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The health benefits of a targeted cash transfer: the UK winter fuel payment

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The Health Benefits of a Targeted Cash Transfer: The UK Winter Fuel Payment

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Abstract: Each year the UK records 25,000 or more excess winter deaths, primarily among the elderly. A key policy response is the "Winter Fuel Payment" (WFP), a labelled but unconditional cash transfer to households with a member above the Female State Pension Age. The WFP has been shown to raise fuel spending among eligible households. We examine the causal effect of the WFP on health outcomes, including self-reports of chest infection, measured hypertension and biomarkers of infection and inflammation. We find a robust and statistically significant six percentage point reduction in the incidence of high levels of serum fibrinogen. Reductions in other disease markers point to health benefits, but the estimated effects are not robustly statistically significant.

Keywords: benefits, health, biomarkers, heating, regression discontinuity

JEL Codes: H51, I12

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1. Introduction

Each year, the U.K. experiences Excess Winter Mortality (EWM). In 2014/15 the number of excess winter deaths in England and Wales was estimated at 43,900, the highest level since 1999. EWM has also been documented in Europe (Kunst et al., 1993; Eng and Mercer, 1998; Rose, 1966; Mackenbach et al., 1992; Keatinge and Donaldson, 1995), the USA (Kloner et al., 1999; Lanska and Hoffmann, 1999) and Asia (Cheng, 1993; Ornato et al., 1990). Most EWM occurs among the elderly and is due to respiratory and circulatory diseases (Donaldson, 2010; Lloyd, 2013; ONS Statistical Bulletin 2014/15).[3] In addition to EWM, cold weather is associated with increased demands on health care systems through increased incidence of illness requiring hospitalization or other treatment.

While outdoor temperatures may play a role in EWM,[4] living in a cold *indoor* environment has a direct impact on the health of elderly people (Wilkinson et al. 2001; Marmot et al. 2011; Dear & McMichael 2011; Rudge & Gilchrist 2007).[5] In the U.K., a key policy response to EWM is the Winter Fuel Payment (WFP). The WFP is a labelled but unconditional cash transfer to households containing an older person (male or female) above the female state pension age. The stated intent of the policy is help the elderly deal with the cost of keeping their dwelling warm (Lloyd, 2013; Kennedy & Parkin, 2016) and the labelling of this cash transfer has been shown to be effective in inducing eligible households to increase fuel

[3] In the winter of 2014/2015 36 % of EWM was attributable to respiratory disease and 22.5% to cardiovascular disease (ONS, 2015).

[4] The strong association between exposure to outdoor cold temperatures and mortality or morbidity is well documented in the epidemiological literature (Curwen, 1997; Wilkinson et al., 2001; Keatinge, 1986, 1989, 2002).

[5] Wilkinson et al. (2001) show that deaths attributable to cardiovascular diseases are 23 % higher in winter than the rest of the year and give evidence of a positive association of the EWM with the age of the property and the thermal inefficiency of the buildings. Rudge and Gilchrist (2007) find that their fuel poverty index which includes an energy efficiency rates and income is a strong predictor of the excess winter morbidity measured with number of emergency respiratory hospital admissions.

spending (Beatty et al., 2014).[6] However, the key policy question is whether the WFP improves health of elderly people living in eligible households, and there is little evidence on this point.

The female state pension age, and hence the age cut-off for WFP eligibility, was 60 prior to 2010. It then began to increase so that it will equal the male state pension age of 65 in 2018 and then both will rise to 67 by 2028. Most EWM occurs among individuals over 75, leading Lloyd (2013) to propose that increases in the eligibility age could reduce the financial cost of the WFP with minimal if any reduction in health benefits. But there has been no direct evidence on the health benefits foregone through recent increases in the age cut-off or health benefits that may be lost through further increases.

This paper reports the first tests for health benefits of the WFP based on individual-level data. We measure health outcomes in the Health Surveys for England (HSE), the Scottish Health Survey (SHeS) and the English Longitudinal Study on Ageing (ELSA). These studies include nurse visits, allowing us study biomarkers and physical measures as well as self-reports. To estimate the causal effect of the WFP, we follow Beatty et al., (2014) in employing a regression discontinuity design (RDD). The RDD is thought to be the most convincing of quasi-experimental designs (Lee and Lemieux; 2010).[7] A RDD is possible where there is cut-off in eligibility for treatment, as there is for the WFP: in the period we study, households with no member aged 60 or above are ineligible.[8] An RDD estimates the causal effect of treatment by comparing outcomes just below and above the eligibility cut-off. It estimates a *local* average treatment effect – at the eligibility cut-off. Thus our design estimates the causal effect of the WFP on the health of individuals living in households where the oldest member

[6] Beatty et al. (2014) estimate that eligible households spend 47% of their WFP on fuel. If the payment were treated as other income, eligible household would be expected to spend 3% of the payment on fuel.
[7] The Regression Discontinuity Design was first introduced in the Education literature (see Thistlethwaite and Campbell, 1960) and has been widely adopted in economics (Lee and Lemieux; 2010)
[8] Take up of the WFP is very high, so that there is little difference between eligibility and receipt. See Beatty et al. (2014) for further discussion.

of the household is 61. These are precisely the individuals who lost any health benefits of the WFP as the eligibility age was incrementally increased from 2010, so our empirical strategy directly answers a key policy question.

To the best of our knowledge, Iparraguirre (2014) is the only prior assessment of the health benefits of the WFP. Using aggregate mortality data, Iparraguirre documents a decline in EWM in 2000/2001, coincident with the introduction of the universal WFP.[9] EWM fluctuates significantly from year-to-year with changing winter weather conditions and viral environment. Using time-series econometric techniques, Iparraguirre finds a structural break in the EWM time series for England and Wales in 2000/2001 and estimates that half of the reduction in the EWM in that year can be attributed to the introduction of the WFP. This is an important finding, but it does rest on the ability of the econometric methods to distinguish the policy effects from the very substantial year-on-year fluctuations in EWM. Moreover, the aggregate EWM time-series is necessarily silent on health effects that may precede mortality, and on benefits to particular groups. We add to the evidence base significantly by using a convincing quasi-experimental design in conjunction with individual level data; by considering a variety of measures of circulatory and respiratory illness, including biomarkers[10]; and by testing for health benefits particularly among the group that have been made ineligible by recent changes to the age cut off.

We estimate the effect of the WFP on circulatory and respiratory illness measured four ways: self-reports of chest infection, nurse-measured hypertension, and two blood biomarkers of infection and inflammation.

[9] The WFP was introduced in 1997 but it was initially means-tested and the payment significantly smaller. In 2000/2001 it took its current form (a universal payment to all households containing a person above the female state pension age of between 200 and 300 pounds).

[10] Biomarkers have been increasingly drawing attention in the economic literature as an objective measure of health and a complement of self-reported health measures (see Jurges et al., 2013; Evans and Garthwaite, 2014; Michaud et al., 2016)

Our principal finding is that, among those living in a household that just qualifies for the payment, the WFP leads to a six percentage point reduction in the incidence of high levels of serum fibrinogen (on a base of 12 %). High levels of fibrinogen are considered to be a marker of current infection, and are also associated with chronic pulmonary disease. This effect is statistical significant ($p<0.01$) and very robust. For the other health measures we consider, while point estimates suggest health benefits, the estimated effects are less robust to changes in sample or specification, and rarely statistically significant.

In the next section, we provide further detail on our data, outcomes measures, identification strategy and methods. Section 3 presents our results. Section 4 contains additional discussion of the findings.

2. Data and Methods

Data

The analysis reported in this paper is based on data from the Health Surveys for England (HSE) (2001, 2003, 2004, 2005, 2006, and 2009)[11], the Scottish Health Survey (SHeS) (2003, 2008, 2009) and the English Longitudinal Study on Ageing (ELSA) (wave 2, 2004-05, and wave 4, 2008-09). The HSE and the SHeS are annual cross-sectional surveys of the health conditions of the population in England and Scotland. ELSA is a longitudinal survey that captures the population in England aged 50 and over. The ELSA sample is derived from the 1998, 1999 and 2001 HSE. In all three surveys a face-to-face interview is followed by a nurse visit. In the interview the respondents answer questions on their general health, smoking status and alcohol consumption and other individual characteristics such as education and employment status. After the interview an appointment for the nurse visit is arranged. In the visit a trained nurse asks questions on the health condition of the respondent, takes blood and

[11] HSE 2001 contains hypertension measure and self-reports of chest infection only (not the biomarkers).

saliva samples and reads the blood pressure and several other measures (height, weight, waist, hip, lung function and grip strength). Blood samples are sent to an external laboratory for analysis. ELSA, HSE and SHeS data contain several biomarkers that are recovered from the analysis of the blood samples. Among the biomarkers reported, there are two that are useful for our analysis because they are correlated with inflammation processes and infection and are markers of circulatory and respiratory illness. These are C-reactive and fibrinogen.

Over the period 2003-2009 the Female State Pension Age was 60[12], and so any household with a member over age 60 qualified for the WFP. Following Beatty et al. (2014) we restrict the sample to single men and couples in which the man is the oldest in the household. We discard single women and couples in which the woman is the oldest member of the household because such households qualify for the WFP and the woman's stage pension simultaneously. In household in which the oldest member is male, eligibility for the WFP and the first state pension are not coincident. Thus we avoid any confounding effect of receipt of the state pension on the fuel expenditure and the health outcomes of the elderly. We have not identified any other potential confounding policy directed at persons aged 60 and above. For example, free flu vaccinations are offered to elderly aged 65 or over (Department of Health, 2000).

Health Outcomes

We study four measures of circulatory and respiratory illness:

(i) self-reports of chest infection in the last 3 weeks

(ii) Hypertension

(iii) Serum values of C-reactive protein (CRP) in excess of 10.

(iv) Serum values of Fibrinogen equal or in excess of 4.

[12] In the same period the male state pension age was 65.

During the nurse visit, respondents are asked whether they have experienced any respiratory infection in the preceding 3 weeks (influenza, pneumonia, bronchitis or a severe cold). This self-reported outcome is available only in ELSA and SHeS.

Our second outcome is hypertension, a risk factor for strokes and heart attacks. The World Health Organization (WHO) defines hypertension as systolic blood pressure of 140 mm Hg or above and/or diastolic blood pressure of 90 mm Hg or above (WHO, 2013). Repeated exposure to a cold environment results in an increase in the blood pressure, and high values of systolic and/or diastolic blood pressure (hypertension) is a predictor of heart disease and stroke (Hoffman et al. 1983; Fraser 1986; Wilson et al. 1998; Collins et al., 1985; Collins et al., 1990). In our sample, around the cut-off age for WFP eligibility, about 35 % of respondents are hypertensive.

The other outcomes in our study are CRP and fibrinogen, two acute-phase biomarkers. Serum concentrations of these two biomarkers increase sharply during an inflammatory process. CRP is a blood plasma protein that is indicative of inflammation and infection and a risk predictor of cardiovascular disease. It is considered an indicator of bacterial infection, pneumonia and tissue damage (Tillet and Francis, 1930; Pepys, 2003; Pearson et al., 2003; Simon et al., 2004). The median of CRP in our sample is 1.7 mg/l but its distribution is highly skewed. The value rises within few hours of disease onset. Inflammation and bacterial infection can produce a rise in CRP values up to 1,000-fold (Pepys, 2003; Gruys et al., 2005). Fibrinogen is a coagulation protein produced by the liver that helps the body in the formation of blood clots. The normal range of fibrinogen is 2-4 g/l, but the concentration increases up to 3-fold in the presence of an inflammatory process, infection or tissue damage (Fenger-Eriksen et al., 2008; Gruys et al., 2005; Schmaier, 2012). High concentrations of fibrinogen are also strongly associated with chronic obstructive pulmonary diseases and moderately with coronary heart diseases (Danesh et al., 2005; Duvoix et al., 2012; Mannino et al., 2015). In

the epidemiological literature a value of the C-reactive protein in excess of 10 is taken as evidence that a person has an active infection or inflammatory process. High values of CRP or fibrinogen are considered evidence of current infection and Epidemiologists often discard observations with these high values because of their focus on chronic processes (Pearson et al., 2003).

Table 1. Descriptive statistics. C-reactive protein, Fibrinogen, Hypertension and Self-Reported Chest Infection.

	Age Window	Median	90th percentile	Prob(Illness)
C-reactive protein	58-63	1.7	7	***Prob(CRP>10)*** 0.055
Fibrinogen	58-63	3.1	4	***Prob(Fib≥4)*** 0.125
Hypertension	58-63	-	-	***Prob(Hypertension)*** 0.353
Self-reported Chest Infection	58-63	-	-	**Prob(Chest Infection)** 0.101

Observations with a fractional probability of being eligible to the Winter Fuel Payment are dropped.

However, as our interest is whether the WFP plays a role in reducing the incidence of a respiratory or circulatory disease among the elderly, extreme values (in excess of 10 for CRP) are the appropriate object of our analysis. The epidemiological literature has not defined an equivalent disease threshold for fibrinogen but we take values in excess of the top the standard range (2-4 g/l) as evidence of current infection or inflammation.

Regression Discontinuity Design

The RDD allows health outcomes to vary with the "forcing variable", which is the age of the oldest person in the household of subject *i* at the time of the interview *t*. Denote this by (A_{it}). The econometric model includes smooth functions of the value of the forcing variable

relative to the cut-off age (A_{it} - *60*). It also includes an indicator (or dummy) variable, D_{it}, for whether a respondent's household was eligible for the last WFP payment before the interview at which health outcomes were measured. Finally, it includes additional covariates X_{it}, to increase the precision of the estimator by capturing individual background variation in health (unrelated to the WFP).[13]

Thus the econometric model is:

$$H_{it} = \beta_0 + f(A_{it} - 60) + \tau D_{it} + f(A_{it} - 60) \times D_{it} + X_{it}\gamma + e_{it}$$

We employ both linear and quadratic functions for *f( )*. The model is estimated by ordinary least squares. Note that all of the health measures (H_{it}) we consider are binary so that $E[H_{it}] = Prob(H_{it} = 1)$ and this is a linear probability model. The parameter of interest is τ, which measures the local causal effect of the WFP on $Prob(H_{it} = 1)$, around the cutoff. Formally:

$\tau = \lim_{A \downarrow 60} E[H_{it}|A_{it} = 60, X_{it} = x] - \lim_{A \uparrow 60} E[H_{it}|A_{it} = 60, X_{it} = x]$.

As the H_{it} are measures of illness, if the WFP improves health τ should be negative. We report standard errors that are robust to heteroscedasticity and clustering by the age in years of the oldest member of the respondent's household. Because we look at multiple health outcomes, we also report p-values adjustment for multiple testing using the Romano-Wolf algorithm (Romano and Wolf, 2016).

[13] The assumption behind the RDD is that all health determinants apart from WFP eligibility should evolve smoothly with A_{it}, including (but not limited to) the covariates X_{it}. For the covariates X_i, we can test this by estimating an RDD in X_i. There should be no discontinuity in the X_i at the 60 or, equivalently, observables should be balanced between eligible and not eligible in the region of the cut-off (analogous to covariate balance in a randomized trial). We have tested this and cannot reject for balance for any of the included covariates X_i (see the notes in Table 2 for a complete list). This implies that the point estimate of the treatment effect is not affected by the inclusion of the covariates, which we confirm in our robustness checks. The covariates can, however, improve precision by reducing the unexplained variation in the outcome variable (again, as in a randomized trial).

The WFP was between £200 and £300 (about 300-450 USD) during the period 2002-2009 when our data were collected and it was paid in November-December[14]. Eligibility is determined by the age of the old household member in the preceding September. In our data ages are recorded in years. That means, the WFP status of some households with an oldest member aged 60 or 61 can only be determined probabilistically (for details see the online Appendix).

3. Results

We begin with the now standard graphical presentation of the RDD in Figures 1 through 4. Each figure corresponds to one of our four measures of circulatory and respiratory illness. The vertical axis measures the incidence of illness, after regression-adjustment for covariates at the individual level. These covariates are listed in the notes to the figure but of course exclude age and WFP eligibility. The horizontal axis measures the age of the oldest member of a respondent's household. Each plotted point is the average value of the illness measure for a given year of age (of oldest household member). As our illness measures are binary, this mean is a probability. The cut-off for WFP eligibility (at age 61) is indicated in Figures 1 through 4 by the vertical line and separate least-squares best-fit lines are plotted to the left and the right of the cut-off. A treatment effect is indicated by a discontinuity between these two best-fit lines at the cut-off.

[14] From 2000 to 2007 the WFP was £200 for most eligible households but £300 for households with an over-80s member. In 2008 the WFP was temporarily uplifted to £ 250 for over 60s and to £ 400 for over 80s but this increase was reversed in the Budget of March 2011.

Figure 1: Effect of the Winter Fuel Payment on the probability of having a C-reactive protein level larger than 10.

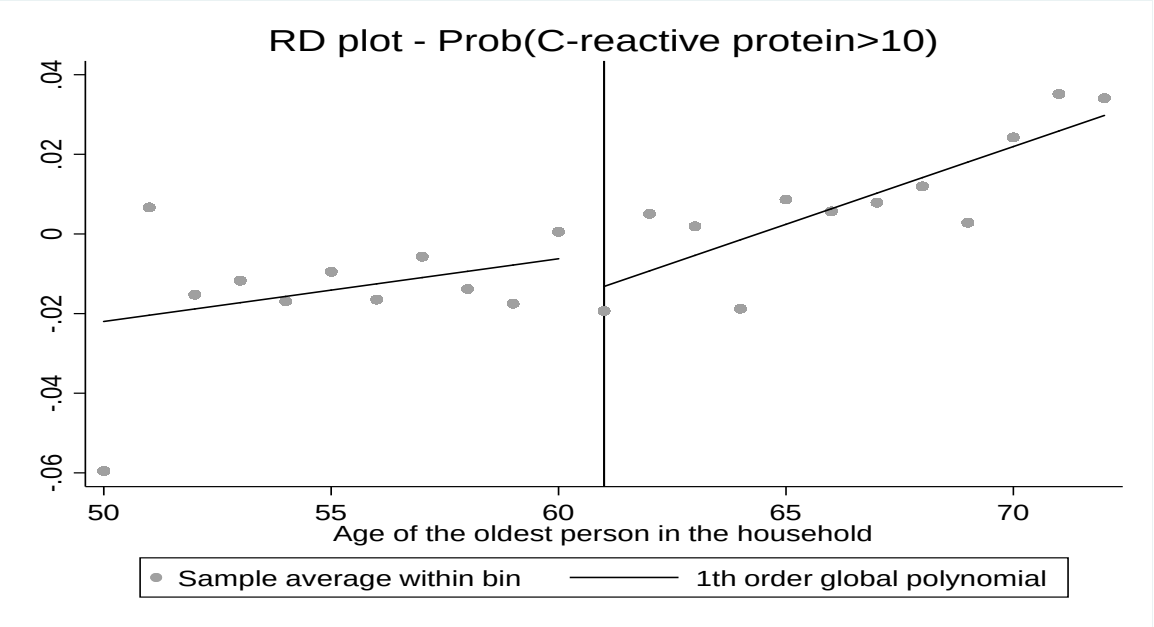

Figure 1 plots the residuals of a regression of the Prob(C-reactive protein>10) on type of household, gender, smoker status, Body Mass Index, waist, education, income, employment status vs age of the oldest person in the household.

Three of the four figures indicate decline in illness incidence with WFP eligibility. The exception is self-reported chest infection. The plots also indicate that the paths of illness incidence across age of the old household member are quite noisy, with significant year on year fluctuations. Although we have substantial sample sizes (each point represents about 400 observations), we are modelling relatively rare events (in our sample 5.5 % of the elderly just below the cut-off present a CRP value larger than 10 and 12.5 % a fibrinogen value in excess of 4, see Table 1). To assess the magnitudes and statistical significance of the discontinuities visible in these figures we turn to formal RDD estimates (as described above). These are reported in Table 2.

Figure 2 Effect of the Winter Fuel Payment on the probability of having a fibrinogen level larger than 4.

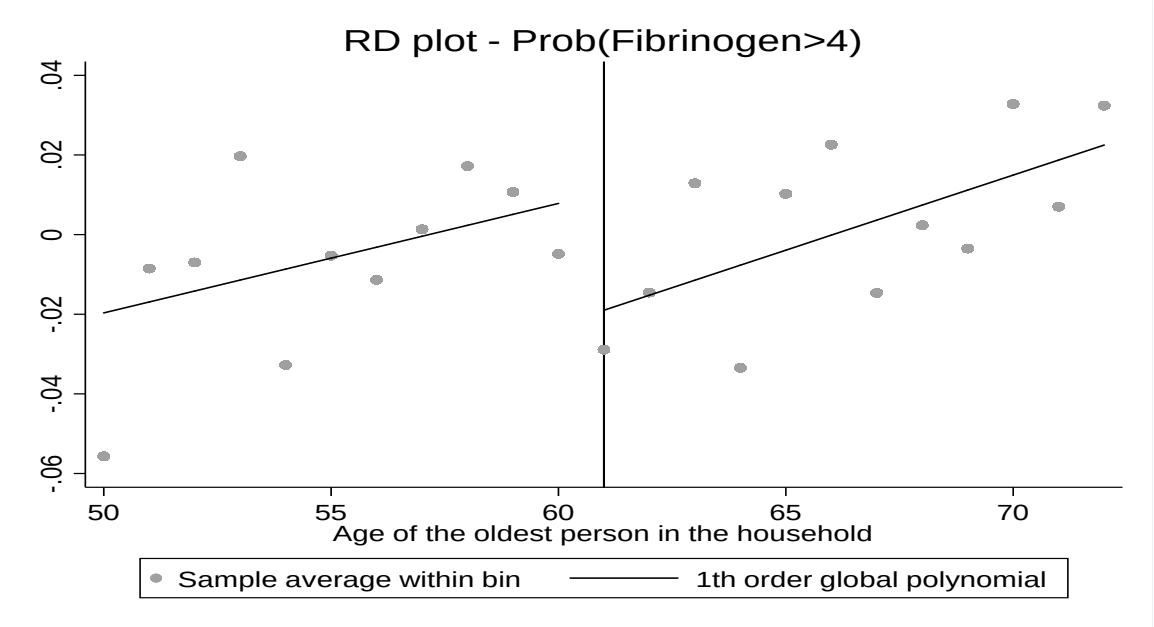

Figure 2 plots the residuals from a regression of the Prob(Fibrinogen>4) on type of household, gender, smoker status, Body Mass Index, waist, education, income, employment status vs age of the oldest person in the household.

Figure 3 Effect of the Winter Fuel Payment on the probability of having had a recent chest infection.

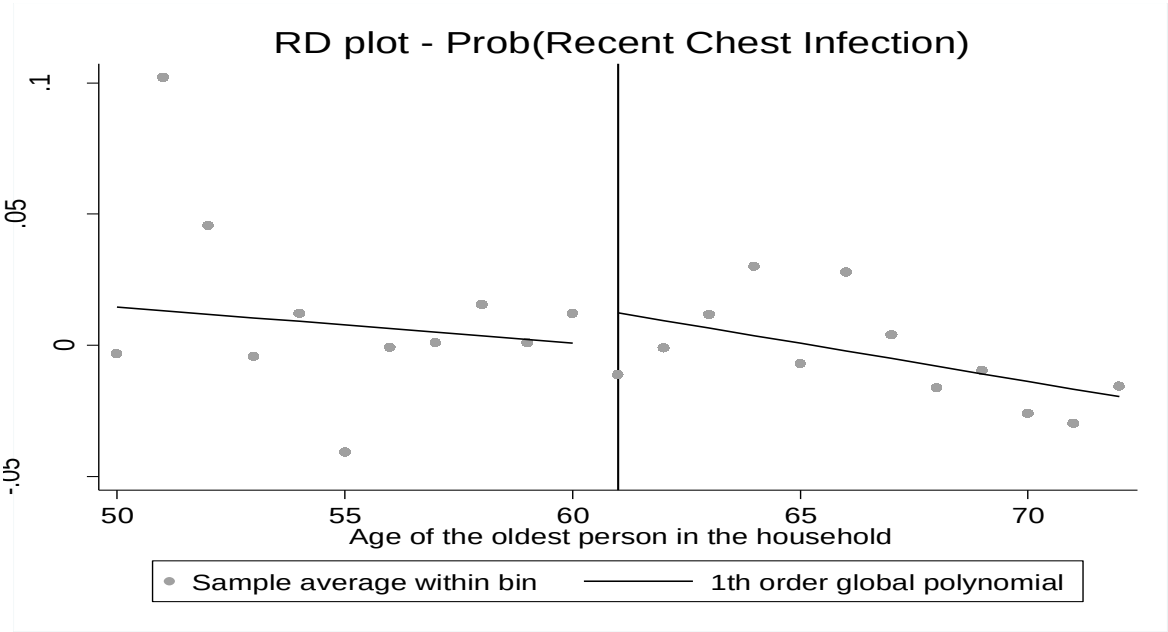

Figure 3 plots the residuals from a regression of the Prob(Chest Infection in the last 3 weeks) on type of household, gender, smoker status, Body Mass Index, waist, education, income, employment status vs age of the oldest person in the household.

Figure 4 Effect of the Winter Fuel Payment on the probability of having hypertension.

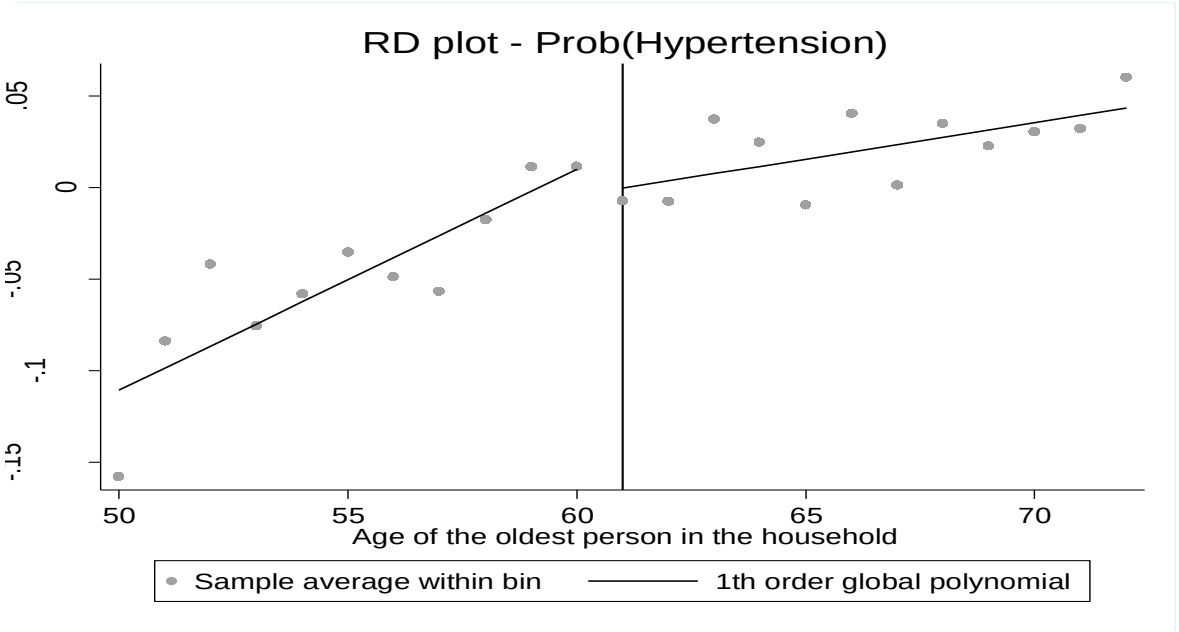

Figure 4 plots the residuals from a regression of the Prob(Hypertension) on type of household, gender, smoker status, Body Mass Index, waist, education, income, employment status vs age of the oldest person in the household.

In Table 2 each column gives the estimate of the WFP effect on the health outcomes in our preferred specification with linear functions of the forcing variable, *f()*, covariates, and a sample age window (for the age of the oldest member in the household window) of 50 to 72 years. The point estimates suggest that the WFP improved the health of the elderly at age 61, reducing all our measures of illness. Effect sizes are 1 to 6 percentage points.

However, the WFP only has a statistically significant effect at 5 % level on having a high concentration of fibrinogen. This finding is robust to the adjustment for multiple testing using the Romano-Wolf algorithm (see the third line in Table 2). The WPF decreases the probability of a fibrinogen value in excess of 4 g/l by 5.5 percentage points. As 12.5 % of the elderly just below the cut-off have a value of fibrinogen in excess of 4, our estimate implies a 44 % reduction in the incidence of this measure of illness at the age cut-off. Data on the CRP are noisier and the discontinuity effect at the cut-off is not statistically significant at conventional levels. Nonetheless, the magnitude of the WFP effect (1.2 percentage points) is

sizeable and implies a 22 % reduction in the incidence of illness by this measure, again at the cut-off.[15]

Table 2. The impact of the Winter Fuel Payment on predictors of infection.

Effect of the WFP on Fibrinogen, C-reactive protein, Self-reported Chest Infection and Hypertension				
	Fibrinogen	**C-reactive protein**	**Self-reported infection**	**Hypertension**
Causal Effect of Eligibility **[95% Confidence Interval]**	-.055*** [-.077; -.033]	-.012 [-.044; .020]	-.024* [-.049; .001]	-.018 [-.049; .012]
Minimum Detectable Effect (at 80% power)	±0.028	±0.040	±0.031	±0.038
Unadjusted P-Value **(Adjusted for Multiple Testing)**	0.000 (0.022)	0.418 (0.221)	0.058 (0.091)	0.207 (0.119)
Number of observations	3,974	4,517	4,569	6,295
Age Window	55-65	55-65	55-65	55-65

Standard Errors clustered by age of the oldest household member. The RDDs have a linear specification in the age of oldest member in the household. Additional covariates in the RDD: type of household, gender, smoker status, Body Mass Index, waist, education, income, employment status vs age of the oldest person in the household.

*** p<0.01 **p<0.05 *p<0.1

In Column 3 we report the effect on self-reporting a chest infection in the last 3 weeks and in Column 4 we report the effect on the incidence of hypertension. The effects are about 2 percentage points, but neither is statistically significant at 5 % level.

The effect on incidence of Fibrinogen above the normal range is both the largest point estimate and the most precisely estimate effect. To get an idea of the power of our tests, we calculated, for each outcome, the minimum effect size we would have 80% power to detect. These are displayed in the second row of Table 2. Although we have quite large samples sizes, minimum detectable effects are quite large. This is partly because we are examining the incidence of extreme values, and partly because we only have clean identification of treatment effects at the eligibility cut-off and must model the evolution of illness incidence on either side of the cut-off.

[15] The fraction of elderly just below the age 61 cut-off with CRP value larger than 10 is 6.3%.

To increase our confidence in the main result reported in Table 2 we conducted several robustness checks including: omitting covariates; varying the data window or the degree of the polynomial in the running variables; and omitted those households whose eligibility could only be determined probabilistically. Our main result of a significant effect on extreme values of fibrinogen and is robust to all of these variations. We also conducted falsification tests. We found no discontinuity in the incidence of extreme values of fibrinogen at placebo age cut-offs. We also found no effect of WFP eligibility on the *median* value of fibrinogen – indicating that effect is just on the incidence of extreme values, indicative of disease. Full details of our robustness checks and falsification tests are available in the Online Appendix.

Turning to subsample analysis, we follow Kling et al. (2007) and create a Poor Health Index and implement the RDD on this new measure. This both improves the statistical power of detecting effects of the same sign, and reduces problems of multiple testing. The Poor Health Index combines our indicators of cardiovascular and respiratory diseases in a single measure. We exclude self-reports of chest infection and focus on our binary objective measures, serum-Fibrinogen in excess of 4, serum-CRP in excess of 10 and Hypertension.[16] For each of these outcomes we calculate the *z-scores* subtracting the mean of the group of people just below the eligibility cut-off and dividing by the standard deviation of the same group. The Poor Health Index is the average of the three *z-scores* and a low value of the index is evidence of better health.

We first present the impact of the WFP on the Poor Health Index graphically in Figure 5. As in the Figures reported previously, a discontinuity at the eligibility cut-off is evidence of an effect of the WFP on health. The data in Figure 5 are still noisy as in the analysis of the single

[16] Self-reports of chest infection is the only measure that does not show a clear pattern in the data and is not reported in HSE.

objective health outcomes, but there is a visible drop in the Poor Health Index around the eligibility cut-off, indicating improved health.

Figure 5 Effect of the Winter Fuel Payment on the Poor Health Index.

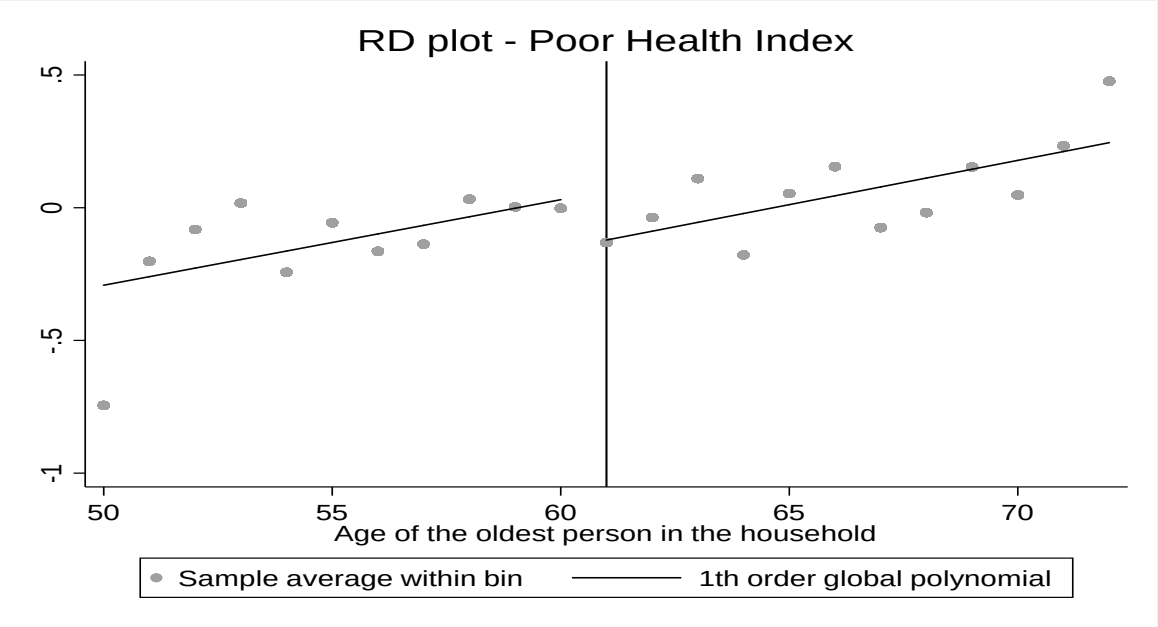

Figure 5 plots the residuals from a regression of the Poor Health Index on type of household, gender, smoker status, Body Mass Index, waist, education, income, employment status vs age of the oldest person in the household.

In Table 3 we show the size of the effect of the WFP on the Poor Health Index for different subsamples. An estimate for the full sample is presented in Column 1 and shows a statistically significant decrease in the Poor Health Index of 0.23 standard deviations. In the Online Appendix we show that the reduction of the Poor Health Index is in the range of 0.2 to 0.45 standard deviations and robustly statistically significant at 5 % level when we change our RDD specification in the ways listed above.

Table 3. Impact of the Winter Fuel Payment on the Poor Health index in sub-groups.

All sample	Colder Months Only	Low-Income (1st quartile)	Low Education
-.225**	-.367*	-.039	-.460***
[-.418; -.032]	[-.772; .039]	[-.433; .354]	[-.681; -.239]
N= 3481	N= 2351	N= 786	N= 980

Standard Errors clustered by age of the oldest member level. 95% Confidence Interval. Linear Specification in age of oldest household member. Age Window: 55-65. Colder months exclude June, July, August and September. Low-Educated highest qualification reported: No Qualification, NVQ level 1, NVQ level 2. Additional covariates in the RDD: type of household, gender, smoker status, Body Mass Index, waist, education, income, employment status vs age of the oldest person in the household.

*** p<0.01 **p<0.05 *p<0.1

In the second Column of Table 3, we report the estimates on a sample which excludes observations with a nurse visit in summer. The rational is that we do not expect any beneficial effect of the WFP on health in the summer months. Consistent with this expectation we find a slightly larger reduction in the Poor Health Index than in the full sample (a point estimate of 0.36 standard deviations that is statistically significant at 10% level). Next we estimate the effect of the WFP on the Poor Health Index for low-income respondents (Column 3). Beatty et al. (2014) show a particularly significant increase in the fuel expenditure for poorer households. These households should therefore experience larger health benefits. We find an effect magnitude of -0.04 standard deviations that is not precisely estimated, in part because of the reduction in the sample size. Finally, we consider the effect of WFP eligibility among low education respondents. Here we find a very large and statistically significant effect of around 0.46 standard deviations. For older households, education may be a better indicator of economic resources than current income. Alternatively, low education households may be more susceptible to effect of the labelling.

4. Discussion

We find evidence to suggest that raising the cut-off age for WFP eligibility has had a negative effect on the health of individuals made ineligible. We find a robust and statistically

significant effect for only one of the individual illness measures we consider, though point estimates for all the markers we consider point in this direction. Reductions of 1 to 6 percentage points (for fairly rare events) are large effect sizes. Using a Poor Health Index that combines our illness markers, we find particularly large effects for low education individuals.

For healthcare providers, these results highlight the need to be sensitive to inadequate indoor heating as a potential winter health risk, perhaps particularly among low education individuals who fall just short of eligibility for the WFP.

For policy makers, our results suggest that the tightening of eligibility for the WFP that has come with increases to the Female State Pension age may not have come without health costs. Our RDD estimates indicate a causal effect of the WFP on the health of individuals living in households where the oldest member of the household is 61. These are precisely the individuals who lost any benefits of the WPF as the eligibility age was incrementally increased from 2010. Our subsample analysis, finding particularly large effect for low education individuals, may point to means testing as a better way of rationing the program. At a minimum, further research is needed to determine the loss of health benefits associated with potential future increases in the eligibility age.

Ethics approval:

This secondary data analysis did not require ethics review but the underlying surveys all obtained ethics approval. (Waves 2, 4 of ELSA, 2001, 2003, 2004, 2006 HSE: MREC; HSE 2009: Oxford B Ethics committee; 2003 SHeS: MREC for Scotland; 2008, 2009 SHeS: MREC for Wales).

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ONLINE APPENDIX

A. Eligibility for WFP

Eligibility for the WFP is determined by the age of the oldest household member in the preceding September. Thus a respondent's household will have received a WFP in the December prior to the nurse visit date only if the oldest member of the household was 60 in the September immediately before that December. All households with an oldest member aged 59 or less at the date of the nurse visit will not have received a WFP. All households with an oldest member aged 62 or more at the date of the nurse visit will have been eligible for at least one WFP, and, given the very high take-up this benefit, almost surely received it. For households with an oldest member aged 60 or 61, whether they have been eligible for a WFP will depend on both the date of the nurse visit and the birthday of the oldest member of the household. A complication is that, although the month of the nurse visit is known, ages are recorded in the data in years. That means, the WFP status of some households with an oldest member aged 60 or 61 can only be determined probabilistically. This is described in Table A.1.[17] In our identification strategy we deal with this in two ways. First, we define D_{it} according to Table A.1, so that $D_{it} = 0$ if $A_{it} < 59$, $D_{it} = 1$ if $A_{it} > 61$ and $D_{it} \in [0, \frac{1}{12}, \frac{2}{12}, \dots 1]$ if $A_{it} \in 60{,}61$. Second, as a robustness check, we re-estimate the model dropping all observations for which WFP cannot be discretely determined. Note that when these cases are dropped, $D_{it} = 1[A_{it} > 60]$ (exactly), where 1[.] is an indicator function.

[17] For example, if an individual has the nurse visit in January, their household will have received a WFP in December (one month before), as long as the oldest member is more than 60 years and 4 months old, so that they were 60 in the preceding September. If the oldest member of the household reports age 60 and was born in August, the household will have been eligible for a WFP in December. However, if the oldest member of the household reports age 60 and was born in October, the household will not have been eligible for a WFP in December. Of those oldest members of a household aged 60 in years at a given nurse visit, 2/3 will be older than 60 years and 4months, and 1/3 will be 60 years four months or less.

Table A.1, Winter Fuel Payment eligibility.

Month of the nurse visit	Eligibility age	WFP eligibility Aged 60	WFP eligibility Aged 61	WFP eligibility Aged 62
January	60 + 4 months	8/12	1	1
February	60 + 5 months	7/12	1	1
March	60 + 6 months	6/12	1	1
April	60 + 7 months	5/12	1	1
May	60 + 8 months	4/12	1	1
June	60 + 9 months	3/12	1	1
July	60 + 10 months	2/12	1	1
August	60 + 11 months	1/12	1	1
September	61	0	1	1
October	61 + 1 months	0	11/12	1
November	61 + 2 months	0	10/12	1
December	61 + 3 months	0	9/12	1

B. Individual Measures: Robustness Checks and Falsification Test

In Table B.1 we explore the robustness of our results by varying our RDD specification in 5 ways. We first implement a quadratic polynomial for *f( )*, the function of the forcing variable relative to the age cut-off. We then re-estimate the models without including covariates in our specification. We further investigate whether our findings are sensitive to a change in the choice of the sample age window (either wider or narrower).

Table B.1 Robustness checks. The impact of the Winter Fuel Payment on predictors of infection.

Effect of the WFP on Fibrinogen, C-reactive protein, Self-reported Chest Infection and Hypertension				
	Fibrinogen	**C-reactive protein**	**Self-reported infection**	**Hypertension**
Quadratic specification in age of oldest household member [95% Confidence Interval]	-.079*** [-.132; -.026]	-.030 [-.073; .013]	.001 [-.028; .029]	-.089*** [-.132; -.046]
No additional covariates [95% Confidence Interval]	-.046*** [-.069; -.024]	-.010 [-.042; .023]	-.026* [-.057; .004]	-.014 [-.043; .015]
Narrower Age Window: 57-63 [95% Confidence Interval]	-.087*** [-.118; -.056]	-.033** [-.066; -.001]	-.015*** [-.024; -.006]	-.049*** [-.072; -.025]
Wider Age Window: 50-70 [95% Confidence Interval]	-.044*** [-.068; -.019]	-.015 [-.038; .008]	.015 [-.009; .040]	-.022 [-.050; .005]
Dropping observations whose eligibility cannot be discretely determined [95% Confidence Interval]	-.060*** [-.091; -.030]	-.012 [-.047; .024]	-.015 [-.046; .017]	-.032 [-.073; .009]

Standard Errors clustered by age of the oldest member level. Age window in the quadratic in age of oldest household member specification and no additional covariates specification: 55-65. Additional covariates in the RDD: type of household, gender, smoker status, Body Mass Index, waist, education, income, employment status vs age of the oldest person in the household.

*** p<0.01 **p<0.05 *p<0.1

Finally we drop the observations with the oldest member of the household aged 60 or 61 for whom we cannot determine whether they received the WFP or not exactly. We find that our estimates of the discontinuity effect for the fibrinogen are robust to any of these changes in the RDD specification. The coefficient of the WFP effect is always statistically significant at 1 % level and the effect size lies between -0.044 percentage points and -0.087 percentage points. [18] This implies a reduction of 35 % to 70 % in the incidence of a high serum concentration of fibrinogen at the age cut-off. For the other measures of illness we find a negative coefficient in all the specifications indicating an improvement in health with WFP

[18] All estimates are statistically significant at 5% level after adjusting for multiple testing except for the specification with a quadratic function of the forcing variable, where p=0.074.

eligibility. However, the estimates are variable and rarely statistically significant at conventional levels.

Table B.2 Falsification Tests: Effect of a "placebo" eligibility at age 55 and age 65, and effect on above median fibrinogen concentration.

	Effect of WFP on Fibrinogen
Cut-off age 55	-.015
[95% Confidence Interval]	[-.057; .026]
Age Window	50-60
Cut-off age 65	.004
[95% Confidence Interval]	[-.052; .060]
Age Window	60-70
Prob(Fibrinogen≥3.1)	.009
[95% Confidence Interval]	[-.046; .065]
Age Window	55-65

Standard Errors clustered by age of the oldest member level. Additional covariates in the RDD: type of household, gender, smoker status, Body Mass Index, waist, education, income, employment status vs age of the oldest person in the household.

*** p<0.01 **p<0.05 *p<0.1

We now provide some further checks on our main finding of a WFP effect on the incidence of high concentrations of fibrinogen. In Table B.2 we present falsification tests for an effect at age cut-offs of 55 and 65. As these are not the eligibility cut-off, we should find no effect at these ages. As a further falsification test we check for an effect on the incidence of fibrinogen concentrations above the sample median. The idea here is that having an above-median concentration of fibrinogen is not a marker of disease. If we are measuring a reduction in disease incidence, that effect should be observed only in the upper tail of the distribution (as in our main estimates) and not around the median.[19] As Table B.2 illustrates,

[19] The median fibrinogen in the neighbourhood of the age cut-off is 3.1 (see Table 1).

we do not find any evidence of an effect across these specifications. This increases our confidence.

We also considered what our estimated effects for the incidence of fibrinogen concentration in excess of 4g/l imply for levels fibrinogen in the upper tail of the distribution. To do this we estimated a quantile regression version of the RDD. Note that our base specification studies the probability that measured serum Fibrinogen exceeds a specified cut-off, and how this probability differs with WFP eligibility holding the cut-off constant at *k*.:

$$P_{it}(WFP_{it}) = Prob(H_{it}^{Fib} > k|WFP_{it})$$

A quantile regression inverts this relationship, holding the probability constant (at the chosen quantile, *1 - P*) and asking, essentially, how the cut-off varies with WFP eligibility.

$$k_{it} = F_{1-P}(H_{It}^{Fib}|WFP_{it})$$

In our sample $prob(H_{It}^{Fib} = 1) \approx 12\%$ and the RDD estimates show that this falls by 6.1 percentage points with WFP eligibility. In this robustness check we consider how the 85th and 90th conditional quantiles of H_{It}^{Fib} vary with WFP eligibility (corresponding to *P = 0.15* and *P = 0.1*). We find in both cases a drop in Fibrinogen of about 0.11 g/l. However the effects are less precisely estimated than the probability models.[20]

C. Poor Health Index: Robustness Checks

In Table C.1 we compare our findings on the Poor Health Index by varying our RDD specification in the same way we conducted robustness checks on single health outcomes in Appendix B. In Column 2 we implement a quadratic polynomial for the function of the forcing variable *f( )*, in Column 3 and 4 we change the choice of the sample age window and in Column 5 we drop the observations whose WFP eligibility cannot be determined exactly.

We find that the WFP reduces the Poor Health Index in the range of 0.2 to 0.45 standard deviations. All the point estimates in Table C.1 are statistically significant at 5 % level.

[20] Inference for quantile regression is not straight forward. Asymptotic standard errors are not regarded as reliable and we employ a bootstrap procedure. Full details and results are available from the authors on request.

Table C.1 The impact of the Winter Fuel Payment on the Poor Health Index.

Linear Specification in age of oldest household member	Quadratic specification in age of oldest household member	Narrower Age Window	Wider Age Window	Dropping observations whose eligibility cannot be discretely determined
-.225**	-.449***	-.445***	-.194**	-.286**
[-.418; -.032]	[-.642; -.257]	[-.607; -.283]	[-.376; -.013]	[-.563; -.010]
N= 3481	N= 3481	N= 2343	N= 5709	N= 3142
Age Window: 55-65	Age Window: 55-65	Age Window: 57-63	Age Window: 50-70	Age Window: 55-65

Standard Errors clustered by age of the oldest member level. 95% Confidence Interval. Additional covariates in the RDD: type of household, gender, smoker status, Body Mass Index, waist, education, income, employment status vs age of the oldest person in the household.

*** p<0.01 **p<0.05 *p<0.1