The impact of prescription charges on health outcomes at age 60, a regression discontinuity design analysis

Alex Bell

Professional Economist BSc and Apprenticeship Level 6

School of Economics

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Executive Summary

This study investigates whether health outcomes significantly change at age 60, due to individuals over 60 years old being exempt from prescription charges. This study examines the general population, using one wave each of biomarker data from the English Longitudinal Survey of Ageing and self-reported health data from the UK Household Longitudinal Survey. Data is cross-sectional and was collected between 2016-2019. A Regression Discontinuity Design is used to evaluate whether there is a significant break in the relationship between age and health outcomes at age 60. This study modifies the Regression Discontinuity Design to account for other prescription charge exemptions and the discretisation of age to maintain survey respondents' anonymity. Coefficients are estimated using both OLS and the survey package in R which accounts for complex survey design. No significant change in health outcomes at age 60 was found, despite coefficient signs suggesting health outcomes improved. This result suggests free prescriptions do not significantly impact health outcomes amongst the general population around age 60. This could reflect the lack of effectiveness of prescriptions, the success of other prescription charge exemptions at mitigating the impacts of prescription charges on health, or the difficulty obtaining clear impacts of prescription charges when looking at general population data.

AI Statement

I acknowledge the use of generative AI in code development in this paper. However, the work reported remains my own.

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1 Introduction

Prescription charges are a per-item charge for medication prescribed by General Practitioners (GPs) in England. The recent cost of living increases and the continued increases in the prescription charge have resulted in some patients foregoing medications to support dependents and meet basic living costs (Prescription Charges Coalition, 2023; Wickware, 2023). Prescription charges are mostly paid by people with long-term health conditions on modest wages (British Broadcasting Corporation, 2017). Skipping prescriptions can put these people at risk of developing additional health conditions and worsen their quality of life (Wickware, 2023). Healthcare organisations are calling on the UK government to freeze prescription charges and update the list of prescription charge exemptions to include individuals with a wider range of long-term health conditions (Parkinsons UK, 2024).

However, an ageing population (Warner, 2022), subdued economic growth (Islam, 2025) and increased economic uncertainty (Booth, 2025) have put pressure on UK government finances. The evidence on overprescription of medication is uncertain (Dowden, 2023), but reducing the scope or real-terms size of prescription charges risks encouraging overprescription. Such overprescription may worsen vulnerable people's health, alongside inefficiently distributing limited government funds and medication supplies (Department for Health and Social Care, 2021).

The null hypothesis this study tests is:

H_0: Free prescriptions have no statistically significant impact on health outcomes at age 60.

This study uses a Regression Discontinuity Design (RDD) to test H_0. RDD is a quasi-experimental approach, first proposed by Thistlethwaite and Campbell (1960), which uses arbitrary policy cutoffs created by policy eligibility criteria. For this study, the cutoff is the exemption of adults older than 60 from prescription charges. This prescription charge cutoff might result in a measurable difference in health outcomes between individuals just above and below age 60, who would otherwise have similar health outcomes. RDD is appropriate because the age-cutoff for prescriptions is well-established, cannot be manipulated and differs from the UK State Pension and Winter Fuel Payment age-cutoffs. Cross-sectional datasets of individuals from the UK Household Longitudinal Survey and the English Longitudinal Survey of Ageing nurse visits were used. Individuals included in the analysis are aged 50-69, live in England and were surveyed between 2016-2019.

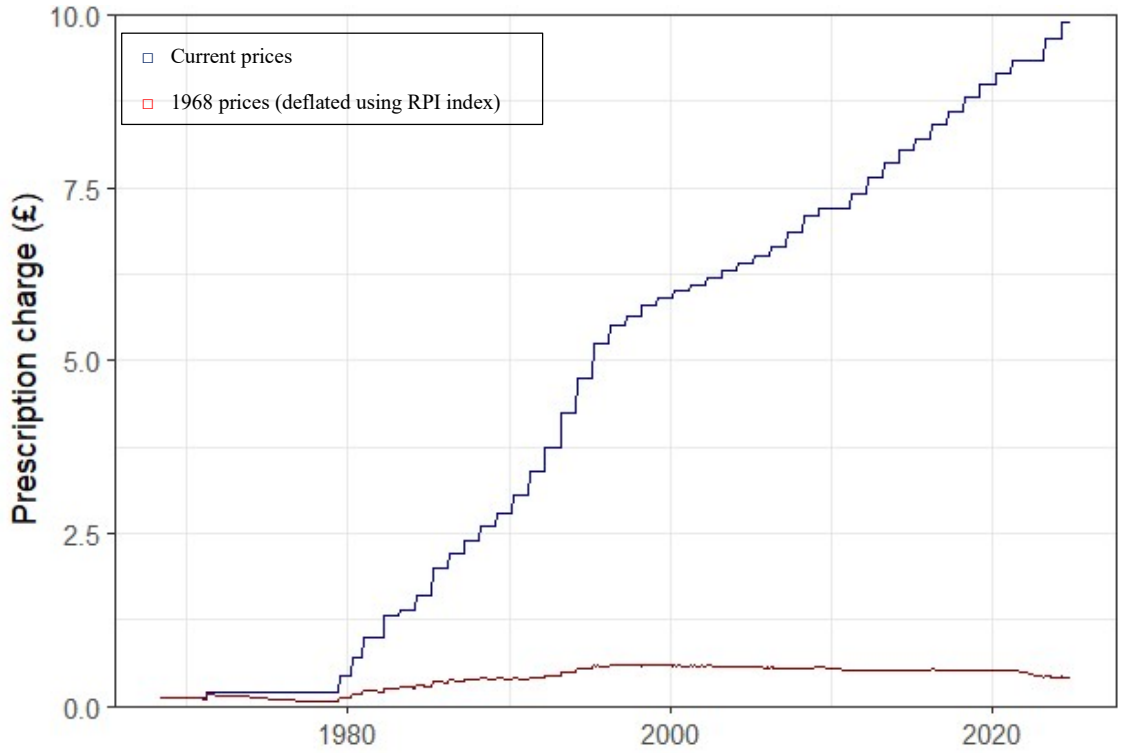
This study complements existing literature since most general population evidence focuses on the price elasticity of demand for prescription charges rather than the impact of prescription charges on health outcomes. An application of RDD with a discrete age is provided which could help researchers analysing other policies with age-cutoffs using RDD who face similar data constraints. This study also provides UK evidence to complement the existing US literature, especially important given the US uses an insurance-based rather than state-funded healthcare system.

1.1 Policy context

Prescription charges were first introduced in the UK in 1952. Excluding a brief hiatus between 1965 and 1968, prescription charges have remained in place in England ever since (Parkin, 2024). Prescription charges were abolished in: Wales in 2007, Northern Ireland in 2010 and Scotland in 2011 (Parkin, 2024).

Figure 1 shows the current prescription charge is £9.90 per item (National Health Service (NHS), 2023a), much larger than the 12.5p charge in 1968 (O'Brien, 1989). Prescription charges in England have remained steady in real terms.

Figure 1: Per-item non-discounted prescription charge 1968-2024



Sources: O'Brien, 1989; NHS, 2023a; Consumer Price Inflation team, 2025; UK Parliament, 2025

Besides exemptions for over 60s, a range of other prescription charge exemptions protect the most vulnerable individuals from prescription charges including: recipients of some state benefits, pregnant women and individuals with some medical conditions (National Health Service Business Services Authority (NHSBSA), 2025). These exemptions mean that only 40% of the UK population are liable to pay prescription charges (O'Brien, 2023), compared to around 63% of the population being aged between 16-64 in the 2021 census (Office for National Statistics (ONS), 2024). In 2023-24, 10% of prescriptions dispensed in the UK had prescription charges (Wormald, 2024).

Prescription Payment Certificates (PPCs) cover all NHS prescriptions over 3 months for £32.05 or 12 months for £114.50 (NHS, 2023c). PPCs provide a discount on prescription charges for frequent prescription users who are not eligible for an exemption. Around half of prescription charges are paid using PPCs (O'Brien, 2023).

The NHS raised £693m from prescription charges in 2023-24 (Wormald, 2024), suggesting prescription charges raise considerable revenue despite the wide range of exemptions.

2 Literature review

2.1 Economic theory

Grossman (1972) modelled demand for healthcare such as prescription drugs as a derived demand from the demand for health. Grossman (1972) considered health to be a capital stock set at birth based on genetics. Health capital naturally depreciated over time at an increasing rate, but this depreciation could be partially offset by health investments such as lifestyle changes and medicines. Grossman (1972) suggested individuals optimise their investment in health capital by equating the extra utility from one more unit of healthy time to the extra cost of maintaining their health to provide that extra unit of healthy time, such as paying for extra prescriptions. However, Grossman's optimisation rested on the assumptions that individuals operated in free markets and anticipated how quickly their health would depreciate.

Behavioural economics offers further insights into why individuals fail to optimise their prescription consumption. Loss aversion means individuals overvalue the short-run side effects and out-of-pocket costs of prescriptions; status-quo bias means individuals resist switching to or starting more effective courses of prescriptions; individuals may get fatigued or emotional when thinking about their health and avoid health-related decisions (Rice, 2013). GPs prescribing medications may be biased towards drug brands they are familiar with and develop rules of thumb for prescribing drugs that fail to account for patient heterogeneity (Frank, 2004). Prescribing mistakes could deter patients from following their GP's advice and paying for prescriptions in the future. Behavioural economics literature suggests an underconsumption of prescription drugs in a free market, which provides a rationale for government intervention through subsidising prescriptions or providing free prescriptions.

Free prescriptions prevent the market rationing prescriptions based on individual willingness-to-pay and market prices (Remler and Greene, 2009). The law of diminishing marginal utility suggests the marginal benefit of extra prescription consumption due to free prescriptions may be small (Berkman, Kahn and Livingston, 2016). Free prescriptions could introduce a moral hazard by reducing the incentive for individuals to make lifestyle changes that would improve their health (Minhas, 2011). The government could use a prescription charge to mitigate these risks.

Nyman (2007) suggested some of the moral hazard from free prescriptions identified by Minhas (2011) might be efficient and welfare improving. Nyman (2007) believed that

willingness-to-pay for prescriptions was mistakenly defined based on individual's ability to pay for healthcare out-of-pocket. Nyman (2007) felt that income transfers to individuals when a third-party paid for their healthcare, expanding their budget constraint, were being mistaken for moral hazard implying the benefits of free prescriptions were being understated.

The theoretical literature suggests a tension exists between reducing the barriers to accessing prescriptions which improve people's health and the risks of wasteful consumption of prescriptions if they are too easy to access. Empirical studies observing the impact of prescription charges on health outcomes can provide evidence to help resolve this tension.

2.2 The Price Elasticity of Demand for Prescriptions

Initial studies estimating the price elasticity of demand (PED) for prescriptions used time series data of prescription charges and prescription sales in the UK. The studies focused on the 1970s and 1980s, during which prescription charges increased from 12.5p to £2.20 (O'Brien, 1989). Lavers (1989) and O'Brien (1989) each fitted simultaneous equation models to a monthly time-series to identify a demand curve, and therefore the PED, for prescriptions whilst allowing both the price and quantity of prescriptions to be endogenous. Hughes and McGuire (1995) extended this research by fitting a Dynamic Error Correction Model to the time series, which allowed separate long-run and short-run PEDs to be estimated. However, Hughes and McGuire (1995) used just 21 observations which made obtaining reliable PEDs difficult (Hitiris, 2000). Ryan and Birch (1991) used monthly data instead and were able to estimate more robust short-run and long-run PEDs using a linear Partial Adjustment Model. The time series studies found that a 1% increase in prescription charges would reduce prescription demand by 0.1-0.33% in the short-run and 0.09-0.37% in the long-run.

More recent literature used panel data from administrative records or surveys rather than time series data. Individual-level information provides opportunities to mitigate endogeneity such as reverse causality between prices and quantities of prescriptions, and unobserved heterogeneity between individuals and over time. Contoyannis et al. (2005) and Smart and Stabile (2005) both exploited prescription charge policy discrepancies between provinces and over time in Canada to identify PEDs. Both studies constructed instrumental variables and included individual-specific and time-specific fixed effects to identify the PED whilst mitigating endogeneity. Van Vliet (2004) estimated the PED by comparing prescription expenditures of individuals in Dutch administrative data who had insurance plans with varying deductibles. Van Vliet (2004) accounted for past health outcomes, different

household sizes and unfilled insurance claims to mitigate bias. The elasticities obtained from these panel data studies suggested a 1% increase in prescription charges would reduce prescription demand by 0.08-0.29%. The PEDs for prescriptions were lower than other healthcare services examined by the panel data studies. The PEDs were also lower than the time series PEDs. The time series PEDs may have been inflated if unobserved heterogeneity resulted in the error term being correlated with prescription charges.

Studies which focused on the elderly suggested they are more sensitive to prescription charges. Klick and Stratmann (2005) used differences in Medicare access and prices for over-65s between US states to identify PEDs, obtaining an elastic PED of 1.01%. Tamblyn et al. (2001) compared elderly individuals' medication purchases before and after prescription charges were introduced in Quebec in 1996, finding that prescription charges reduced the mean daily use of essential and non-essential drugs by 9.12% and 15.14% respectively. Grootendorst's (1997) analysis of Canadian administrative data using a Tobit Fixed Effects Model found that free prescription drugs for over-65s did not permanently increase drug use apart from in lower-income males. However, Gemmill, Thomson and Mossialos (2008) suggested this result may have been because Grootendorst (1997) could only control for the unhealthiest individuals in the first year of the sample.

Whilst the PEDs obtained vary, the literature suggests that the PED for prescriptions is negative but inelastic.

2.3 Prescription Charges and Health Outcomes

Several studies expanded on the estimation of prescription PEDs by investigating how changes in prescription use, due to changes in prescription charges, impact health outcomes.

Atella et al. (2006) examined an administrative dataset of individuals in an Italian health authority. The individuals were prescribed ACE inhibitors, a drug used to treat high blood pressure and heart disease, around the time the Italian government abolished and subsequently reintroduced prescription charges in 2001-02. Using a logit model, Atella et al. (2006) found that prescription charges reduced adherence to courses of prescriptions, increasing hospitalizations and mortality rates. The results from Atella et al. (2006) are supported by US studies which compared individuals at risk of cardiovascular disease who were on insurance plans with varying deductibles (Cole et al., 2006; Yang et al., 2011; Choudhry et al., 2012).

Studies focused on other chronic conditions also observed a rise in adverse health outcomes when prescription charges increased. Campbell et al. (2011) compared US asthma patients on MarketScan whose monthly prescription charges increased by >=$5 to patients whose monthly prescription charges increased by <$5. Campbell et al. (2011) fitted a Poisson regression model which found that patients whose monthly prescription charges increased by >=$5 experienced more asthma related outpatient visits and emergency room visits compared to patients whose prescription charges increased by <$5 per month. Li et al. (2007) evaluated the impact of prescription charge increases on elderly individuals with Rheumatoid Arthritis by running first-differenced regressions on administrative data from British Columbia using instrumental variables to circumvent endogeneity. Li et al. (2007) found that a 1% rise in prescription charges increased GP visits by 0.04-0.06%.

A more recent study by Norris et al. (2023) used a Randomised Control Trial to assess the impact of removing prescription charges on health outcomes. Norris et al. (2023) used a sample of 160,000 people with chronic health conditions from deprived areas in New Zealand. The participants were randomly assigned to be exempt from prescription charges or continue to pay prescription charges. Norris et al. (2023) found that the prescription charge exemptions significantly decreased hospitalisations and admissions for mental health problems. However, Norris et al. (2023) felt the sample used for the trial was too small to definitively answer their research question.

The few existing studies focused on the general population found prescription charge increases had no significant impact on health outcomes. Motheral and Fairman (2001) carried out a Difference-in-Differences analysis comparing 7000 individuals in the US Midwest who switched to a health insurance scheme which increased prescription charges to a control group of 13,000 individuals over a year. Motheral and Fairman (2001) found that the higher prescription charge significantly reduced prescription use, but did not significantly impact GP visits, inpatient visits or emergency room visits. Fairman, Motheral and Henderson (2003) carried out a follow-up analysis over a longer 30-month period, comparing a treatment group of 3500 individuals to a control group of 4000 individuals, which reaffirmed the conclusions from Motheral and Fairman (2001). Liu et al. (2011) used Difference-in-Differences to assess the impact of Medicare part D, a benefit program in the US which reduced prescription drug costs, on health outcomes among 1000 near elderly and elderly patients who were eligible for Medicare. Liu et al. (2011) observed no significant impact of prescription charge decreases in emergency department use or hospitalisations.

The few general population studies investigating the impact of prescription charges on health outcomes do not provide conclusive results, contrary to studies assessing sub-groups of patients with chronic health conditions. There are also few studies which use UK data, where results may differ from the US general population studies given healthcare in the UK is state-provided rather than insurance-based. This study therefore investigates the impact of prescription charges on health outcomes amongst the general population in England.

3 Methodology

3.1 Empirical specification

Unless otherwise stated, this study runs all RDD models in R using an Ordinary Least Squares (OLS) estimator and reports heteroskedasticity-consistent (EHW) standard errors calculated using the sandwich package (Zeileis, 2004, 2006; Zeileis, Köll and Graham, 2020). Coefficient estimates, robustness checks and H_0 are assessed at the 95% significance level.

All RDD models presented use the following naming convention, based on similar research on Winter Fuel Payments by Crossley and Zilio (2018). H_i refers to the health outcome used as the dependent variable, either self-reported health or a biomarker. A_i denotes age which has been normalised by subtracting 60 from the original age so that $A_i = 0$ at the age-cutoff for prescription charges as suggested by Kolesár and Rothe (2018, p. 2285). $\Theta(A_i)$ is equal to 1 if $A_i \geq 0$ and equal to zero if $A_i < 0$. The coefficient for $\Theta(A_i)$, τ, approximates the discontinuity in health outcomes at the age-cutoff. $f(A_i)$ is the smooth function describing the relationship between A_i and H_i where $\Theta(A_i) = 0$. $f(A_i) \cdot \Theta(A_i)$ is the smooth function describing the relationship between A_i and H_i where $\Theta(A_i) = 1$. RDD assumes that $f(A_i)$ and $f(A_i) \cdot \Theta(A_i)$ are continuous at $A_i = 0$, meaning no other policies with cutoffs at $A_i = 0$ impact H_i (Cattaneo, Idrobo and Titiunik, 2019, pp. 12-13). Satisfying this assumption means H_0 can be expressed as H_0: $\tau = 0$. T_i is equal to 1 if the individual is exempt from prescription charges for any reason and equal to 0 otherwise. All models include an error term ε_i, intercept β_0 and covariates γ_i.

Lee and Card (2008, p. 657) state that estimating τ using a discrete A_i relies on imposing functional form assumptions on $f(A_i)$ and extrapolating $f(A_i)$ to $A_i = 0$. $\hat{\tau}$ is a biased approximation of τ estimated using discrete A_i. Lee and Card (2008, pp. 659-664) stated that extrapolating $f(A_i)$ is only consistent where the modelling error for $f(A_i)$ is random and uncorrelated with A_i. Dong (2015, p. 425) explained that the rounding error created by discretising A_i into whole years would not meet Lee and Card's (2008, pp. 659-664) condition for consistency. All values of A_i are rounded down, meaning the rounding error for individuals for whom $A_i = 0 - e$ (where $e \to 0$) is greater than the rounding error for individuals for whom $A_i = 0 + e$. However, Dong (2015, pp. 426-430) stated the bias in $\hat{\tau}$ can be quantified if: $f(A_i)$ is a polynomial, the mean of H_i can be identified for each discrete

value of A_i, the cutoff is defined in terms of the discrete A_i, and the raw moments of the rounding error distribution for A_i can be identified[1].

Kolesár and Rothe (2018, p. 2277) advise that RDD models with discrete A_i should be run over a limited age-range. This study uses the age-range $-5 \leq A_i \leq 4$ to exclude the State Pension age of 65. Models use a linear polynomial for $f(A_i)$ because the limited distinct values of A_i mean a more complex functional form risks overfitting the model (Lee and Card, 2008, pp. 657-658).

Dong (2015, p.430) stated that if $f(A_i)$ does not change where $A_i = 0$, the bias in $\hat{\tau}$ equals zero. Model 1 therefore imposes assumptions $f(A_i) \cdot \Theta(A_i) = 0$ and $T_i = \Theta(A_i)$ to create a baseline sharp RDD specification.

Model 1

$$H_i = \beta_0 + \hat{\tau}\Theta(A_i) + f(A_i) + X_n\gamma_i + \varepsilon_i$$

Where: $\tau = \hat{\tau}$

Model 2 relaxes the assumption $f(A_i) \cdot \Theta(A_i) = 0$ using the equation provided by Dong (2015, p. 430) to correct the bias in $\hat{\tau}$ where $f(A_i) \cdot \Theta(A_i) \neq 0$ using the raw moments of a uniform distribution. Table 1 shows that the raw moments of distribution of birthdays, which represents the distribution of the rounding error of discrete A_i, are similar to a uniform distribution. This suggests the bias correction formula for a uniform distribution from Dong (2015, p.428) is appropriate for Model 2.

Table 1: Comparing raw moments of distribution of birthdays

Source	**1st moment**	**2nd moment**	**3rd moment**	**4th moment**
Uniform distribution	0.500	0.333	0.250	0.200
Murphy (1996) 480,040 US life insurance applicants	0.506	0.339	0.254	0.203
UK live births 1994-2015	0.504	0.336	0.252	0.201

Figures rounded to 3 d.p. Source: Dong (2015, p.428), ONS (2015).

[1] These assumptions are additional to the standard RDD assumptions.

Model 2

$$H_i = \beta_0 + \hat{\tau}\Theta(A_i) + f(A_i) + f(A_i) \cdot \Theta(A_i) + X_n\gamma_i + \varepsilon_i$$

Where:

$$f(A_i) \cdot \Theta(A_i) = \left[c_1 A_i + c_2\left(A_i{}^2\right) + c_3\left(A_i{}^3\right) + c_4\left(A_i{}^4\right)\right] \cdot \Theta(A_i)$$

Recover τ using the formula from Dong (2015, p. 430):

$$\tau = \hat{\tau} - \frac{1}{2}c_1 + \frac{1}{6}c_2 - \frac{1}{30}c_4$$

Recovering τ using a linear polynomial $f(A_i)$ in Model 2 requires imposing restrictions $c_2 = 0$ and $c_4 = 0$. As advised by Dong (2015, p.431), bootstrapping through the boot package (Davison and Hinkley, 1997; Canty and Ripley, 2024) is used to estimate standard errors for τ. Bootstrapping involves re-running Model 2 on subsamples of the data[2] to re-estimate τ. The standard deviation of these re-estimates of τ is the bootstrapped standard error estimate.

The assumption $\mathrm{T}_i = \Theta(A_i)$ is only satisfied if individuals are only eligible for prescription charge exemptions if $\Theta(A_i) = 1$ (Cattaneo, Idrobo and Titiunik, 2019, p. 34). However, England has several other prescription charge exemptions targeted at individuals with specific health conditions or lower incomes (NHSBSA, 2025). Models 1 and 2 filter out individuals eligible for prescription charge exemptions for reasons besides being over 60 to ensure $\mathrm{T}_i = \Theta(A_i)$ holds, reducing the sample size and increasing the risk of biased data.

Model 3 is a fuzzy RDD which follows the approach by Dong (2015, pp. 431-432) to relax the assumption $\mathrm{T}_i = \Theta(A_i)$, allowing the full sample the be used. Model 3 estimates τ using a Wald estimator, which is the ratio of the effect of $\Theta(A_i)$ on H_i and the effect of $\Theta(A_i)$ on T_i, meaning τ accounts for other prescription charge exemptions captured in T_i. Model 3 firstly uses $\Theta(A_i)$ as an instrument to predict T_i :

[2] This study used 1000 subsamples of the data when bootstrapping.

Model 3 (first stage)

$$T_i = \beta_0 + \hat{\tau}_2 \Theta(A_i) + f(A_i) + f(A_i) \cdot \Theta(A_i) + X_n \gamma_i + \varepsilon_i$$

Where:

$$f(A_i) \cdot \Theta(A_i) = \left[s_1 A_i + s_2 \left({A_i}^2 \right) + s_3 \left({A_i}^3 \right) + s_4 \left({A_i}^4 \right) \right] \cdot \Theta(A_i)$$

Model 3 then uses a reduced-form equation, identical to Model 2 but using the full sample, to obtain parameters $\hat{\tau}$, c_1, c_2, c_3 and c_4.

Model 3 recovers τ using the extension to the bias correction formula for fuzzy RDD provided by Dong (2015, p. 432).

Model 3 (recovering τ)

$$\tau = \frac{\hat{\tau} - \frac{1}{2} c_1 + \frac{1}{6} c_2 - \frac{1}{30} c_4}{\hat{\tau}_2 - \frac{1}{2} s_1 + \frac{1}{6} s_2 - \frac{1}{30} s_4}$$

Recovering τ using a linear polynomial for $f(A_i)$ requires imposing restrictions $c_2 = 0$, $c_4 = 0$, $s_2 = 0$ and $s_4 = 0$. Model 3 also used bootstrapping to recover the standard error for τ.

3.2 Data

UK Household Longitudinal Survey (UKHLS) wave 9 data (Institute for Social and Economic Research (ISER), 2024c) and English Longitudinal Survey of Ageing (ELSA) wave 8/9 nurse visits data (Banks *et al.*, 2025) were accessed through the UK Data Service with End User Licence Access. ELSA surveys individuals aged 50 or over and their partners in England (NatCen Social Research (NatCen), 2020a, p. 4). UKHLS surveys individuals of all ages in households across the UK and was filtered for individuals in England. Both the UKHLS and ELSA data were filtered for individuals aged 50 to 69, providing an age-range of 10 years either side of the prescription charge age-cutoff. The models use an age-range of 5 years either side of the age-cutoff but some robustness checks require a larger age-range.

This study does not use multiple waves of ELSA/ UKHLS data because:

- Nurse visits are less frequent than the main interviews in ELSA (NatCen, 2020b, p. 4).
- The Winter Fuel Payment age and Women's State Pension age were both 60 until 2010 (Department for Work and Pensions, 2020; Mackley, 2025).
- COVID-19 impacted data collection methods, response rates, and people's attitudes towards their health (ISER, 2024b).

ELSA conducted wave 8/9 nurse visits between May 2016 and July 2019 (NatCen, 2020a, p. 15). 2,952 individuals from the wave 8/9 nurse visits were aged 50 to 69 and had at least a partially filled blood sample. Biomarker levels were measured from blood samples taken at the nurse visit (NatCen, 2020b, p. 16). Using biomarker data avoids the reporting bias in self-reported health data due to individuals imperfectly recalling their recent health or concealing health conditions for social approval (Althubaiti, 2016). Each biomarker covers a specific aspect of an individual's health; this study considers three biomarkers outlined in Table 2. Ferritin and HbA1c have positively skewed distributions, so model runs for Ferritin and HbA1c will be log-linear.

Table 2: Descriptive statistics and definitions for ELSA biomarkers

	Unit	Mean	S.D.	Med.	Min.	Max.	NAs
Cholesterol A fatty substance in blood. High cholesterol indicates cardiovascular disease risk.	mmol/l	5.3	1.1	5.3	2.2	9.9	99
Glycated Haemoglobin (HbA1c) A byproduct of glucose sticking to red blood cells. High HbA1c indicates diabetes risk.	mmol/ mol	39.4	8.6	38	21	131	144
Ferritin A protein which indicates iron levels. High Ferritin indicates excess iron.	ng/ml	155.6	137.0	120	4	2048	99

Figures rounded to 1 d.p. where applicable. Source: Banks et al., 2025.

UKHLS wave 9 data was collected between January 2017 and May 2019 (ISER, 2024a) and includes 9,322 individuals aged 50 to 69. The UKHLS wave 9 data contains a Physical Health Components Summary (SF12PCS) score and a Mental Health Components Summary (SF12MCS) score between 0-100 for each individual surveyed (ISER, 2024d, p. 30). Both scores are derived from each individual's self-reported answers to a 12-question survey about their health during the previous 4 weeks (NHS, 2022). Table 3 contains descriptive statistics for the scores.

Table 3: Descriptive statistics for UKHLS self-reported health variables

	Mean	S.D.	Med.	Min.	Max.	NAs
SF12PCS	47.8	11.4	51.8	4.9	71.5	652
SF12MCS	49.5	10.1	52.0	0	72.8	652

Figures rounded to 1 d.p. where applicable. Source: ISER, 2024c

Both the UKHLS and ELSA data contain a Likert self-reported health score which ranges from 1 (excellent health) to 5 (poor health) (NatCen, 2020a, p. 12; ISER, 2024d, p. 30). The UKHLS and ELSA data also contain covariates which capture differences in living standards and genetics between individuals that might impact health outcomes. These variables are recoded into the dummy variables outlined in Table 4.

Table 4: Descriptive statistics and definitions for dummy variables

	Definition	%=1 ELSA	%=1 UKHLS
Good health	1 if individual reports "good", "very good" or "excellent" health, 0 otherwise	81.8%	74.1%
Female	1 if individual is female, 0 otherwise	57.0%	54.2%
White	1 if individual's ethnicity is White British or Other White, 0 otherwise	95.4%	82.7%
Degree	1 if individual has a degree (or equivalent) qualification, 0 otherwise	1.1%	27.0%
Cohab	1 if individual is married or living with a partner, 0 otherwise	74.3%	74.5%
Homeown	1 if individual owns a home outright or owns a home with a mortgage, 0 otherwise.	85.7%	79.8%

Figures rounded to 1 d.p. Source: ISER, 2024c; Banks et al., 2025.

Both the UKHLS and ELSA data report each individual's age in whole years to maintain the anonymity of respondents (NatCen, 2020a, p. 19; ISER, 2024d, p. 5). Table 5 compares the discretised age variables in UKHLS and ELSA.

Table 5: Descriptive statistics for discretised age

	Mean	S.D.	Med.	Min.	Max.	NAs
Age (ELSA)	60.8	5.9	62	50	69	0
Age (UKHLS)	59.0	5.8	59	50	69	0

Figures rounded to 1 d.p. where applicable. Source: ISER, 2024c; Banks et al., 2025.

T_i is a proxy for individuals who are exempt from prescription charges based on NHS guidance (NHSBSA, 2025). T_i cannot perfectly match NHS guidance because ELSA and UKHLS data contain missing data (NatCen, 2020a, p. 21; ISER, 2024d, p. 22) and do not contain the variables to cover all the reasons an individual could be exempt from prescription

charges. Table 6 compares T_i to the dummy variable indicating if the individual is over 60, $\Theta(A_i)$.

Table 6: Descriptive statistics and definitions for prescription charge exemption indicators

	Definition	%=1 ELSA	%=1 UKHLS
$\Theta(A_i)$	1 if individual is over 60, 0 otherwise	60.3%	45.6%
T_i	1 if individual exempt from prescriptions for any reason that could be observed in the data, 0 otherwise	65.4%	52.1%

Figures rounded to 1 d.p. Source: ISER, 2024c; Banks et al., 2025.

4 Results

4.1 RDD plots

Figures 2-8 plot the mean for a given health outcome at each age and fit separate linear polynomials for individuals aged under 60 and aged 60 or over, providing descriptive results before running the RDD models.

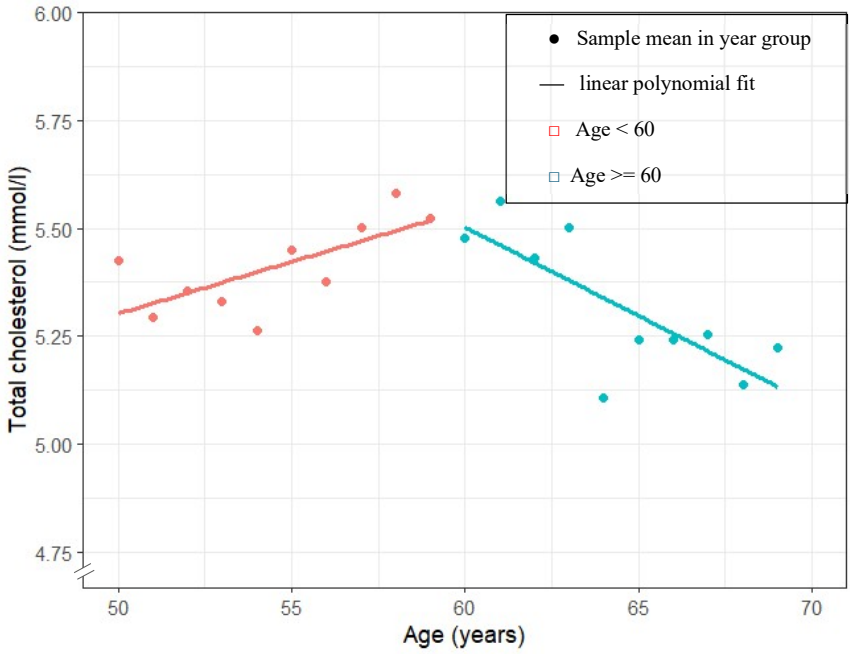
Figures 2-4 suggest that the trend of mean biomarker levels increasing with age, which would indicate older individuals are at greater risk of chronic health conditions, is stronger for adults aged under 60. Decreases in Ferritin between ages 57-58 and Cholesterol between ages 60-69 may impact the validity of some models. Changes in mean biomarker levels between ages 59-60 seem no larger than changes in mean biomarker levels between other ages.

Figures 5-6 indicate that mean SF12PCS scores decrease with age whilst mean SF12MCS scores increase with age. Older individuals feel their physical health is worse but their mental health is better. Neither mean SF12PCS scores nor mean SF12MCS scores change much between ages 59-60.

Figures 2-6 suggest that the RDD models may return insignificant results for τ. However, Figures 2-6 do not account for differences in the demographic mix or the share of respondents eligible for prescription charge exemptions between ages.

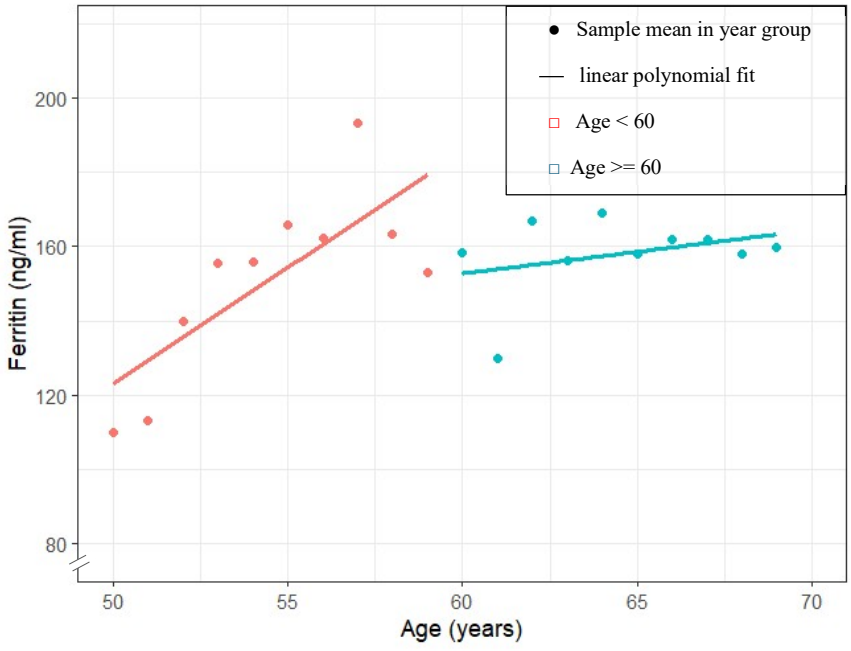
Figures 7-8 indicate that a higher percentage of respondents in the ELSA data report good health than the UKHLS data for most ages. There are large fluctuations in the share of respondents reporting good health between ages 50-59 in the ELSA data compared to the UKHLS data, unsurprising given the ELSA nurse visit sample is older and smaller. The percentages of individuals reporting good health in the ELSA and UKHLS data do not change much between ages 59-60.

Figure 2: Cholesterol RDD plot



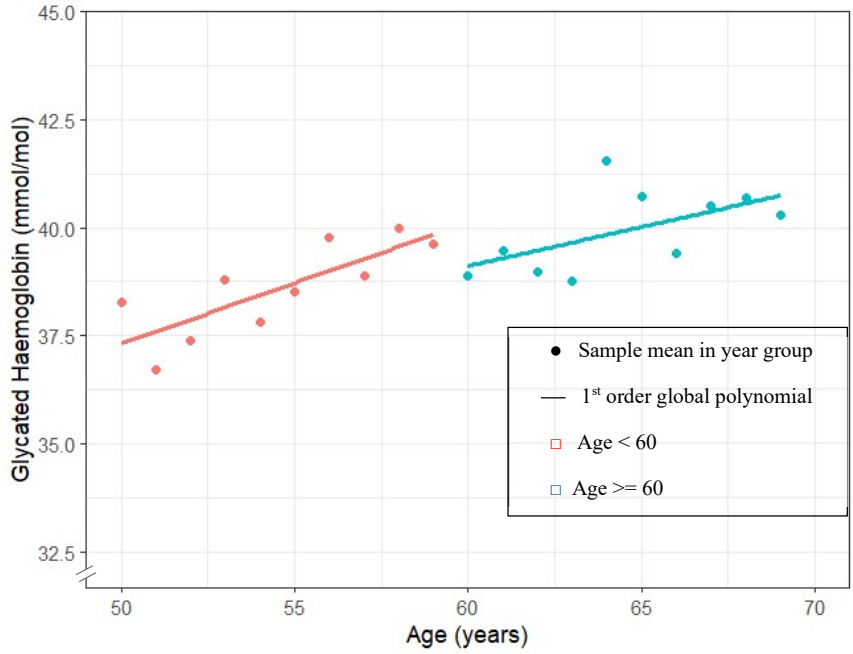
Source: Banks et al., 2025.

Figure 3: Ferritin RDD plot



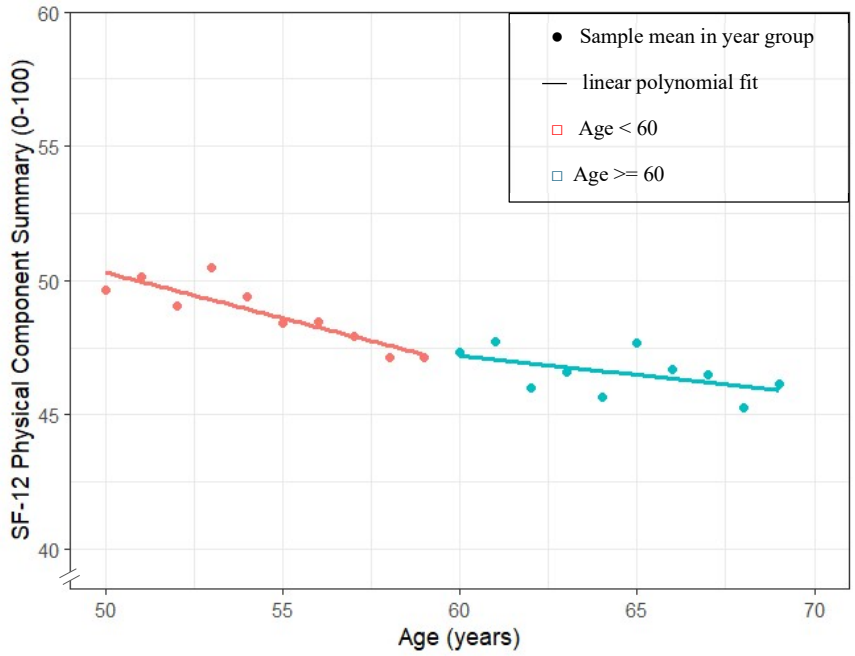
Source: Banks et al., 2025.

Figure 4: Glycated Haemoglobin (HbA1c) RDD plot



Source: Banks et al., 2025.

Figure 5: SF-12 Physical Components Summary (SF12PCS) RDD plot



Source: ISER, 2024c.

Figure 6: SF-12 Mental Components Summary (SF12MCS) RDD plot

Source: ISER, 2024c.

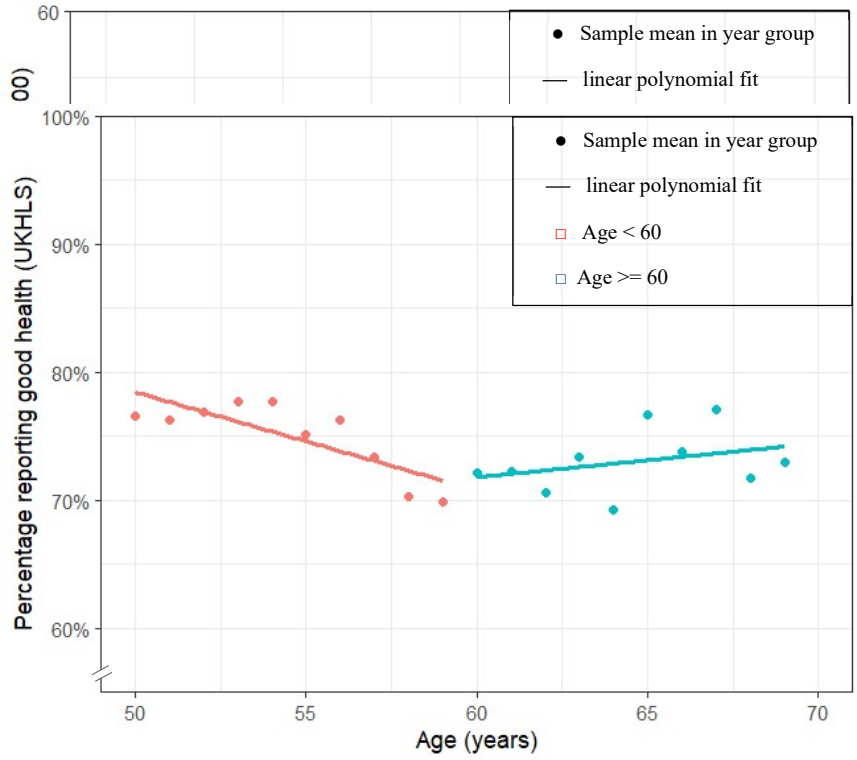
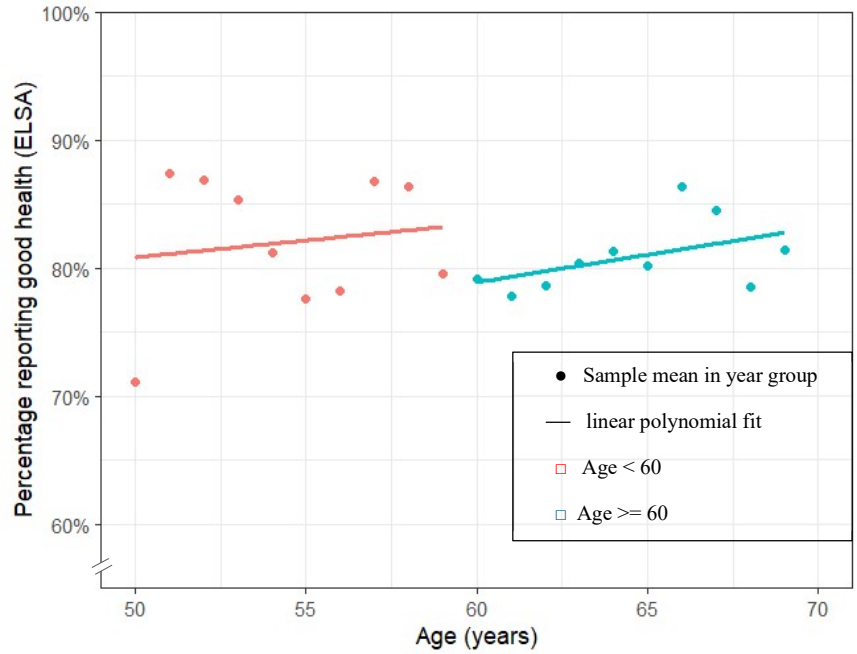


Figure 7: UKHLS percentage reporting good health RDD plot

Source: ISER, 2024c.

Figure 8: ELSA percentage reporting good health RDD plot



Source: Banks et al., 2025.

4.2 OLS RDD regressions

4.2.1 Discontinuity in health outcomes at age 60

Table 7 shows that τ is negative for ln(HbA1c) and ln(Ferritin), and positive for Cholesterol and SF12PCS across all 3 models. The estimates for τ in Model 3 suggest self-reported physical and mental health improve at age 60 but provide mixed results for the biomarkers. There is insufficient evidence to reject H_0: $\tau = 0$ for all estimates of τ in Table 7.

Table 7: Summary of RDD estimates for τ

	Dependent variable (ELSA)			Dependent variable (UKHLS)	
	Cholesterol	**ln(HbA1c)**	**ln(Ferritin)**	**SF12PCS**	**SF12MCS**
τ	0.141	-0.027*	-0.115	0.217	-0.088
Model 1	(0.133)	(0.016)	(0.095)	(0.657)	(0.615)
τ	0.131	-0.027	-0.114	0.220	-0.094
Model 2	(0.130)	(0.016)	(0.094)	(0.657)	(0.638)
τ	0.055	-0.029	-0.119	0.852	0.359
Model 3	(0.149)	(0.024)	(0.103)	(0.816)	(0.701)

Standard errors in parentheses. P-values: * <0.1, ** <0.05, *** <0.01. Covariates for all models: Female, White, Degree, Cohab and Homeown. Source: ISER, 2024c; Banks et al., 2025.

Not rejecting H_0 suggests that exempting over 60s from prescription charges does not significantly impact their health outcomes. Given prescriptions have a negative PED (Gemmill, Thomson and Mossialos, 2008), the result might suggest that increasing the number of prescriptions taken is an ineffective way of improving health outcomes. Prescriptions are typically used for managing symptoms rather than curing illness (Pizzorno, 2016). Additional prescriptions consumed without prescription charges may have little marginal benefit, given the law of diminishing marginal utility. Negative impacts of overprescription including increased hospital visits and medication dependency (Department for Health and Social Care, 2021, pp. 20-24) may counteract the benefits of free prescriptions. Prescriptions are used to manage both insufficient and excessive iron levels (NHS, 2023b, 2024), which may explain insignificant results for Ferritin.

However, the design of this study may also explain why H_0 was not rejected. This study looks at a general population sample rather than focusing on poorer individuals, individuals

from ethnic minority backgrounds, or individuals with health conditions. The literature review found the PED for prescriptions amongst the general population is inelastic. Other studies which investigated the general population also found prescription charge changes had no significant impact on health outcomes (Motheral and Fairman, 2001; Fairman, Motheral and Henderson, 2003; Liu *et al.*, 2011). Many individuals with health conditions or low incomes, who might have more elastic PEDs because prescription charges make up a higher share of their income, are exempt from prescription charges (NHSBSA, 2025). Prescription charge exemptions could be successfully mitigating the impacts of prescription charges on health outcomes.

4.2.2 General functional form linking age and health outcomes

Table 8 shows that the A_i coefficients for all biomarkers had positive signs in all models apart from Model 1 for Cholesterol. However, Model 1 does not account for the peak in Cholesterol at around age 60 for both men and women, evidenced by medical literature (Kreisberg and Kasim, 1987; Carroll, 2005) and the RDD plots. The A_i coefficients for most models are not statistically significant. The narrow age-range and the discretisation of A_i may be making age-related trends in biomarkers difficult to observe.

Table 8: Summary of RDD estimates for $f(A_i)$

	Dependent variable (ELSA)			Dependent variable (UKHLS)	
	Cholesterol	**ln(HbA1c)**	**ln(Ferritin)**	**SF12PCS**	**SF12MCS**
A_i	-0.022	0.006**	0.016	-0.328***	0.243**
Model 1	(0.022)	(0.003)	(0.016)	(0.115)	(0.106)
A_i	0.019	0.005	0.011	-0.289*	0.173
Model 2	(0.031)	(0.004)	(0.022)	(0.159)	(0.152)
A_i	0.025	0.006	0.005	-0.350**	0.136
Model 3	(0.030)	(0.005)	(0.022)	(0.167)	(0.152)
$A_i\ \Theta(A_i)$	-0.082*	0.001	0.008	-0.080	0.144
Model 2	(0.044)	(0.006)	(0.032)	(0.231)	(0.213)
$A_i\ \Theta(A_i)$	-0.093**	0.001	0.007	-0.159	0.100
Model 3	(0.043)	(0.007)	(0.030)	(0.244)	(0.212)

Standard errors in parentheses. P-values: * <0.1, ** <0.05, *** <0.01. Covariates for all models: Female, White, Degree, Cohab and Homeown. Source: ISER, 2024c; Banks et al., 2025.

The A_i coefficient for SF12PCS was negative and statistically significant in Model 1 and Model 3; the larger UKHLS sample may have allowed a more precise estimate. Lower SF12PCS scores suggest older individuals feel their physical health is worse, suggesting the stock of health is declining with age in line with Grossman's (1972) health capital theory. The coefficients for A_i for SF12MCS were positive but not statistically significant. Approaching retirement can temporarily improve mental health (Vo and Phu-Duyen, 2023) but this improvement is offset by declining physical health, social isolation and reduced income amongst older people (World Health Organisation, 2023).

The coefficient for $A_i \cdot \Theta(A_i)$ was negative and statistically significant in Model 3 for Cholesterol, which is expected given Cholesterol peaks at around age 60 for both men and women (Kreisberg and Kasim, 1987; Carroll, 2005). Other results for $A_i \cdot \Theta(A_i)$ were not statistically significant and coefficient signs were the same as A_i.

4.2.3 Other covariates

For models with dependent variables SF12PCS and SF12MCS the coefficients for covariates Degree, Homeown and White all had the expected positive signs and were statistically

significant. The coefficients for Cohab also had the expected positive sign but were not statistically significant for SF12PCS in Model 1 or Model 2. The coefficients for Female were negative and statistically significant. This result could reflect worse health in women, perhaps due to gender biases in healthcare (Winchester, 2021), or men underreporting bad health due to social desirability bias (Ramsay and Bunn, 2023).

Amongst models with biomarker dependent variables the coefficients for covariates varied depending on the biomarker and model used. The ELSA sample was smaller than the UKHLS sample, which could be impacting the efficiency of the biomarker models. The inconsistent coefficients reflect differing socioeconomic, racial and gendered patterns for different health conditions.

4.3 Re-estimated RDD coefficients using survey package

ISER (2024d) outline why complex surveys such as the UKHLS and ELSA cannot be considered random samples:

- Stratification: The population was split into subgroups. The surveys sample each subgroup with a different probability to ensure smaller subgroups are represented.
- Response bias: Some subgroups of individuals are more likely to be difficult to contact, refuse to be surveyed, not provide a blood sample, or have dropped out of the study. UKHLS deliberately oversamples households in areas with large ethnic minority populations. Sample weights account for response bias and sampling error.
- Clustering: Groups of respondents, such as respondents in the same household, are selected jointly to reduce survey costs.

The OLS models, which are designed for random samples, may be producing biased results. All coefficient estimates and standard errors were recalculated using the survey package (Lumley, 2010, 2024), which runs linear models accounting for clustering, stratification and sample weights.

Tables 9 and 10 present the recalculated RDD estimates for τ , A_i and $A_i \cdot \Theta(A_i)$. The sign and size of the estimates of τ for Cholesterol and SF12MCS change when adjusting for survey design. The revised estimates for τ more consistently suggest mental health outcomes improve at age 60 but τ remains statistically insignificant in all models.

The coefficients for A_i change signs for SF12PCS and are only statistically significant in Model 1 for SF12PCS; the coefficients for $A_i \cdot \Theta(A_i)$ are all statistically insignificant and change signs for most models. These changes cast doubt on the estimates and conclusions obtained for A_i and $A_i \cdot \Theta(A_i)$ from the OLS models.

Table 9: Survey design adjusted RDD estimates for τ

	Dependent variable (ELSA)			Dependent variable (UKHLS)	
	Cholesterol	**ln(HbA1c)**	**ln(Ferritin)**	**SF12PCS**	**SF12MCS**
τ	-0.020	-0.025	-0.141	0.603	0.792
Model 1	(0.244)	(0.020)	(0.114)	(0.966)	(0.923)
τ	0.006	-0.024	-0.132	0.638	0.817
Model 2	(0.160)	(0.019)	(0.112)	(0.811)	(0.653)
τ	-0.076	-0.024	-0.139	0.852	1.506*
Model 3	(0.216)	(0.027)	(0.122)	(0.816)	(0.856)

Standard errors in parentheses. P-values: * <0.1, ** <0.05, *** <0.01. Covariates for all models: Female, White, Degree, Cohab and Homeown. Source: ISER, 2024c; Banks et al., 2025.

Table 10: Survey design adjusted RDD estimates for $f(A_i)$

	Dependent variable (ELSA)			Dependent variable (UKHLS)	
	Cholesterol	**ln(HbA1c)**	**ln(Ferritin)**	**SF12PCS**	**SF12MCS**
A_i	-0.004	0.005	0.022	-0.511***	-0.003
Model 1	(0.041)	(0.004)	(0.019)	(0.174)	(0.169)
A_i	0.031	0.006	0.034	-0.239	0.188
Model 2	(0.054)	(0.005)	(0.026)	(0.233)	(0.220)
A_i	0.036	0.005	0.027	-0.427*	-0.009
Model 3	(0.050)	(0.006)	(0.025)	(0.237)	(0.229)
$A_i\ \Theta(A_i)$	-0.088	-0.003	-0.030	-0.566	-0.399
Model 2	(0.081)	(0.007)	(0.037)	(0.360)	(0.343)
$A_i\ \Theta(A_i)$	-0.114	0.002	-0.029	-0.300	-0.124
Model 3	(0.332)	(0.008)	(0.036)	(0.358)	(0.337)

Standard errors in parentheses. P-values: * <0.1, ** <0.05, *** <0.01. Covariates for all models: Female, White, Degree, Cohab and Homeown. Source: ISER, 2024c; Banks et al., 2025.

4.4 Comparing RDD linear probability models using ELSA and UKHLS data

Table 11 shows that estimates of τ , $\Theta(A_i)$, A_i and $A_i \cdot \Theta(A_i)$ differed between the UKHLS and ELSA data for linear probability models (LPM) run with the same dependent variable good health. The differing composition of the two samples could lead to different coefficient estimates for the same dependent variable, especially given some individuals who could not provide a blood sample such as fasting individuals could have responded to general survey

questions. The significant estimate for τ for ELSA good health in Model 3 may be spurious since LPMs are not suitable for causal inference.

The size and signs of coefficients for covariates were similar between the LPM models run with UKHLS and ELSA data. The larger UKHLS sample permits more precise coefficient estimates, which may explain why coefficients for Homeown, Degree, White and Cohab were only statistically significant for the UKHLS good health models.

Table 11: Coefficient estimates for RDD LPM models for good health

	ELSA good health			UKHLS good health		
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
$\boldsymbol{\tau}$	-0.051	-0.054	-0.108**	0.001	0.001	0.027
	(0.045)	(0.043)	(0.052)	(0.027)	(0.027)	(0.030)
$\boldsymbol{\beta_0}$	0.631***	0.654***	0.526***	0.527***	0.511***	0.356***
	(0.080)	(0.086)	(0.078)	(0.033)	(0.036)	(0.033)
$\boldsymbol{\Theta(A_i)}$	-0.051	-0.061	-0.097**	0.001	0.007	0.027
	(0.045)	(0.046)	(0.047)	(0.027)	(0.027)	(0.027)
$\boldsymbol{A_i}$	0.007	0.014	0.015	-0.005	-0.010	-0.014**
	(0.008)	(0.011)	(0.011)	(0.005)	(0.006)	(0.006)
$\boldsymbol{A_i \cdot \Theta(A_i)}$	-	-0.014	-0.005	-	0.012	0.008
		(0.015)	(0.016)		(0.009)	(0.009)
Female	-0.009	-0.009	0.013	-0.009	-0.009	-0.012
	(0.008)	(0.022)	(0.022)	(0.013)	(0.013)	(0.013)
Homeown	0.195***	0.195***	0.274***	0.165***	0.165***	0.252***
	(0.046)	(0.046)	(0.039)	(0.022)	(0.022)	(0.020)
Degree	0.039	0.037	0.009	0.082***	0.082***	0.105***
	(0.082)	(0.081)	(0.089)	(0.013)	(0.013)	(0.014)
White	0.059	0.059	0.035	0.048**	0.048**	0.040**
	(0.063)	(0.064)	(0.058)	(0.021)	(0.021)	(0.020)
Cohab	0.034	0.034	0.087***	0.068***	0.068***	0.104***
	(0.029)	(0.029)	(0.029)	(0.017)	(0.017)	(0.017)

Standard errors in parentheses. P-values: * <0.1, ** <0.05, *** <0.01. Covariates for all models: Female, White, Degree, Cohab and Homeown. Source: ISER, 2024c; Banks et al., 2025.

4.5 Other robustness checks for OLS RDD models

F-tests found that all models were statistically significant. Table 12 shows that all RDD models only explained a small part of the variation in health outcomes, and that Models 1 and 2 had fewer observations.

Table 12: Adjusted R-squared and number of observations

	Dependent variable (ELSA)			Dependent variable (UKHLS)	
	Cholesterol	**ln(HbA1c)**	**ln(Ferritin)**	**SF12PCS**	**SF12MCS**
$\boldsymbol{Adj.R^2}$ **Model 1**	0.058	0.022	0.117	0.051	0.033
$\boldsymbol{Adj.R^2}$ **Model 2**	0.058	0.021	0.116	0.051	0.033
$\boldsymbol{Adj.R^2}$ **Model 3**	0.073	0.037	0.106	0.109	0.073
$\boldsymbol{N}$ **Model 1**	1024	1014	1024	3658	3658
$\boldsymbol{N}$ **Model 2**	1024	1014	1024	3658	3658
$\boldsymbol{N}$ **Model 3**	1193	1180	1192	4195	4195

Source: ISER, 2024c; Banks et al., 2025.

Using the lmtest package (Zeileis and Horthorn, 2002), models were tested for: functional form misspecification using the Ramsey Regression Equation Specification Error (RESET) test, heteroskedasticity using the Breusch-Pagan test and autocorrelation using the Breusch-Godfrey test. The RESET test suggested that only Model 3 for SF12PCS was misspecified, although the RESET test is not confirmation that the other models are the best specifications. The Breusch-Pagan test suggested there was sufficient evidence to conclude that all models for SF12PCS, SF12MCS and ln(HbA1c) were subject to heteroskedasticity. Standard errors for all coefficient estimates were EHW standard errors, to prevent incorrect inferences about the significance of coefficients due to heteroskedasticity. The Breusch-Godfrey test suggested there was sufficient evidence to conclude models for SF12PCS and SF12MCS were subject to autocorrelation. Autocorrelation might reflect individuals within the same household responding similarly to the survey; coefficients were re-estimated using the survey package to account for clustering.

Model reruns test whether functional form or input data changes impact the estimate of τ, indicating the robustness of the original OLS RDD models. The model reruns used involved:

- Placebo age-cutoffs at ages 59 and 61.

- Age-range $-10 \leq A_i \leq 9$
- Quadratic polynomial $f(A_i)$.
- Interaction terms between Female and $f(A_i)$.
- No covariates.
- Covariates as dependent variables.

Each model rerun had little notable impact on τ across all or most models. τ was statistically significant for ln(HbA1c) when running Model 2 with age-range $-10 \leq A_i \leq 9$, but τ remained insignificant for ln(HbA1c) in Model 3. τ was significant in all models using ELSA data with dependent variable Degree, indicating the RDD models using ELSA data are not robust. However, rerunning the models without covariates had little impact on τ . The sign for τ for Cholesterol changed when Models 2 and 3 were re-run with quadratic polynomial $f(A_i)$, but τ remained statistically significant.

Overall, the robustness checks do not indicate that the RDD models are subject to type-two errors, where models fail to reject a false H_0.

5 Limitations and research suggestions

This study used age in years which required assuming the functional form for $f(A_i)$ reducing the efficiency of the estimation and meant that individuals almost year away from the age-cutoff being were recorded as the same age as individuals a few days away from the age-cutoff. The limited range of ages made it very difficult to identify a causal effect, particularly given prescriptions are a relatively small expenditure item for most people. Age in months is available for both UKHLS and ELSA data with Special License Access (NatCen, 2020a, p. 19; ISER, 2024d, p. 5). Age in months could provide enough distinct values for continuity-based RDD analysis, as outlined by Cattaneo, Idrobo and Titiunik (2019, pp. 39-87), which requires a continuous age variable but has less restrictive functional form assumptions.

The RDD models may underestimate the impact of prescription charges on health outcomes since they only measure the change in health outcomes at the age-cutoff and only account for the health outcomes of individuals within the limited age-range used to run the regressions. People may change their prescription usage before reaching 60 in anticipation of free prescriptions or after reaching 60 having realised they are entitled to free prescriptions. The abolition of prescription charges in other UK nations provides an opportunity to compare health outcomes between England and elsewhere in the UK. Cohen et al. (2010) conducted a descriptive comparison of health outcomes in England and Wales after Wales abolished prescription charges; Difference-in-Differences could extend this analysis to account for time-invariant differences between UK nations. A Randomised Control Trial, similar to Norris et al. (2023), could also be used to investigate the impact of prescription charges on individuals over a wider age-range.

Cross-sectional data was used, which meant the RDD models compared different age cohorts at a given time. This prohibited the investigation of health outcomes of a given age cohort over time and the separation of short-run and long-run effects of prescription charges on health outcomes. Whilst the prescription charge age-cutoff remains 60, additional waves of ELSA and UKHLS data may permit RDD using panel data. New UKHLS biomarker data, which will be the first collected for the UKHLS since 2012 (ISER, 2025), will also provide useful comparative data to ELSA.

Crossley and Zilio (2018) used biomarker cutoff points for chronic illnesses such as cardiovascular disease rather than biomarker levels as their dependent variable when analysing the impact of Winter Fuel Payments on health outcomes using RDD, although it is

unclear whether the method provided by Dong (2015) can be adapted to more sophisticated limited dependent variable models than LPMs.

6 Conclusions

This study finds insufficient evidence to prove that prescription charges significantly impact health outcomes at age 60, despite coefficient signs suggesting improved self-reported health and reduced risk of chronic illnesses at age 60. The results may have arisen because making prescriptions free is an ineffective way of improving health. Free prescriptions might correct for people's tendency to underinvest in their health capital, but they may also encourage overconsumption of prescriptions with little marginal benefit. The results could also reflect the difficulty of identifying a significant impact of prescription charges using general population data; prescription demand is price inelastic amongst the general population. These results in isolation cannot say whether prescription charge exemptions should be changed, such as increasing the prescription charge age-cutoff above 60. A closer examination of individuals with health conditions or low incomes is necessary to test how well existing prescription charge exemptions mitigate the impacts of prescription charges on health outcomes.

Insufficient evidence was found to reaffirm a significant relationship between age and health outcomes. This insignificant result may be driven by the limited age-range and the discrete age variable used by this study; coefficient signs align with Grossman's (1972) model which assumes health capital depreciates with age. The changes in the age coefficients when accounting for the survey design of the UKHLS and ELSA indicate the bias introduced by using OLS with data from complex surveys.

Robustness checks do not indicate that RDD models could arrive at a different result for this research question given the UKHLS and ELSA data used. The smaller ELSA sample resulted in less precise estimates than were possible with the UKHLS sample. Using multiple waves of ELSA biomarker data or using UKHLS biomarker data as more data becomes available in the future could lead to different results.

This study provides one of the few general population level and UK-based analyses of the impact of prescription charges on health outcomes. It also provides an application of the RDD bias correction formula outlined by Dong (2015), which could be useful for future

research using discrete age variables. Nonetheless, future UK studies seeking to understand the impact of prescription charges on health outcomes may benefit from focusing on individuals with specific health conditions or from disadvantaged backgrounds.

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