renewable energy with a regression discontinuity design (RDD). Because estimates from the RDD are sensitive to the choice of bandwidth size and functional form, we present various combinations between different bandwidths (6, 8 and 10) and functional forms (linear, quadratic and cubic). Further, we also allow the slope of the relationship between renewable energy installment and age to be different on either side of the cut-off age of 60. Results consistently find a negative effect of the WFP on the propensity to install renewables. Models with optimal functional forms as established by goodness-of-fit tests and Akaike Information Criterion (AIC), show that WFP recipients are around 2.7 percentage points less likely to install renewable energy technologies. This drop corresponds to 62% of households substituting away from renewable investments just after receiving the payment. Given the universality of the WFP this is a considerable distortion. We restricted our sample to homeowners only, as they are more likely to make investments, however results still hold when considering renters too, albeit the size of the effect is smaller. The effect is larger for households, which do not contain members under the age of 45. Falsification tests show that the WFP has either increased or had no effect on the propensity to invest in one's home through remodelling their kitchen or purchase other consumer durables such as a car. Additionally, placebo WFP eligibility ages generally do not find statistical changes in the propensity to install renewables. This analysis extends the literature on labelling cash transfers by showing that greater consideration should be given to the choice of the specific label when decisions on related products are important to maximising the net social benefits of policies (i.e., in presence of externalities). By looking at the potential distortionary effects on renewables market our paper is the first one to estimate the indirect effects of a labelled cash transfer payment. This paper also shows that indirect effects are especially important in a context in which negative externalities are pervasive and policies that seems at first effective, may ultimately lead to socially inefficient outcomes.

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 and six discuss the results and associated robustness checks, respectively. Section seven studies results for different groups of households, and Section eight 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 the 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. 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. Important for this analysis is that the WFP is not means tested and all households that are 60 or above at the qualifying week receive the payment. 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.

A simple model where the household demands energy services (e.g., heating) through a 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 for energy services.[1] The household's production of energy services is assumed to follow a Cobb-Douglas production funcation and can be modeled using isoquant and isocost curves, which show the household's ability to purchase energy or capital that limits the production of energy services attainable.[2] 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 or cash is always fungible: any unit of money can be substitute for another and that the source of income does not matter for rational consumers. A direct consequence of this is that labelling of income sources, cash or cash-equivalents (such as vouchers) should not yield any sizeable and statistically significant effect on spending choices. In other words, standard economic theory would predict that the WFP is seen as income. The household increases the use of both capital and energy to produce more enegy services in this case due to the WFP being an increase in income. In this case, the WFP would lead to a little rightward shift of the isocost curve as in Figure 1.

However, recent literature shows that money with a label attached is treated like a price subsidy to the labelled 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

[1]The household has also a budget for all other goods such as foods, cloths. So, the budget constraint for energy services is a part of overall budget constraint for all goods the household consumes.

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

to use simple heuristics to make financial and consumption decisions. In particular, individuals have mental budgets for different expenditure categories (food, clothes, education and, say, energy or energy related matters) that they treat separately. So when in receipt of labelled cash transfers, the money is used disproportionately more to purchase goods suggested by the label. Use of mental accounting implies that the household may treat the WFP as a price subsidy to energy, which would pivot out of the isocost curve to allow more energy to be used as in Figure 2. 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 income effect. If the substitution effect (towards energy and away from capital) dominates the output effect, less capital is used and vice versa. To summarise, 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.

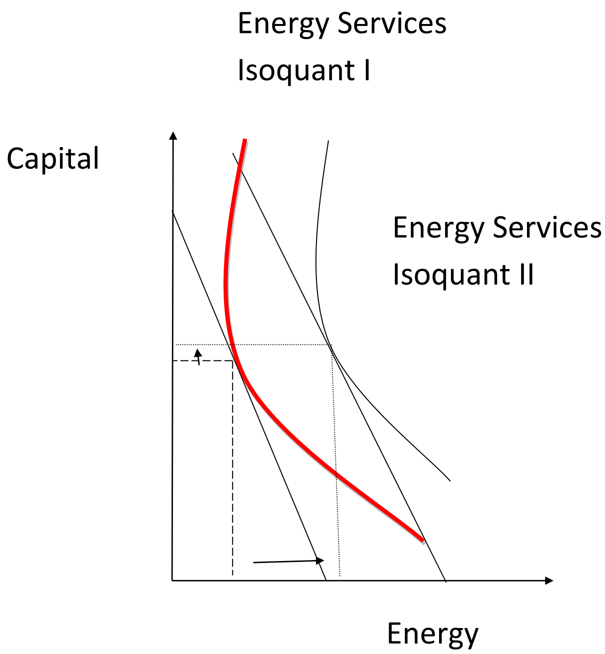

Figure 1: Impact of the WFP as income on use of energy and capital

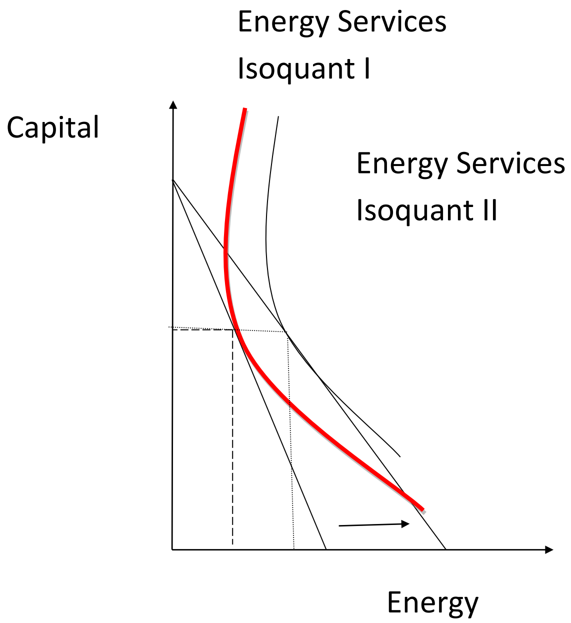

Figure 2: Impact of the WFP as a price subsidy to energy on use of energy and capital

Examples of households' use of mental accounting can be found in development, agricultural and financial economics, using clean identification strategies or natural field experiments. Abeler and Marklein (2008) shows 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 (2012), using a clean identification strategy, 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. A recent paper found that the cash incentives to education that are labelled, but not conditional on school attendance, performs as well as more expensive conditional cash transfers in Morocco (Benhassine et al., 2013). The paper closest to the current resarch is Beatty et al. (2011), which estimates the effect of the WFP on share of total expenditure spent on fuel, holding total expenditure constant. Beatty et al. (2011) finds 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 distortionary effects on the renewables market, decreasing the propensity to install these technologies. 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 renewables and towards more energy usage. 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 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 is the last wave and sampled individuals 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 and2011. Most of the analyses will focus only on households which own their home, though an estimation using all households is also given below.

Both waves of the BHPS and USS ask the household whether they have installed solar photovoltaic (PV) panels, solar water heaters or a micro wind turbine.[3] A variable y is created that equals one if any of the three renewable technologies have been installed and is zero otherwise. 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.[4] 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.

Given the eligibility requirement of the WFP discussed above, a sharp RDD requires that the assignment variable, denoted by 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. The data provides the month and year of birth as well as the month and year of the survey. As we do not have any data on whether households receive the WFP, it is crucial to remove any measurement error in x, especially at 60.[5] 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 denote survey month and birth month respectively. We assign $1, 2, 3, \ldots, 12$, to both

[3] Other waves of the BHPS and USS do not contain these questions.

[4] During our sample period there were no government subsidy payments available for generation from these renewable.

[5] Otherwise, we could have applied the fuzzy RDD with the measurement error in x (Battistin et al., 2009).

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.[6] For other combinations of BM and SM, we subtract 1 from $SY - BY$. This adjustment is undertaken to ensure the eligibility of households. In the first case, the oldest members aged 60 years old are considered as 60, 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 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 90% according to Beatty et al. (2011), 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 treatment or receiving the WFP, $Pr(D = 1|x)$, is sharply discontinuous at 60.

To have an idea about the discontinuity in the propensity of renewable energy installments around the cutoff age of 60, Table 1 shows the distribution of households that own houses (number of observations) and means of y by age cell in x and 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 declines a bit 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 renewable energy falls

[6]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.

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	0.0207	145	0	205	0.016	188	0	20	0.0108	558
51	0.0083	120	0.0041	241	0	194	0	17	0.0035	572
52	0	93	0.0087	231	0.0214	187	0	11	0.0115	522
53	0	113	0.0039	254	0.0226	177	0	14	0.009	558
54	0	125	0.0092	217	0.0106	188	0	11	0.0074	541
55	0.0172	116	0.0093	214	0.0122	164	0	9	0.0119	503
56	0.0076	132	0	210	0.0231	173	0.0769	13	0.0114	528
57	0	101	0.0097	206	0.0106	188	0	11	0.0079	506
58	0	90	0.0091	220	0.0061	163	0.1	20	0.0101	493
59	0.0174	115	0.0195	205	0.046	174	0	14	0.0276	508
60	0.008	125	0.0215	186	0.0174	172	0	20	0.0159	503
61	0.0074	136	0.0041	245	0.0144	209	0	12	0.0083	602
62	0.0165	121	0.0161	249	0.0092	217	0	8	0.0134	595
63	0.0095	105	0.0053	188	0.0047	215	0	15	0.0057	523
64	0.0198	101	0.0145	207	0.0062	162	0	12	0.0124	482
65	0.0097	103	0	194	0.0058	173	0	11	0.0042	481
66	0.0341	88	0.0164	183	0.0411	146	0	15	0.0278	432
67	0	99	0.0179	168	0.0169	178	0	11	0.0132	456
68	0.0198	101	0	172	0.0072	139	0.0769	13	0.0094	425
69	0.0112	89	0.0286	175	0.0142	141	0	8	0.0194	413
70	0	98	0.0261	153	0.0318	157	0	7	0.0217	415

initially and then increases from 66 and on. This provides first evidence that y might be discontinuous at 60 and that the WFP might have an affect on the probability of renewable energy installment.

4 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. 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 (e.g., the age of the oldest member is greater than or equal to 60 in September of the given year) or non-treated if not eligible (e.g., the age of the oldest member is below 60), where the cutoff point is age of 60. Hence, selection on the treatment is on the basis of observable age of the oldest member in the qualifying month, which is independent of the outcome and cannot be manipulated.

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 WFP receipt. In other words, this assumption ensures that households on the left-hand side of the cutoff represent a good counter factual. 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:

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

Given the assumption reported above, any jump in the propensity of renewable energy installment at the threshold of 60 years of age is brought about by the discontinuity in the WFP. The causal effect can be interpreted as the average treatment effect (ATE) of the WFP program on the propensity of installing renewable energy of households near the cutoff point.

Figure 3 shows the probability of installing renewable energy, y, against the age of the oldest household member, x, – the assignment variable. Each point represents the propensity of installing renewable energy technology for a particular age-year of the survey cell (i.e., they are not single observations). The line is estimated from a non-

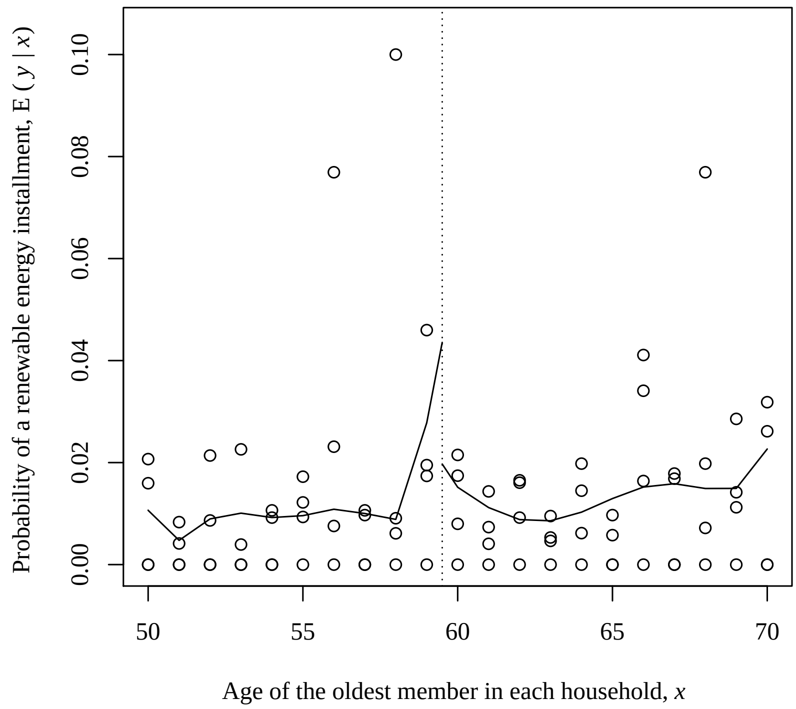

Figure 3: Discontinuity in renewable energy installment at age 60 (Predicted line from series estimator)

parametric series estimator (Li and Racine, 2007). It passes through means by age-year and provides an indication of the discontinuity in the probability of installing renewable energy at the cutoff age of 60. The size of discontinuity is the ATE of the WFP program on the probability of installing renewable energy. The estimated line in the figure shows the expected shape as seen from Table 1. The scattered points in the graph help in identifying the presence of some outliers, which may drive the magnitude of the discontinuity. However, in Table 1 there are outliers only in year 2011 when there are few observations, alleviating concerns about outliers effecting our results.

Intuitively, one way of estimating the causal effect would be to run two separate regressions: one for the left-had side of the cutoff and one for the right-hand side. A more direct way of estimating the ATE, and one that is typically used in the literature, is to run a pooled regression on both sides of the cutoff. This has the advantage of obtaining the standard errors of the causal effects directly. Figure 3 shows that there are different shapes of the predicted lines on either side the discontinuity point. To allow for different functional forms on either side of the cutoff, a regression model should include interaction terms between the treatment indicator and the assignment variable and its polynomial orders. Following Lee and Lemieux (2010), we present the RDD equation in the polynomial form:

$$y = \alpha + \beta_1(x-60) + \cdots + \beta_k(x-60)^k + \delta_1 D*(x-60) + \cdots + \delta_k D*(x-60)^k + \rho D + \eta, \quad (2)$$

where y is a dummy variable indicating whether the household has installed renewable technologies at home, and the coefficient, ρ, is the parameter of the causal effect of the WFP. The assignment variable is normalized by subtracting 60 from x, because this normalization gives a guarantee that the coefficient on D is still a causal effect in the case of interactions between D and the assignment variable and its polynomial forms (Angrist and Pischke, 2009).

It follows from this, that there are two important choices to be made in the RDD framework: the bandwidth around the sharp eligibility threshold and the order of the polynomial of $x - 60$ (k here). Incorrectly specifying equation (2) would lead to a biased estimate of the ATE. With regard to the size of the bandwidth, 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.

The order of the polynomial 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. Following Lee and Card (2008), the optimal polynomial order for the functional form is chosen with a goodness-of-fit test. The specification choice procedure is to add a higher order term to the polynomial until the age cell dummies are no longer jointly significant. The optimal polynomial order selection does not vary when using the Akaike Information Criterion (AIC).

In spite of using the optimal bandwidth and/or the optimal polynomial order, the ATE estimation will be biased if the identification assumption does not hold. The identification assumption – the local randomisation assumption – states that both observed and unobserved covariates that affect the outcome are continuous at the cutoff age, 60. These covariates are predetermined and unaffected by the WFP program. For instance, when the forcing variable is age it is typical to worry about changes in employment status. Here, 60 is the women retirement age in the UK. In order to check for the validity of our design, we will be testing for the presence of discontinuities in observed covariates. The absence of any significant discontinuity will be taken as reassurance that local randomisation is an appropriate assumption.

5 Results

Table 2 shows the estimated values of ρ from the OLS regressions of equation (2) under three different bandwidths (6, 8 and 10) and three orders of polynomials (linear, quadratic and cubic). Each model includes year dummies to control for year of the survey. Reported t-ratios are estimated from age-cluster adjusted standard errors. According to the cross validation method, the optimal bandwidth is 10 (for details see Figure A.1 in Appendix). The table shows which polynomial performs better after our goodness-of-fit test and AIC.

Table 2: The effect of the WFP on renewable energy installment

Bandwidth	Models without interaction			Models with interaction		
	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
10	-0.0076*[a]	-0.0076*	-0.0078	-0.0080*	-0.0129*	-0.0213**
	[-1.8159]	[-1.8025]	[-1.3834]	[-1.8717]	[-1.9048]	[-2.0652]
8	-0.0064	-0.0068	-0.0105	-0.0075	-0.0176**	-0.0267***[a]
	[-0.9177]	[-0.9881]	[-1.0191]	[-1.1089]	[-2.2901]	[-4.3267]
6	-0.0103	-0.0107	-0.0038	-0.0121	-0.0179**	-0.0509***[a]
	[-1.1680]	[-1.2453]	[-0.3139]	[-1.5302]	[-2.5025]	[-16.0693]

Note : t-ratios in brackets are estimated from cluster adjusted robust standard errors at age level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[a] Optimal polynomial orders of $x - 60$ according to the goodness of fit test suggested by Lee and Card (2008) and AIC.

The optimal bandwidth is equal to 10 according to the cross validation method suggested by Imbens and Lemieux (2008).

The sample is restricted to owners only. Year of the survey dummies are included in each regression.

The discontinuity parameters are all negative. The majority of these parameters are statistically significant in specifications with interactions (between $x - 60$ and its polynomial terms, and D). Only linear models under 8 and 6 bandwidths show insignificant results. However, visual and formal tests of functional form indicate that the linear approximation is not the most appropriate in this case (see Figure 3 and Lee and Card (2008) and AIC tests in Appendix). Figure 3 shows not only that the probability of renewable energy installment has a non-linear trend but also different shapes on either side of the cutoff age. This strongly suggests that the specifications with interactions are the most appropriate. Within these models, the narrower the bandwidth, and the higher the order of polynomials, the larger is the estimated parameter. Looking only at statistically significant results of models with optimal polynomial order (i.e., linear with bandwidth 10 or cubic with bandwidth 8 or 6), the value of the discontinuity ranges between -0.008 and -0.05. According to the cubic specification, which is optimal in 2 out of 3 cases, the values are higher on average and more stable, ranging from -0.02 and -0.05. Using the middle point of both these latter ranges suggest that receiving the WFP leads reduces the propensity to install renewable technologies by 2.7 percentage points. A more conservative estimate is provided by the quadratic specification, which estimated decline in the probability of renewables installment ranges between 1.2-1.8 percentage points.

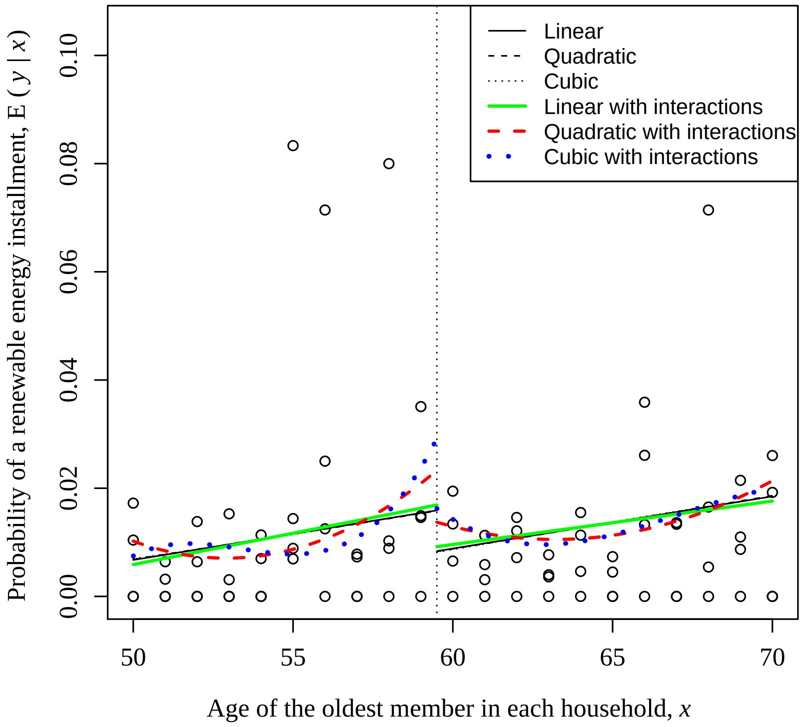

Figure 4: Discontinuity in renewable energy installment from estimated models in Table 2

Figure 4 provides a graphical representation of the estimated effects using a bandwidth of 10. Every specification have a discontinuous jump down at the age of 60. This provides further evidence that households who are in receipt of the WFP are less likely to install renewable technologies at home.

As specified above, the basic underlying assumption of the RDD is local random

Table 3: Discontinuities in observed covariates (using a bandwidth equal to 10)

	Discontinuity	Robust t-ratio
Employment (1=yes, 0=no)	-0.0495	-1.3510
Household size	0.0268	0.4595
Log of annual income of household	-0.0559	-1.1514
Qual1 (1=higher education, 0=others)	-0.0249**	-2.6708
Qual2 (1=first degree, 0=others)	-0.0026	-0.1642
Qual3 (1=A-level and related, 0=others)	-0.0177	-1.0158
Qual4 (1=O-level and related, 0=others)	-0.0099	-0.4533
Qual5 (1=no qualification, 0=others)	-0.0058	-0.3258

Note : t-ratios are estimated from cluster adjusted robust standard errors at age level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The sample is restricted to owners only. Year dummies are used in each regression.

Each row represents a separate regression of Y on each covariate using the optimal polynomial order of $x - 60$. This varies with each regression.

assignment around the cutoff age of 60. One way to check the validity of the above results is to examine whether the covariates are discontinuous around the threshold. To test the local randomization, we check discontinuities in some observed covariates that may affect the outcome variable (Imbens and Lemieux, 2008). One may argue that at the age of 60 other things change that could be related to the outcome of interest, for example employment status. Indeed, women retirement age in UK is 60. 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 covariate is regressed on D, $(x - 60)$, $D * (x - 60)$ and year dummies under the optimal bandwidth of 10. As the number of covariates increases, some discontinuities will be statistically significant by random chance. As suggested by Lee and Lemieux (2010), regression of each covariate is run as seemingly unrelated regression to perform the test of joint discontinuities. Table 3 shows only the coefficient of the discontinuity for every covariate. We see that the covariates are not significantly discontinuous at the cutoff with the exception of having higher education, which coefficient is statistically significant at 5% level (See Figure A.2 to A.9 in Appendix for graphical analysis of these discontinuities using a bandwidth of 10).

Table 4: First stage of the Residualizing Approach – Regression of renewable energy installment on observed covariates (using a bandwidth equal to 10)

	Coefficient	Robust t-ratio
Employment (1=yes, 0=no)	-0.0054*	-1.9468
Household size	0.0005	0.5544
Log of annual income of household	0.0005	0.8999
Qual1 (1=higher education, 0=others)	0.0239***	3.8232
Qual2 (1=first degree, 0=others)	0.0122***	3.2309
Qual3 (1=A-level and related, 0=others)	0.0055*	1.7392
Qual4 (1=O-level and related, 0=others)	0.0056	0.8758
Constant	0.0056	0.8758
Observations	9242	
Adjusted R^2	0.0027	

Note : t-ratios are estimated from cluster adjusted robust standard errors at age level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The sample is restricted to owners only. Year dummies are used in each regression.

These results indicate that the local randomisation is fairly satisfied. However, and taking into account the significant discontinuity in higher education, we follow Lee and Lemieux (2010)) who suggested to incorporate observed covariates into the estimation of equation (2) by ”residualizing” the propensity of installing renewable energy and then perform formal RDD on the residuals. Under this method, there are two stages. First, an OLS regression is run of the outcome variable on observed covariates denoted by W under bandwidth equal to 10. Estimated coefficients from this first stage regression are reported in Table 4.

From the regression in Table 4, the predicted renewable energy installment is obtained, which is $\mathrm{E}(Y|W)$ and the residuals, $(y - \mathrm{E}(Y|W))$. Next, the second stage OLS regressions is run of equation (2) by replacing Y by $(Y - \mathrm{E}(Y|W))$. In other words, the portion of the variation in the propensity of renewable energy installment that is driven by observable household characteristics is netted out leaving the WFP to explain the residual variation in the outcome.

Table 5: Second Stage of the Residualizing Approach – The effect of the WFP on the residual propensity of renewable energy installment

Bandwidth	Models without interactions			Models with interactions		
	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
10	-0.0104**	-0.0104**	-0.0112*	-0.0110**	-0.0179**[a]	-0.0275**
	[-2.1960]	[-2.1950]	[-1.7602]	[-2.2861]	[-2.3443]	[-2.3620]
8	-0.0090	-0.0098	-0.0149	-0.0108	-0.0232**	-0.0347***[a]
	[-1.0986]	[-1.2459]	[-1.2679]	[-1.4011]	[-2.7119]	[-5.5389]
6	-0.0142	-0.0148	-0.0069	-0.0166*	-0.0239***	-0.0576***[a]
	[-1.3899]	[-1.5007]	[-0.4920]	[-1.8465]	[-3.1542]	[-12.3979]

Note : t-ratios in brackets are estimated from cluster adjusted robust standard errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[a] Results from models with optimal polynomial orders of $x - 60$ choosen by goodness of fit test of Lee and Card (2008) and AIC.

The sample is restricted to owners only. Year dummies are used in each regression.

Table 5 shows the results of the second stage. We run models with and without interactions using three bandwidths (6, 8 and 10) and three polynomial specifications (linear, quadratic and cubic). As expected, the residualizing approach improves precision. The results corroborate previous findings. If anything, the estimated effects are slightly larger (in absolute term) than in the previous case. The discontinuity of the optimal models suggests a decrease in renewable technology investments between 1.8 and 5.8 percentage points. This is a sizeable distortion.

Figure 5 plots the predicted values from regressions in Table 5. There are discontinuities at the cutoff age. Now, with the residualising approach discontinuity estimates are less affected by the outliers if we compare this with Figure 4.

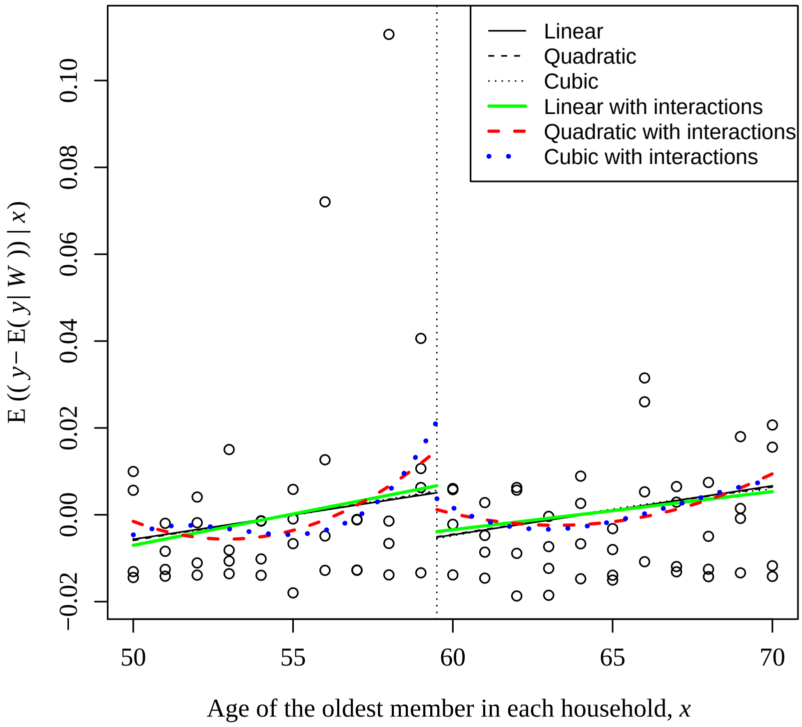

Figure 5: Discontinuity in residual propensity to renewable energy installment from estimated models in Table 5

5.1 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 (i.e., placebo investments) should not vary by whether the household receives the WFP. This WFP mechanism is tested in a couple of ways in this section. The first test checks whether receipt of the WFP leads to a change in the propensity to remodel the kitchen of a household. If the WFP leads households to alter their decisions around energy investments, it should not alter the propensity to remodel one's kitchen. Using data from the English Housing Survey, Table 6 shows the estimation results for equation (2) but with an outcome Y which is a dummy variable equal to one if the household has remodeled their kitchen in the last 12 months and zero otherwise.[7] The estimated effect of the WFP is always statistically insignificant.

Table 6: The effect of the WFP on kitchen remodelling

Bandwidth	Models without interactions			Models with interactions		
	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
10	0.006	0.006	-0.002	0.006	-0.013	-0.019
	[0.47]	[0.49]	[-0.13]	[0.47]	[-0.74]	[-0.68]
8	0.003	0.004	-0.003	0.003	-0.027	0.027
	[0.22]	[0.28]	[-0.15]	[0.22]	[-1.28]	[0.73]
6	-0.002	-0.006	0.001	-0.009	-0.007	0.058
	[-0.13]	[-0.38]	[0.07]	[-0.52]	[-0.31]	[0.86]

Note : t-ratios in brackets are estimated from cluster adjusted robust standard errors at age level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The sample is restricted to owners only. Income, educational qualification, employment and year dummies are included in each regression.

Next, an analysis of whether the WFP led to a change in the probability of investing in some common durable goods – Colour TV, Freezer, Washing Machine, Tumble Dryer, Dish Washer, Micro Wave and Car – is tested. Again, equation (2) is re-estimated with an outcome of a dummy variable equal to one if the household has purchased any of the above items in the last 12 months and zero otherwise. Most of the results in Table 7 are not only insignificant, but also change signs of discontinuities (sometimes positive and sometimes negative).

Taken together, these two tests support the claim that the mechanism behind the change in the propensity to install renewable technologies found in Table 2 is due to the WFP and not a result of income effects or a change in age across the two groups.

[7] An alternative placebo outcome of the propensity to remodel the bathroom was also estimated. The results are equivalent to those presented in Table 6 and are available by request.

Specifically, this consitutes further evidence that the WFP is seen as price subsidy for energy.

Table 7: Discontinuities in probabilities of buying other durable goods

Bandwidth	Colour TV	Freezer	Washing Machine	Tumble Dryer	Dish Washer	Micro Wave	Car
10	0.0134	0.0029	-0.0338	0.0234	0.0023	0.0172	0.0095
	[0.2756]	[0.1925]	[-1.2383]	[1.1988]	[0.0988]	[0.6212]	[0.6012]
8	0.0572	-0.0024	0.0028	0.0089	-0.0101	0.0491*	0.0057
	[1.4006]	[-0.1493]	[0.1518]	[0.5101]	[-0.4684]	[1.8963]	[0.3747]
6	0.0736	0.0164	0.0403**	-0.0004	0.0234	0.0636**	0.0120
	[1.5089]	[0.9098]	[2.2063]	[-0.0316]	[0.9362]	[2.2659]	[0.6908]

Note : t-ratios in brackets are estimated from cluster adjusted robust standard errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The sample is restricted to owners only. Income, educational qualification, employment and year dummies are included in each regression.

Quadratic models allowing different slopes in either side of the cutoff age are run.

Table 8: 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	0.0068	0.0034	-0.0066	0.0026	0.0072	0.0010
	[1.6570]	[1.2284]	[-1.0331]	[0.3603]	[0.6319]	[0.0830]
8	0.0087**	-0.0055	0.0044	0.0024	0.0109	-0.0221*
	[2.1467]	[-1.2112]	[0.9651]	[0.3027]	[0.7902]	[-1.8410]
6	0.0026	-0.0016	0.0061	0.0113	-0.0126	-0.0080
	[0.9664]	[-0.2887]	[0.7861]	[1.0431]	[-1.3782]	[-0.6742]

Note : t-ratios in brackets are estimated from cluster adjusted robust standard errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The sample is restricted to owners only. Income, educational qualification, employment and year dummies are included in each regression.

Regression models consider different slopes in either side of cutoff ages.

Similarly, if the WFP is the mechanism behind the reduction in the probability to install renewable energy, there should not be any significant discontinuities in the probability of renewable energy installments at other age levels where receipt of the WFP does not change. 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) 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.[8] Table 8 shows that most estimates of the discontinuity at 55 or 65 are statistically insignificant and those that are significant change between positive and negative. This result is consistent with WFP leading to a change in propensity to invest in renewable energy.

6 Further Investigation

Next, an investigation is performed into which groups of households play a key role in the results obtained above. One may argue that investments in durable goods, such as renewable energy, vary by ages of household members. Younger members will have a longer life expectancy which implies a longer stream of benefits from renewable energy installments compared to older members.[9] In the analyses above, the assignment variable controls for the effect of age of oldest member and ignores the age of other members of the household. In Table 9, we show estimates of the effect of the WFP (values of ρ) for two groups of households: without members below 45 years of age and with at least one member below that age. The first category indicates a household with lower life expectancy than that of the second category of households. The propensity

[8] Beatty et al. (2011) chosen 66 age level in place of 65 to avoid the effect of retirement, which occurs at 65. However, in our view if we change one year age, results should not be changed drastically.

[9] A counter argument could be made that the value of the renewable energy benefits are capitalized into the house and thus age of the homeowner does not impact expected benefits.

Table 9: Discontinuities in the probability of renewable energy installment by age composition of households

	No member below 45			At least one member below 45		
Bandwidth	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
10	-0.0179**	-0.0248***	-0.0374***	0.0019	-0.0063	-0.0110
	[-2.4434]	[-3.1521]	[-7.5280]	[0.2030]	[-0.4666]	[-0.6362]
8	-0.0168**	-0.0323***	-0.0344***	0.0010	-0.0087	-0.0301*
	[-2.1228]	[-5.1147]	[-4.3309]	[0.0922]	[-0.5451]	[-1.9837]
6	-0.0259***	-0.0246***	-0.0586***	-0.0008	-0.0201	-0.0562***
	[-3.4107]	[-3.3757]	[-9.4088]	[-0.0613]	[-1.3378]	[-4.4257]

Note : t-ratios in brackets are estimated from cluster adjusted robust standard errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The sample is restricted to owners only. Income, educational qualification, employment and year dummies are included in each regression.

Regression models consider different slopes in either side of the cutoff age.

of renewable energy installments is statistically lower for households in receipt of WFP without members younger than 45 relative to those household not in receipt (but within the bandwidth) without members younger than 45. The results comparing households in receipt of the WFP with at least one member younger than 45 to those not in receipt but also with at least one member younger than 45 are mostly insignificant. These results imply that the household composed exclusively of older citizens change their decisions concerning renewable energy installment once in receipt of the WFP.

Finally, Table 10 reveals how the effect of the WFP on renewable energy installment on all households, whether they own the house or not. It is potentially more difficult for a renter to convince their landlord to install renewable energy technologies, however the results given in Table 10 are quite similar to those in Table 2, albeit less sizeable. All estimates are negative and the estimates that correspond to the Lee and Card (2008) goodness of fit test are all statistically significant. The magnitude of the coefficients in Table 10 are similar to that of Table 2.

Table 10: The effect of the WFP on renewable energy installment for owners and renters (ρ)

Bandwidth	Models without interaction			Models with interaction		
	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
10	-0.0073	-0.0074	-0.0069	-0.0078*	-0.0099*[a]	-0.0131**
	[-1.6440]	[-1.7011]	[-1.0093]	[-1.8434]	[-1.8589]	[-2.1007]
8	-0.0063	-0.0068	-0.0080	-0.0074	-0.0119**	-0.0175**[a]
	[-1.1905]	[-1.3716]	[-1.0493]	[-1.5794]	[-2.1241]	[-2.9081]
6	-0.0087	-0.0089	-0.0014	-0.0100	-0.0112*[a]	-0.0376***
	[-1.2893]	[-1.3841]	[-0.1553]	[-1.7359]	[-1.8872]	[-8.6413]

Note : t-ratios in brackets are estimated from cluster adjusted robust standard errors at age level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[a] Optimal polynomial orders of $x - 60$ according to the goodness of fit test suggested by Lee and Card (2008).

Year dummies are included in each regression.

The optimal bandwidth is equal to 10 according to the cross validation method suggested by Imbens and Lemieux (2008).

7 Conclusions

When cash transfers are labelled, does the labelling affect household decisions on related goods? While there is growing evidence building that the label of a cash transfer alters recipients decisions on purchases of the labelled 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 analysis 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 fuel labelled cash transfer it can lead to an increase in the amount of fuel used Beatty et al., 2011 and a substitution away from more efficient capital. This theoretical result is confirmed when taken to data. The sharp eligibility criteria of the WFP allows for an estimation of the casual impact of the WFP on propensity to install renewable energy with a RDD. In other words, the effect of the WFP is for households to choose energy sources which pollute more. Results using several bandwidth and functional forms agree that on average WFP recipients are around 2.7 percentage points less likely to install renewable energy technologies. This is the middle point of a range of values that go from 1 to 5 percentage points. The results are not only statistically significant, but also economically relevant. Our models predict that a minimum of 42% up to 78% of households whose oldest member turns 60 would have invested in renewable energy but refrain to do so after receiving the WFP. Considering the universality of the transfer, this is a considerable number.

The WFP mechanism is confirmed by null results on falsification tests. Households do not alter their propensity to invest in their homes or other durable goods, such as kitchen remodelling or purchase of a new car, and placebo cutoff ages show no change in installation of renewable energy.

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 goodness of fit test suggested by Lee and Card (2008)

		Estimated F	Critical F	Optimal?
Bandwidth=10	Linear	1.52	F(J-K=18, N-J=10595)=1.57	Yes
	Linear with interactions	1.59	F(J-K=17, N-J=10595)=1.57	No
	Quadratic	1.61	F(J-K=17, N-J=10595)=1.57	No
	Quadratic with interactions	1.47	F(J-K=15, N-J=10595)=1.67	Yes
	Cubic	1.71	F(J-K=16, N-J=8641)=1.67	No
	Cubic with interactions	1.53	F(J-K=13, N-J=8641)=1.67	Yes
Bandwidth=8	Linear	1.81	F(J-K=14, N-J=8641)=1.67	No
	Linear with interactions	1.83	F(J-K=13, N-J=8641)=1.67	No
	Quadratic	1.90	F(J-K=13, N-J=8641)=1.67	No
	Quadratic with interactions	1.74	F(J-K=11, N-J=8641)=1.83	Yes
	Cubic	1.99	F(J-K=12, N-J=8641)=1.75	No
	Cubic with interactions	1.61	F(J-K=9, N-J=8641)=1.88	Yes
Bandwidth=6	Linear	2.17	F(J-K=10, N-J=6684)=1.83	No
	Linear with interactions	2.24	F(J-K=9, N-J=6684)=1.88	No
	Quadratic	2.39	F(J-K=9, N-J=6684)=1.88	No
	Quadratic with interactions	1.65	F(J-K=7, N-J=6684)=2.01	Yes
	Cubic	2.45	F(J-K=8, N-J=6684)=1.94	No
	Cubic with interactions	1.19	F(J-K=5, N-J=6684)=2.21	Yes

Note : According to Lee and Card (2008), goodness of fit test (where K is the number of parameters in the restricted model and J is the number of age cells used in the regression) chooses the optimal polynomial order of $x - 60$ when the estimated F is less than the critical F at the 5% significance level. The last column indicates models with optimal polynomial orders. This test also reveals that under 6, 8 and 10 bandwidths, quadratic, cubic models with interactions are optimal models.

Table A.2: Optimal polynomial order selection using the Akaike Information Criterion (AIC)

Bandwidth	Models without interaction			Models with interaction		
	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
10	51459.28	51461.277	51463.271	51461.028	51459.962	51461.885
8	40110.064	40111.517	40112.675	40110.624	40109.958	40109.27
6	29511.083	29512.873	29512.947	29511.568	29506.899	29505.339

Note : The optimal polynomial order is the one with minimum AIC value.

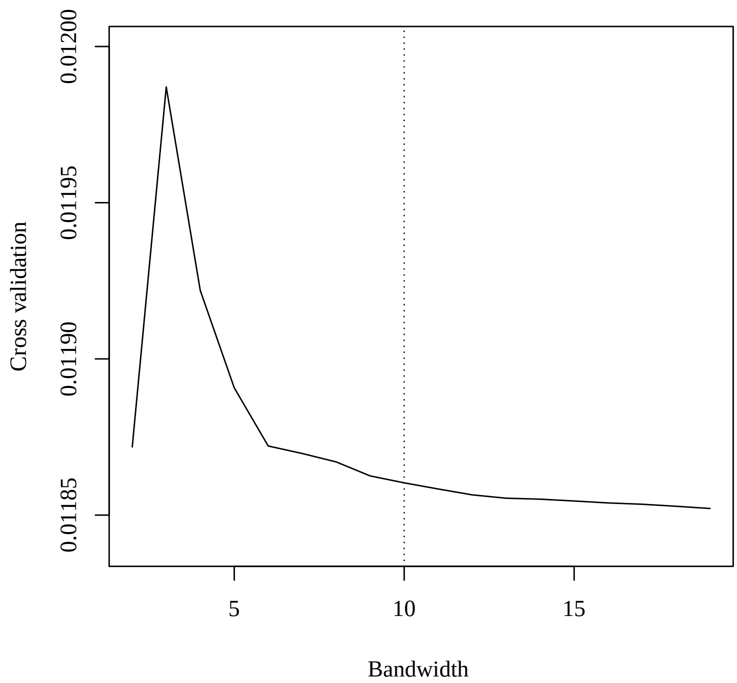

Figure A.1: Plotting cross validation against bandwidth for choosing the optimal bandwidth in Table 2

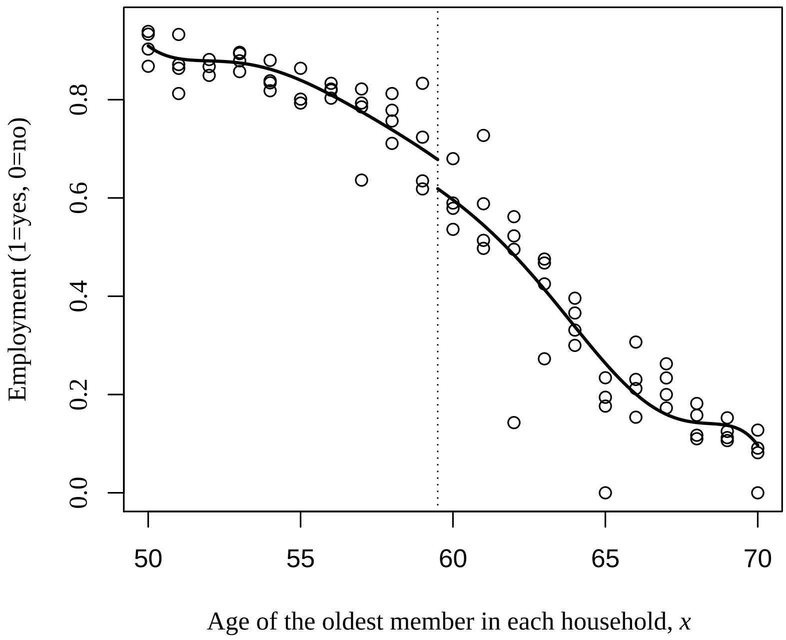

Figure A.2: Discontinuity in employment of the oldest member

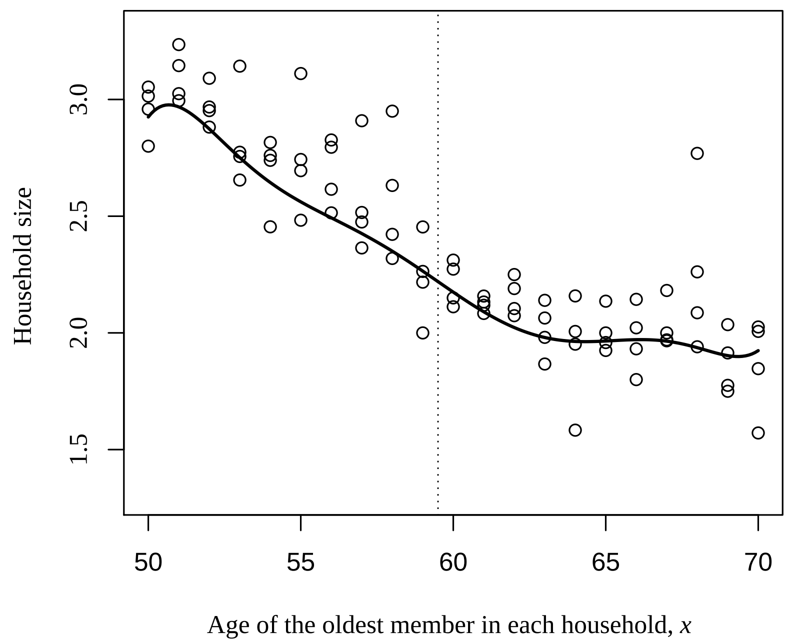

Figure A.3: Discontinuity in household size

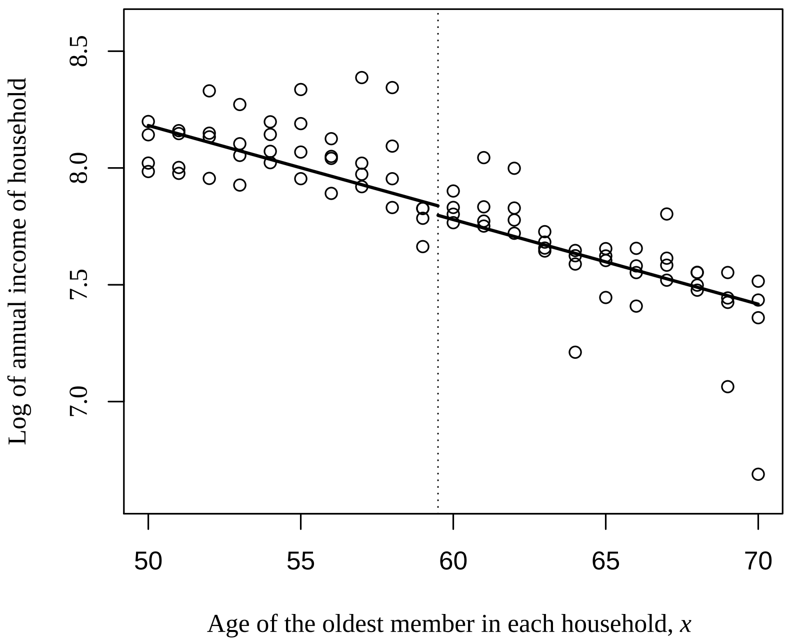

Figure A.4: Discontinuity in log of income

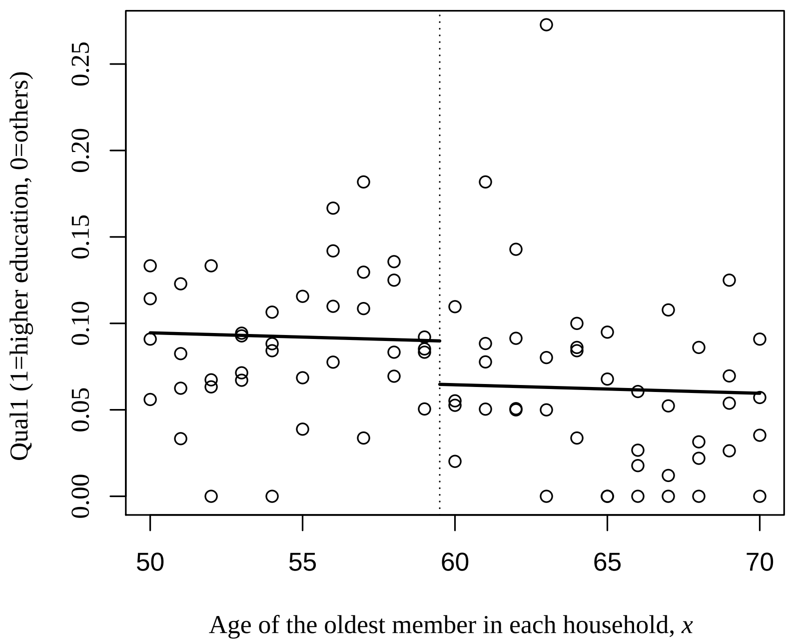

Figure A.5: Discontinuity in obtaining higher education

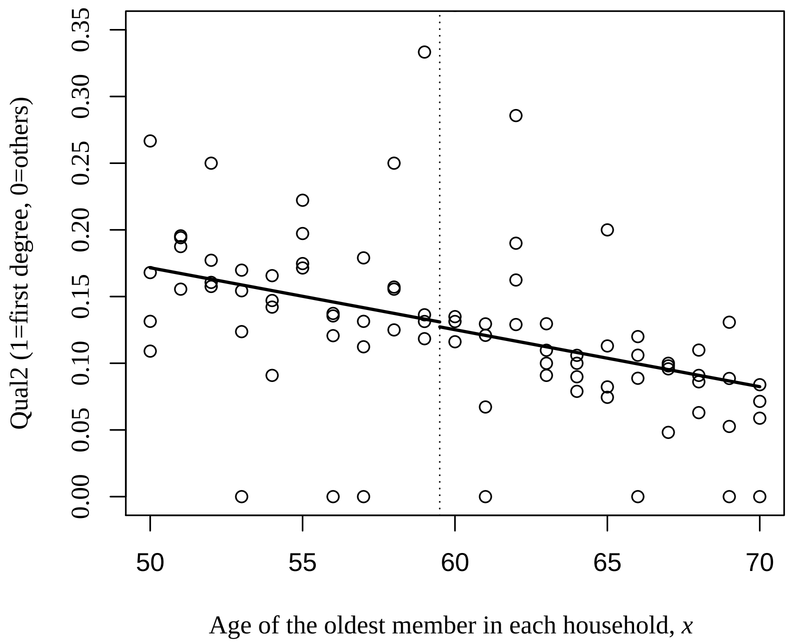

Figure A.6: Discontinuity in obtaining first degree

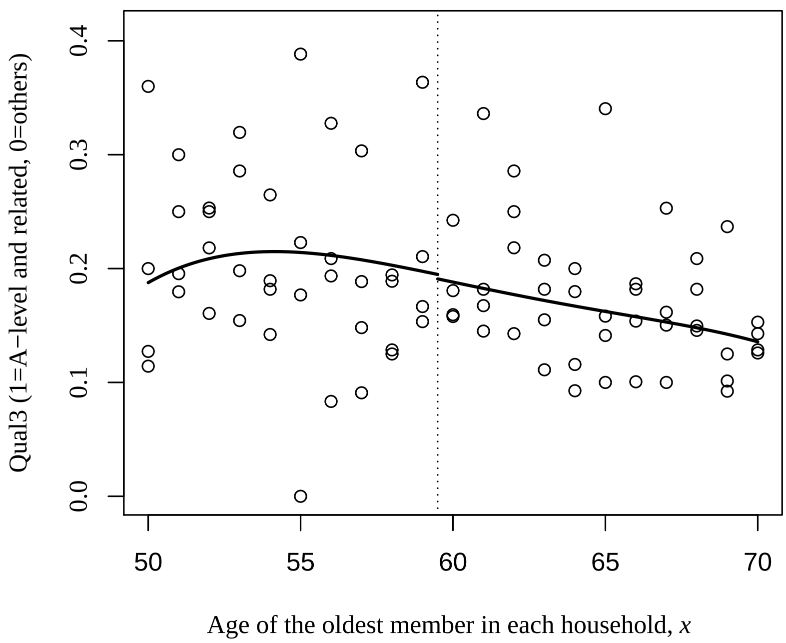

Figure A.7: Discontinuity in obtaining A-level

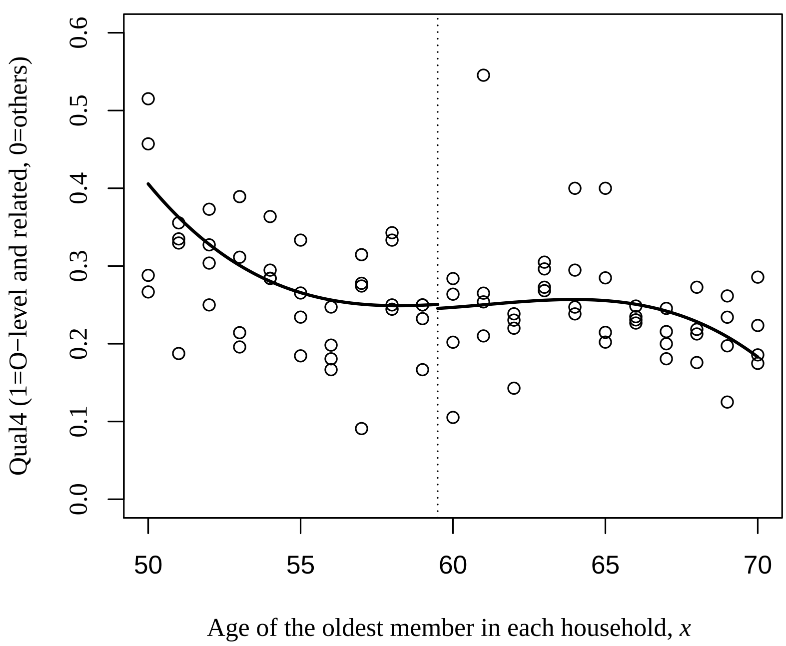

Figure A.8: Discontinuity in obtaining O-level

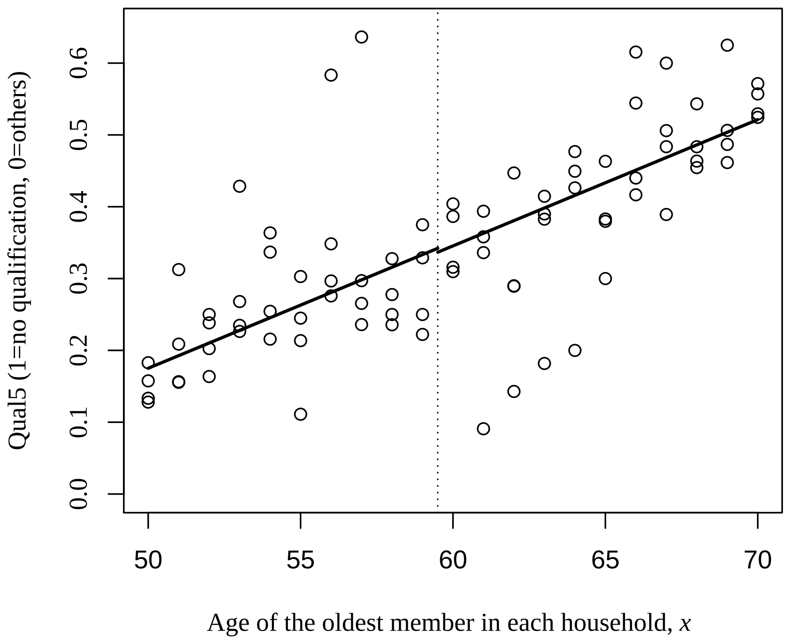

Figure A.9: Discontinuity in having no qualifications