Direct and spillover effects on health of increased income for the elderly: evidence from a Chilean pension program *

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Abstract

We estimate the effect of a permanent income increase on the health outcomes of the elderly poor and their relatives. Our regression discontinuity design exploits an eligibility cut-off in a Chilean *basic pension* program that grants monthly payments to retirees without a contributory pension. Using administrative data we find that, four years after applying, *basic pension* recipients are 2.6 percentage points less likely to die. Additionally, we observe spillover effects on working-age relatives, who are more likely to have a newborn. Results suggest that increasing the elderly's income can improve their health and benefit younger household members.

Keywords: pension, elderly, spillover effects, mortality, fertility.
JEL Classification: I14, I38, J14.

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1 Introduction

As a result of a rapidly aging population, health inequalities amongst the elderly have received increased attention over the last two decades. Researchers and policymakers have documented large and ever-widening life expectancy inequalities across income groups in both developed and developing countries [Hoffman, 2008; Brønnum-Hansen and Baadsgaard, 2012; Tarkiainen et al., 2012; OECD, 2017]. For instance, a recent OECD [2018] report shows that, at retirement age, high-income earners live longer than low-income earners: 1.6 years longer in the US, 3.6 in Chile, 3.25 in the UK and 2.9 in South Korea.[1]

Despite a large body of literature documenting that, at all ages, wealthier people enjoy better health on average [Marmot, 2005; Braveman et al., 2010; Waldron, 2013; Chetty et al., 2016], substantial debate remains on whether an income increase for the elderly poor can improve their health. It may be the case that unobserved characteristics, such as genetic factors, are able to explain both higher income and better health. Alternatively, better health could be the cause of higher income (reverse causality). Differences in health status may also be the result of cumulative conditions related to income inequalities at earlier ages, such as different education levels or exposure to air pollution.

The non-contributory pension program in Chile provides an ideal regression discontinuity design (RDD) that allows us to identify the causal effect of a large permanent income increase for the elderly poor on their health outcomes and on their relatives. Chile is a high-middle income country with a per-capita GDP (PPP) of US$22,297 in 2017 and a life expectancy at age 65 of 19.45 years [World Bank, 2019; OECD, 2019]. Since 2008, Chileans who are aged 65 or over and do not have a *contributory pension* can apply to receive a governmental pension, which provides lifelong monthly payments of approximately 40 percent of the national minimum wage (*basic pension*). Upon receiving applications, the government calculates a specifically designed pension score and assigns a basic pension to applicants who fall below the 60th percentile (cut-off) of the score distribution.

Our study uses administrative data on basic pension applicants from 2011 and 2012, and their household members.[2] This data is paired with their medical history from 2011 to 2016. We first

[1] In the report, high-income earners are defined as those who earn more than three times the average wage and low-income earners are defined as those who earn half of the average wage or less.

[2] The program did not systematically collect information on applicants and their household members prior to 2011, making it unfeasible to conduct the analysis on earlier years.

observe that the pool of applicants consists mostly of women without a history of regular paid employment (e.g. former stay-at-home mothers). As individuals can apply multiple times, we define applicants whose *first* application score fell *below* (*above*) the cut-off and within a certain bandwidth, as our 'treatment' ('control') group. We document that nearly all applicants in the treatment group obtained a basic pension and that 18 percent of applicants in the control group submitted another application at a later time that was successful. Therefore, being in the treatment group increases the probability of receiving a basic pension within four years of the first application by 82 percent. We also show that density and balance tests cannot reject the hypothesis that the pension is as good as 'locally' randomly assigned between treatment and control group applicants. Following these findings, we implement a fuzzy regression discontinuity design to explore the causal effect of the pension on applicants, as well as the spillover effects on their relatives.

We find that receiving a basic pension decreases the probability of dying within four years after applying to the program by 2.6 percentage points (pp.), with an intention-to-treat (ITT) income-mortality elasticity of -0.17. The decrease is statistically significant and remains unaffected when using nonparametric estimations and different sets of controls, bandwidths, or polynomial orders. A survival analysis shows that the beneficial effect on mortality becomes visible one year after the first payment and grows almost monotonically over time. Improvements in health outcomes appear to be driven by fewer incidents of circulatory and respiratory diseases.

The heterogeneous analysis shows that applicants living alone or with only elderly household members are significantly less likely to die and spend fewer days hospitalized, while those living with working-age household members remain unaffected. Interestingly, we find evidence of spillover effects on working-age household members, who are 3.6 pp. more likely to have a newborn child nine months or later after the application was made. Focusing on fertility-age women, this translates into an ITT income-fertility elasticity of 0.35.

Our paper makes two main contributions. First, we provide causal evidence that a permanent income increase for the elderly can reduce their mortality rates at the present time. Salm [2011] finds that two pension increases that occurred in the early 1900s reduced the mortality rates of US veterans. This effect was driven by infectious diseases, decades before the medical revolution of antibiotics [Hare, 1982]. In modern times, the evidence is mixed: studies have estimated negative [Barham and Rowberry, 2013; Jensen and Richter, 2003], insignificant [Cheng et al., 2016], or even positive [Snyder and Evans, 2006; Feeney, 2017, 2018] income elasticities of mortality.

The confidence interval of our estimate encompass most of the negative point estimates of

income-mortality elasticity in previous papers.[3] To reconcile our results with the positive estimates, it is important to note that Snyder and Evans [2006] and Feeney [2017] find that higher pensions increase the probability of retirement and that Fitzpatrick and Moore [2018] show that transition to retirement causes a significant jump in mortality, independently of whether income is affected. On the other hand, the basic pension in Chile is given mostly to people that are already out of the labor force (e.g. former 'stay at home mothers') and thus has arguably a limited impact on retirement transitions. Our analysis is then able to isolate the negative mortality effect of the permanent income increase from the positive mortality effect of the increase in transition to retirement.

Our second contribution is to provide causal evidence that a permanent income increase for the elderly poor can have spillover effects on the fertility of working-age household members. We are not aware of previous papers testing this directly, using administrative data and a regression discontinuity design. This result complements previous findings regarding the spillover benefits of non-contributory pensions on children's height, weight, school enrolment, and attendance [Duflo, 2000, 2003; Edmonds, 2006]; and on working-age relatives' self-reported nutrition, sanitation, and employment [Case, 2004; Case and Menendez, 2007; Ardington et al., 2009]. The presence of spillover effects suggests that the benefits of pension policies extend beyond the welfare of direct recipients and can affect the life choices of younger generations.

The paper is organized as follows. Section 2 presents the basic pension program. Section 3 describes the data and explains the empirical strategy. Section 4 provides evidence for the validity of the RD assumptions. Section 5 presents the results and Section 6 concludes.

2 The basic pension

Since 1980, Chile has had a full-capitalization pension system in which workers must contribute ten percent of their monthly wage into a pension fund run by private companies. Upon retirement, workers receive a pension that is dependent on the amount saved over the course of their working life (*contributory pension*). Until recently, those who had never undertaken paid work received no pension.

During the 2005 presidential campaign, the Chilean pension system was judged to be partic-

[3] Lindahl [2005], Cesarini et al. [2016] and Schwandt [2018] also showed mixed results regarding the impact of increases in wealth, such as lottery prizes, on mortality rates amongst the elderly. Although these studies do belong to a related literature, the effects of unexpected wealth increases might not mirror the effect of a permanent income increase guaranteed by the government.

ularly unfair to stay-at-home mothers, with their role being recognized as unpaid yet central to a fully functioning society in Chile. As a result of this discussion, most of the presidential candidates, including future president Michelle Bachelet, agreed to introduce a government-funded pension for stay-at-home mothers in the poorest households.

On March 11th, 2008, President Bachelet signed ACT 20255 in law. This Act established that every citizen aged 65 or above with no retirement savings would be eligible for a pension consisting of lifelong monthly payments provided by the government (*basic pension*). The introduction of the basic pension took place across Chile simultaneously, and the first payments were delivered on July 1st, 2008. Between 2011 and 2016, our period of analysis, basic pension payments were equivalent to approximately 40 percent of the national minimum wage.

The process for applying for the basic pension is free and identical across Chile. Applicants must apply to the Pension Institute (PI) by filling in a form in the municipality in which they live. Then, the PI calculates a pension score that is specifically designed to assess eligibility for the basic pension. The pension score is comprised of two factors: household income from assets (e.g. contributory pensions from household relatives) and labor income from all household members. Administrative data shows that these two factors account for 60 and 40 percent of total household wealth, respectively. The pension score is then adjusted for household size and the number of disabled household members (for more details on the basic pension and score calculation, see Appendix Section A).

To identify households and calculate the factors mentioned above, the PI follows the same definition of a household used by all Chilean government agencies: a group of people, whether related or not, who live in the same house and share income. Households are registered by the Ministry of Planning (MP). The MP ensures that every person belongs to one household only and visits each household to verify that each registered person lives there. The household records are then provided to the PI, along with each person's unique national identifier number, so that the PI can collect information about each household member across public and private agencies and compute the pension score.

The pension score uses a more comprehensive set of data and it is computed differently to other governmental indices, such as the *social security score*.[4] The calculation of the pension score re-

[4]The *social security score* ("Puntaje de la Ficha de Protección Social") is a proxy means test based on potential and self-reported actual income, disability status, and household composition that allows the government to assign social benefits. The *social security score* does not use administrative data on labor income or on income from other sources such as contributory pensions.

lies upon information from public agencies (e.g. Tax Service) and self-reported information, along with administrative data from private companies (e.g. pension fund companies, banks, etc.). As constructing the pension score requires the coordination of several public and private offices, it is calculated only for people who apply for the basic pension. This means that basic pension applicants do not know ex-ante whether or not they will receive it.

Following the assigning of pension scores, the PI uses an arbitrary cut-off to determine basic pension recipients. This cut-off has changed progressively over time, with changes occurring simultaneously nationwide. The cut-off has increased from covering the poorest 40 percent of the elderly population in July 2008, to covering the poorest 60 percent since July 2011. To determine the 60th percentile for the Chilean population in 2011, the PI used data from the national household survey and estimated a pension score for each household in the survey. The cut-off then corresponds to the 60th percentile of the estimated pension score for the sample of households in the survey. There have been no updates to the pension score cut-off since July 2011, when the 60th percentile was estimated at 1,206 pension score points. Appendix Table C1 shows the cut-offs by date, along with their corresponding payment amounts in Chilean pesos (CLP) and US dollars.

After the decision has been made, applicants receive two pieces of information: whether or not they will receive the basic pension, and the reason why they will not receive it if their application is unsuccessful. Applicants do not have access to the score assigned during the application process.

The government initially considered reassessing basic pension recipients' eligibility every two years. This policy was never enacted and virtually all of those who were assigned the basic pension continued to receive payments every month thereafter.[5] Additionally, according to PI records, 96 percent of recipients in our sample collect their pension in person, by showing their identity card in a bank or PI office. This indicates that the pension payments are effectively being received by recipients.

Overall, the majority of the elderly population who do not receive a contributory pension apply to receive a basic pension. In 2011, 64.3 percent of retirees without a contributory pension received a basic pension [Ministerio de Desarrollo Social, 2011] and an extra eight percent of those without a contributory pension submitted an unsuccessful application according to our records. Appendix Table C12 shows the characteristics of the elderly population without contributory pensions in 2011. The data confirms that this population has an extremely low employment level and

[5]Less than 0.05 percent of recipients who obtained the basic pension between 2008 and 2015 stopped receiving it at some point [Subsecretaría de Previsión Social, 2015]. All of these were for reasons unrelated to the pension score (e.g. emigration).

that pension recipients were predominantly women.

3 Data and empirical strategy

3.1 Pension and health datasets

Our analysis is based on administrative data provided by the Chilean government. First, we have access to all applications for the basic pension made in 2011 and 2012. For each applicant and each applicant's household member, the PI provided us with demographic information regarding their gender, age, town of residency, household *social security score*, unique identifier number (henceforth *ID number*), and unique identifier number for the household.[6] The applicant's ID number allowed us to identify the pension applicant in each household and the household identifier number allowed us to perfectly match each applicant with all of their household members. This dataset also includes application data, such as the pension score, application date, and the outcome of the application. The PI collected all the variables mentioned at the moment of application. The PI also provided us with the outcome of all applications submitted between 2013 and 2016 for those who applied between 2011 and 2012. We do not have access to applicants' data from previous years, as it was not systematically recorded before 2011.

We were also granted access to additional household-level data on the factors that determined the pension score for applications submitted in 2012, the year in which the PI started to systematically record them. For applications submitted in this year, we also obtained household-level data on the total income generated by different groups of household members, as per our definition below (e.g. applicant, working-age household members, etc.).

The second dataset we use is provided by the Ministry of Health and includes the medical history of all applicants and household members in 2011 and 2012, for each year from 2011 to 2016. This dataset contains information about those who died, the date of death, and the cause of death (ICD-10 disease code). It also provides information about any type of vaccinations given to each person and the date when it was received, along with a record of any hospitalization that occurred (with its date, duration, and cause). The Ministry of Health also granted us access to the ID number of each person, which is used to match this dataset to the PI dataset. As all physicians and health

[6]The unique identifier number is anonymous and it is determined using a function applied to the unique tax national identifier number of each applicant and household member. This function is not known to the public. Due to data protection, we cannot observe the unique tax national identifier number of individuals.

centers have the legal obligation to report this information to the central government on a monthly basis, the dataset includes individuals receiving medical attention in both private and public health institutions.

Finally, the Ministry of Health also granted us access to a dataset with all births that occurred between 2011 and 2016 for applicants and household members. This dataset contains the date of birth, along with the weeks of pregnancy, height and weight of each newborn, as well as the ID number of the mother. This data covers births in public and private health centers.

As all datasets contain the ID number of each person, we were able to merge the PI and the health data at an individual level. No observation was lost in this process.

Our study looks at only those applications submitted between July 1, 2011 and December 31, 2012. We do not use applications submitted prior to July 2011 as the 60 percent cut-off point for eligibility was introduced by the government in July 2011 (see Section 2). The most recent health data to which we have access extends until December 2016. This allows us to measure health outcomes for up to four years from the date of application.

We focus our main analysis on basic pension applicants and then conduct a separate analysis for their household members. In Chile, the minimum legal age to claim contributory pension benefits is 65 for men and 60 for women, and the minimum legal working age is 15. We thus define three exclusive groups of household members, based on household members' age: 1) men above 64 and women above 59 years of age (elderly); 2) men aged 16-64 and women aged 16-59 years (working-age); and, 3) individuals below 16 years of age (school-age children). Given the small number of observations in this last group of household members (931), we focus the analysis on the first two groups.

Finally, we observe that 21.2 percent of those who did not receive the basic pension in their first application applied more than one time. To avoid multiple-counting that could potentially bias our estimates, we keep in the sample only the first application made by each applicant in our period of interest.[7] Since the focus of our paper is to use the basic pension to analyze the effect of an income increase on mortality rates and days of hospitalization of the elderly, we accommodate later changes in pension holder status using the 'fuzzy' regression discontinuity framework presented

[7] As those submitting more than one application are self-selected, counting each repeated application separately could bias our estimates of the treatment effect. First, it would give an excessive weight to applicants that applied more than one time. Second, if the type of applicants that submit more than one application are somehow different from the rest (for example, more motivated), we would give an excessive weight to this particular type of applicant. Also, there could be multiple applicants within a household. We observe that less than 1 percent of applicants in our working sample share a household with another applicant.

in the next section.

3.2 Fuzzy regression discontinuity design

To estimate the causal effect of the basic pension on each health outcome, we perform a two-stage least square regression. The set of equations is as follows:

$$\textit{Health Outcome}_{i,h} = \alpha_0 + f_0(Score_h) + \beta_{LATE}\textit{Pension}_h + D_h \times f_1(Score_h) + u_{i,h}, \quad (1)$$

where $Pension_h$ is instrumented using:

$$\textit{Pension}_h = \alpha_1 + g_0(Score_h) + \beta D_h + \mathrm{D}_h \times g_1(Score_h) + v_h, \quad (2)$$

and D_h is a dummy variable defined as follows:

$$D_h = \begin{cases} 1 & \text{if } Score_h \leq 0 \\ 0 & \text{if } Score_h > 0 \end{cases}$$

In this set of equations, *Health Outcome*$_{i,h}$ is one of the health outcomes described in Section 3.1, four years after applying, for person *i* in household *h*. Pension$_h$ is a dummy indicator equal to 1 if the applicant of household *h* has received a basic pension within four years of the first application, and 0 otherwise. D$_h$ is a dummy indicator equal to 1 if the applicant of household *h* obtained a pension score below the cut-off in their first application, and 0 otherwise. *Score*$_h$ is the distance of the first application score from the cut-off point, for the pension applicant of household *h*. f_j and g_j, with $j = 0, 1$, are different functional forms of *Score*$_h$. In our preferred specification, f_j and g_j, are polynomials of order 1 in *Score*$_h$. We check the robustness of our results to different specifications using polynomials of order 2 in *Score*$_h$, nonparametric estimations, logistic regression and different sets of controls. Moreover, we report intention-to-treat (ITT) effects by estimating equation 2, using as dependent variable one of the health outcomes described above.

In each regression, we use triangular kernels, such that the weight of each observation decreases with the distance from the cut-off. The sample is restricted to a bandwidth of 500 points on either side of the threshold. As a robustness check, we also repeat our analysis using the mean-squared error optimal bandwidth approach as proposed by Calonico et al. [2014]. Standard errors are clustered at the province level.[8]

In equation 1, β_{LATE} captures the Local Average Treatment Effect (LATE) of a permanent increase in monthly income on the health outcomes of applicants and household members close to the cut-off.

3.3 Descriptive statistics

Table I reports descriptive statistics for applicants at the moment of their first application and within 500 score points from the cut-off, as well as for their working-age and elderly household members.

This table shows that in our bandwidth sample 87.1 percent of applicants are female. This large share of female applicants is consistent with the basic pension policy aim of benefiting stay-at-home mothers and could be the result of women being less likely to have private pension savings. The average applicant's age is around 66.8. This suggests that applications are submitted shortly after reaching the minimum application age (75 percent are 65 years old) and that we observe the first application ever made for most of our sample.

Pension applicants in the bandwidth are on average below the 40th percentile of the *social security score* distribution, which corresponds to 10,320 *social security score* points, an indication that applicants are poorer than the median Chilean. Even though the pension score cut-off is set at the 60th percentile of the distribution, the average *social security score* for applicants close to the cut-off is well below the 60th percentile. This is not surprising, since the pension score takes into consideration administrative information and factors not used to determine the *social security score*, such as income from household relatives' contributory pensions.

More than half of the applicants in the bandwidth live with a working-age family member and an elderly household member. Looking at the health characteristics of applicants we observe that, over the six months prior to their application, they spent approximately half a day hospitalized.

[8]There are 33 health regions and 54 provinces in Chile. The standard errors are clustered at the province level in our preferred specification, because provinces serve as a good proxy of health regions, but their number is sufficiently high to employ the law of large numbers and make correct use of clustered standard errors. Clustering at the health region level does not change the results of our estimates.

Table I: Characteristics of applicants, and their household members, at the moment of application and within 500 score points around the threshold

	Applicants	Working-age household members	Elderly household members
	(1)	(2)	(3)
Female	0.871	0.363	0.12
Age (years)	66.851	40.364	71.074
Social security score	9,385	9,576	9,836
Household size	2.643	3.685	2.749
Working-age household member	0.571	1	0.434
Elderly household member	0.661	0.47	1
Live with child under 16	0.009	0.018	0.009
Days hospitalized	0.504	0.249	0.49
Influenza vaccination	0.32	0.089	0.347
Pneumonia vaccination	0.061	0.002	0.028
Urban town	0.762	0.737	0.77
Metropolitan region	0.373	0.348	0.368
Received a basic pension	0.699		
Observations	8,499	8,047	5,722

Notes: This table reports the mean of several covariates for applicants whose application score is within 500 score points from the cut-off, and their household members. Column (1) reports means for applicants, Column (2) reports means for working-age household members, and Column (3) reports means for elderly household members. *Health covariates* are computed 6 months before applicants submit their first application.

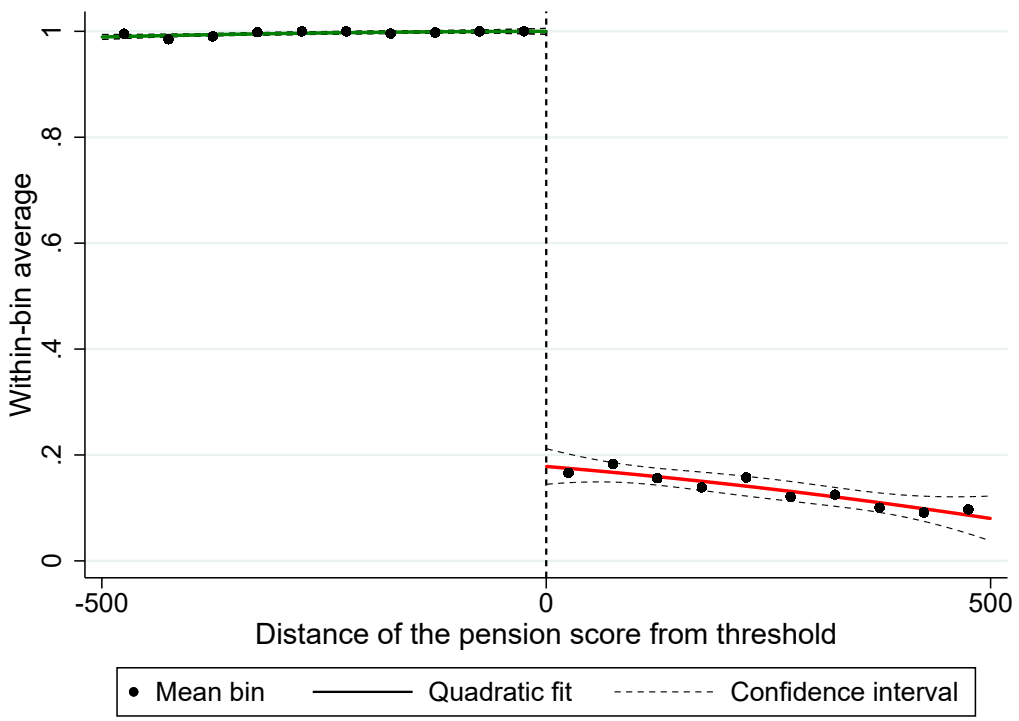
Working-age household members are mostly men (63.6 percent). They are 39 years old on average, which could indicate that they are the applicants' children. Elderly household members are around four years older than applicants, mostly male (88 percent) and, on average, spend half a day hospitalized. These characteristics seem to indicate that most elderly household members are the partners of female applicants.

In sum, the average applicant in the bandwidth is a relatively poor woman, aged 65, who does not have a contributory pension (i.e. without formal employment throughout her life), and lives with a working-age household member (her child) and a male elderly household member (her husband). Finally, around 70 percent of applicants in the bandwidth received a basic pension at some point after 2011.

4 RD validity

4.1 The effect of the pension score on receiving the basic pension

Figure I: First-stage graph



Notes: Each circle represents the average probability of obtaining the basic pension within the four years after the first application, for the applicants in each 50 score-point bin. The solid and dashed lines represent the predicted values and confidence interval, respectively.

Table II: First stage

Variables	RD Coef. (1)	S.E. (2)	t-stat (3)	P-value (4)	BW (5)	N (6)	Control (7)
Received a basic pension	0.820	(0.011)	72.946	0.000	500	8,499	0.181

Notes: This table reports results from an OLS regression of a dummy indicator equal to 1 if the applicant receives the basic pension four years after their first application (and 0 otherwise) on a treatment dummy indicator and deviation of the pension score from the cut-off. Column (1) reports the treatment indicator coefficient and Column (2) reports the standard error of this coefficient, clustered at the province level. Column (3) reports the t-statistic of the treatment dummy indicator coefficient, and Column (4) reports the p-value of this coefficient. Column (5) indicates the range of pension score points from the cut-off in which regressions are performed. Column (6) reports the number of observations used in the regression. Column (7) reports the constant of this regression, showing the fraction of control applicants at the cut-off who received the pension.

Figure I displays the probability of receiving a basic pension in the four years following the first application, for various pension score distances from the cut-off (the 'First Stage'). This figure shows that applicants in the bandwidth with a score below the cut-off in their first application (treatment group) are more likely to receive a basic pension in the following four years than those whose score is just above the cut-off (control group). Column (1) of Table II confirms this result and shows that being in the treatment group increases the likelihood of receiving a basic pension in the next four years by 82 pp. (p-value< 0.001).

Figure I also shows that some applicants obtain a score above the cut-off, but receive a basic pension in the four years after the first application. This is entirely explained by applicants who do not receive a basic pension on their first application, but submit a subsequent application that is successful. In Appendix Section A.2, we describe the characteristics of applicants in the control group that submit more than one application. We document that poorer applicants and those likely to experience changes in their household composition are more likely to submit a second application after an unsuccessful initial attempt.

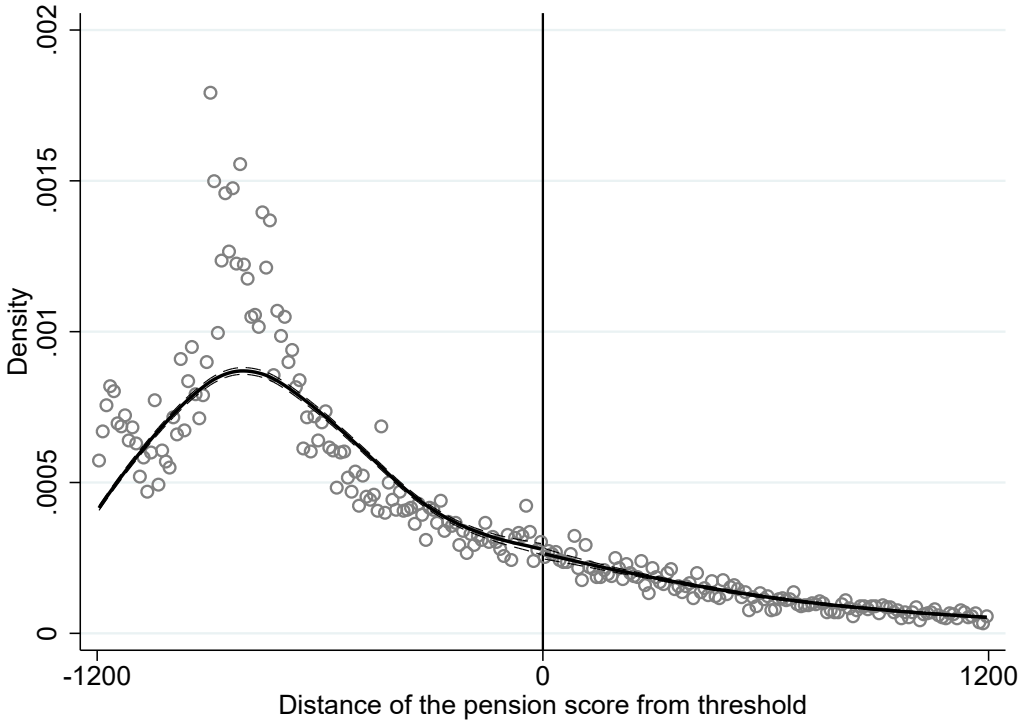
4.2 Continuity of applicants' frequency around the cut-off

Identification of the treatment effect requires that applicants do not manipulate their pension score in order to receive the basic pension. For instance, this assumption would fail if more motivated applicants, who happen to be healthier, are able to adjust their pension score to fall below the cut-off.

To formally confirm the absence of score manipulations, we perform the test developed by McCrary [2008]. Here, we use the density of applicants in 10 score-point bins as the dependent variable in equation 2. As shown in Figure II, the test does not reject the null hypothesis of no discontinuity in the density of applicants (t-statistic of -1.019 and p-value of 0.309). Appendix Figure D1 also shows no discontinuity in the density of applicants' working-age household members (t-statistic of -0.013 and p-value of 0.999) and elderly household members (t-statistic of -1.576 and p-value of 0.115) at the cut-off.

This result is not surprising given that the pension score is not calculated until an individual applies and, accordingly, applicants do not know their score beforehand. This piece of evidence suggests that applicants did not manipulate their first application score in order to receive the pension.

Figure II: McCrary test of applicants



Notes: This figure shows the density of applicants in 10 score-point bins. The solid line plots fitted values from a local linear regression of density on pension score deviations from the cut-off, separately estimated on both sides of the cut-off. The thin lines represent the 95% confidence interval.

4.3 Continuity of predetermined covariates around the cut-off

In order to have comparable treatment and control groups in the RD design, a series of pre-determined characteristics that could affect applicants' health should change smoothly at the cut-off [Lee and Lemieux, 2010]. Appendix Figures D2 and D3 graphically shows that pre-determined covariates do indeed vary smoothly at the cut-off for applicants. Column (3) of Table III reports the results of the t-test performed on the coefficient β, in equation 2, using as a dependent variable one of the 11 individual and household characteristics at the time of application. Panel A of this table confirms the results and shows that only 1 out of the 11 estimations (*pneumonia vaccinations*) is significant at conventional levels for applicants. We do not believe that this represents a systematic difference between treatment and control groups around the cut-off: given the large number of estimations, it is common to have one significant estimation at this significance level. Moreover, having run these regressions as seemingly unrelated regressions, we cannot reject the hypothesis

Table III: Balancing tests

Variables	RD Coef. (1)	S.E. (2)	t-stat (3)	P-value (4)	BW (5)	N (6)	Control (7)
Panel A: applicants							
Female	-0.016	(0.015)	-1.016	0.314	500	8,499	0.890
Age (years)	-0.372	(0.236)	-1.578	0.121	500	8,499	67.57
Days hospitalized	-0.131	(0.154)	-0.851	0.399	500	8,499	0.458
Influenza vaccination	-0.025	(0.020)	-1.281	0.206	500	8,499	0.357
Pneumonia vaccination	0.017	(0.008)	2.019	0.049	500	8,499	0.043
Household size	-0.008	(0.040)	-0.192	0.849	500	8,499	2.634
Social security score	64.687	(181.386)	0.357	0.723	500	8,499	9,737
Elderly household member	0.016	(0.018)	0.872	0.387	500	8,499	0.693
Working-age household member	-0.004	(0.018)	-0.214	0.832	500	8,499	0.548
Live with child under 16	0.002	(0.004)	0.396	0.694	500	8,499	0.006
Municipal income	-2.465	(4.250)	-0.580	0.564	500	8,483	146.7
Panel B: working-age household members							
Female	0.030	(0.024)	1.240	0.221	500	8,047	0.358
Age (years)	-1.090	(0.656)	-1.661	0.103	500	8,047	40.96
Days hospitalized	-0.046	(0.062)	-0.737	0.465	500	8,047	0.172
Influenza vaccination	-0.015	(0.012)	-1.204	0.235	500	8,047	0.094
Pneumonia vaccination	-0.001	(0.003)	-0.271	0.788	500	8,047	0.004
Newborn child	0.007	(0.005)	1.514	0.137	500	8,047	0.006
Household size	0.007	(0.060)	0.121	0.904	500	4,836	3.228
Social security score	147.319	(261.230)	0.564	0.575	500	4,836	9,857
Elderly household member	0.047	(0.026)	1.767	0.084	500	4,836	0.525
Live with child under 16	0.007	(0.006)	1.054	0.297	500	4,836	0.007
Municipal income	-8.321	(5.181)	-1.606	0.115	500	4,828	150.0
Panel C: elderly household members							
Female	0.032	(0.016)	2.016	0.049	500	5,722	0.097
Age (years)	-0.608	(0.358)	-1.702	0.095	500	5,722	71.82
Days hospitalized	-0.038	(0.093)	-0.404	0.688	500	5,722	0.312
Influenza vaccination	-0.026	(0.029)	-0.899	0.373	500	5,722	0.364
Pneumonia vaccination	0.001	(0.006)	0.083	0.934	500	5,722	0.019
Household size	0.050	(0.050)	1.003	0.321	500	5,566	2.679
Social security score	96.419	(199.801)	0.483	0.632	500	5,566	10,165
Working-age household member	0.027	(0.024)	1.147	0.257	500	5,566	0.412
Live with child under 16	-0.000	(0.006)	-0.044	0.965	500	5,566	0.009
Municipal income	-2.603	(5.244)	-0.496	0.622	500	5,558	147.4

Notes: This table reports results from OLS regressions of pre-determined variables on a treatment dummy indicator and deviation of the pension score from the cut-off. Columns (1), (2), (3), and (4) report the treatment indicator coefficient, its standard error clustered at the province level, t-statistic, and p-value, respectively. Columns (5) and (6) report the range of pension score points from the cut-off and the number of observations in the regression, respectively. Column (7) reports the constant of this regression, showing the variable mean for control applicants at the cut-off. Health covariates are defined 6 months before applying.

that the coefficients are jointly insignificant. For the covariates used to calculate the pension score, we only have data for applicants in 2012. Appendix Table C4 reports balancing checks using these covariates, and shows that only 1 out of estimations 14 (*Imputed income*) is significant at the 10 percent level. The evidence presented above suggests that the basic pension is as good as (locally) randomly assigned around the cut-off, after conditioning on pension score deviations from the cut-off.

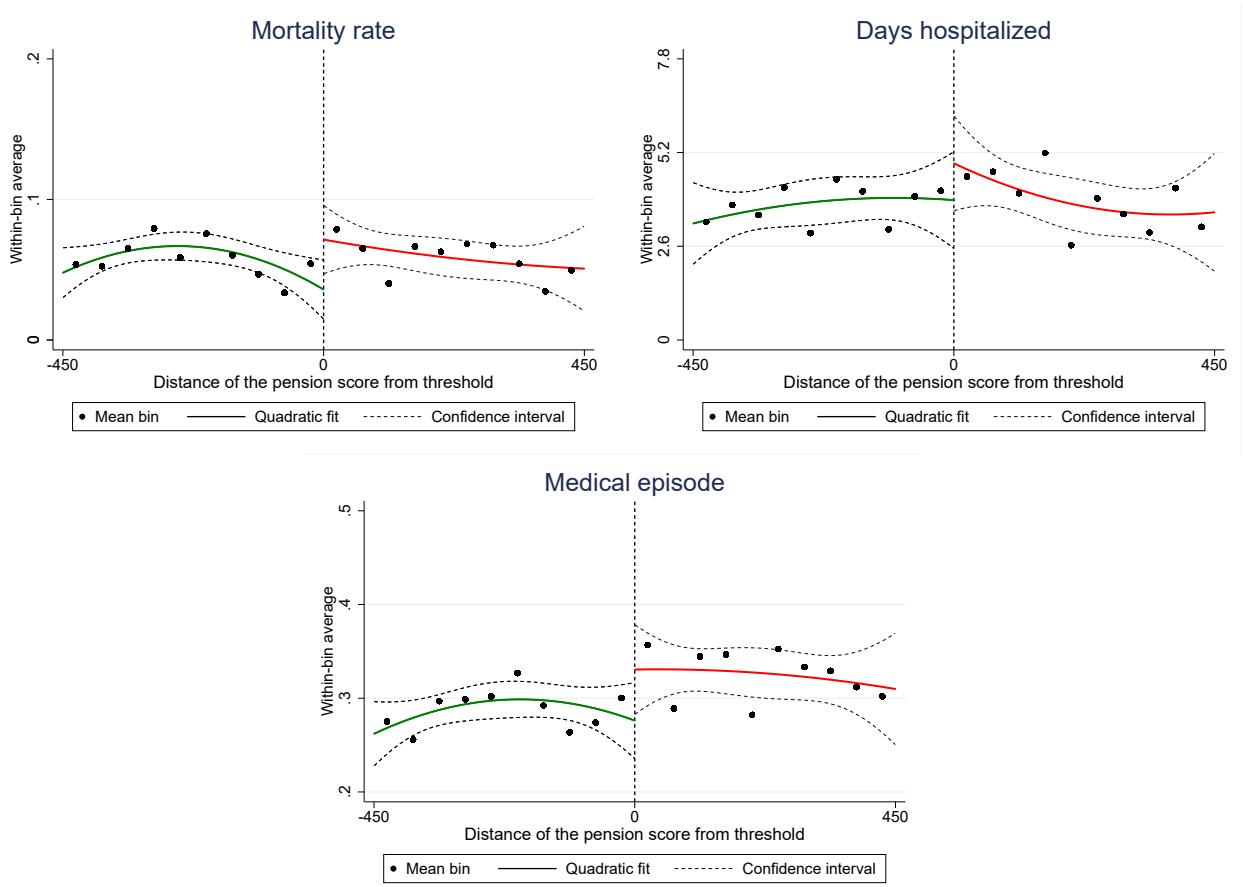
As we also explore the effect of the pension on applicants' household members, we examine whether the same covariates change smoothly at the cut-off for working-age and elderly relatives. Panel B of Table III shows that 1 out of the 11 available covariates (*elderly household member*) is significant for working-age household members, which is in the expected range of significant coefficients at this significance level. However, Panel C of Table III shows that 2 out of the 10 available covariates (*female* and *age*) are statistically significant among elderly household members. This is higher than the expected level. We address the implications of these imbalances in Section 5 by adding these variables as controls and showing that our results on elderly household members do not change.

5 Results

5.1 The effect of receiving a pension on applicants' health

The top left panel of Figure III shows the causal effect of receiving a basic pension from the first application on the probability of dying within four years after applying (henceforth referred to as *mortality*). This panel indicates that applicants in the treatment group were less likely to die within four years of applying than applicants in the control group. Column (1) of Table IV confirms this result and shows that receiving a basic pension significantly decreases the probability of dying by 2.6 pp. (p-value=0.034). The ITT effect of the pension is a 2.1 pp. reduction in the probability of dying from a baseline mortality at the cut-off of 7.0 pp.

Figure III: Effect of the basic pension on mortality, cumulative days of hospitalization and medical episodes of applicants



Notes: Each graph shows the average value of the corresponding variable conditional on the distance of the pension score from the cut-off. The circles represent averages across 50-point bins on either side of the threshold, while the solid and dashed lines represent the predicted values and confidence interval, respectively.

Figure IV illustrates the share of surviving control and treatment group applicants, at different points in time after their first application and adjusted by the deviation of their score from the cut-off, using a Cox proportional hazard model. This figure suggests that the mortality effect manifests itself approximately one year after the first payment and grows almost monotonically over time, reaching a maximum at the end of the studied period. As in Grossman's [1972] health capital model, health production appears to be cumulative over time but, remarkably, health investment returns are already noticeable only a few years after the first payment. This can have relevant policy implications in the context of a middle-income country. According to the evidence presented here, increasing income at a late stage in life could improve the elderly's health, suggesting that it

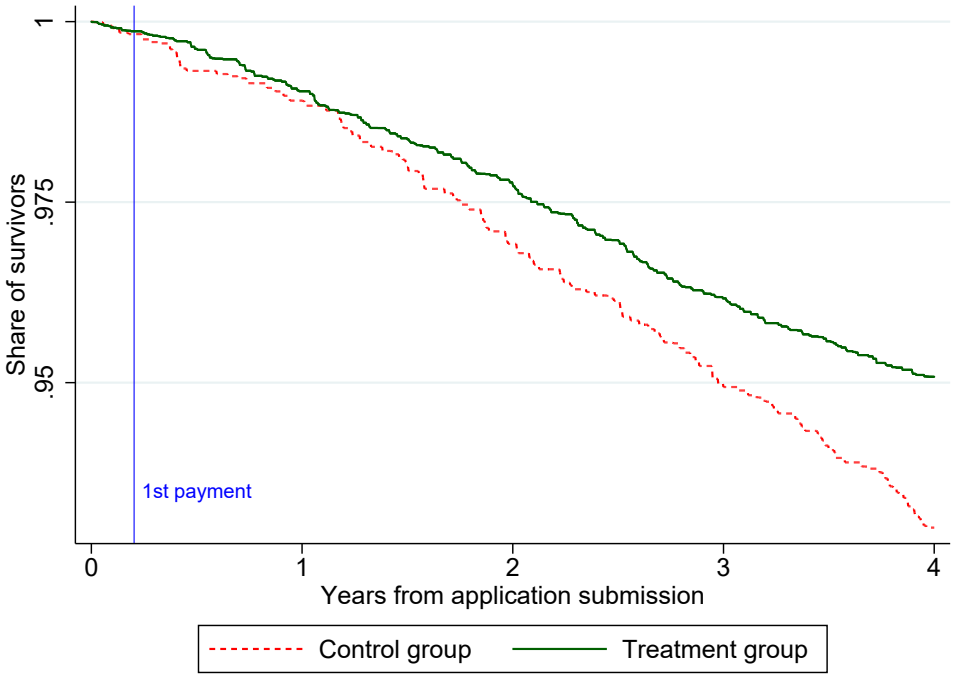
Table IV: Applicants' health outcomes over four years from application

Variables	2sls (1)	S.E. 2sls (2)	RD Coef. (3)	S.E. (4)	P-value (5)	BW (6)	N (7)	Control (8)
Mortality rate	-0.026	(0.012)	-0.021	(0.010)	0.028	500	8,499	0.070
Days hospitalized	-0.801	(0.771)	-0.657	(0.640)	0.298	500	8,499	4.702
Medical episode	-0.051	(0.022)	-0.042	(0.018)	0.019	500	8,499	0.333

Notes: This table reports results, within four years from the date of the first application, from regressions of several dependent variables on a treatment dummy indicator and deviation of the pension score from the cut-off. Column (1) reports the treatment coefficient adjusted by the first stage and Column (2) reports its standard error clustered at the province level. Column (3) reports the treatment indicator coefficient and Column (4) reports its standard error clustered at the province level. Column (5) reports the p-value of the adjusted treatment coefficient reported in Column (1). Column (6) reports the range of pension score points from the cut-off and Column (7) reports the number of observations in the regression. Column (8) reports the constant of the ITT regression, showing the variable mean for control applicants at the cut-off.

may not be 'too late' for a government to invest in the health of the elderly population.

Figure IV: Share of surviving applicants over 4 years from date of application, adjusted by the deviation of pension score from the cut-off.



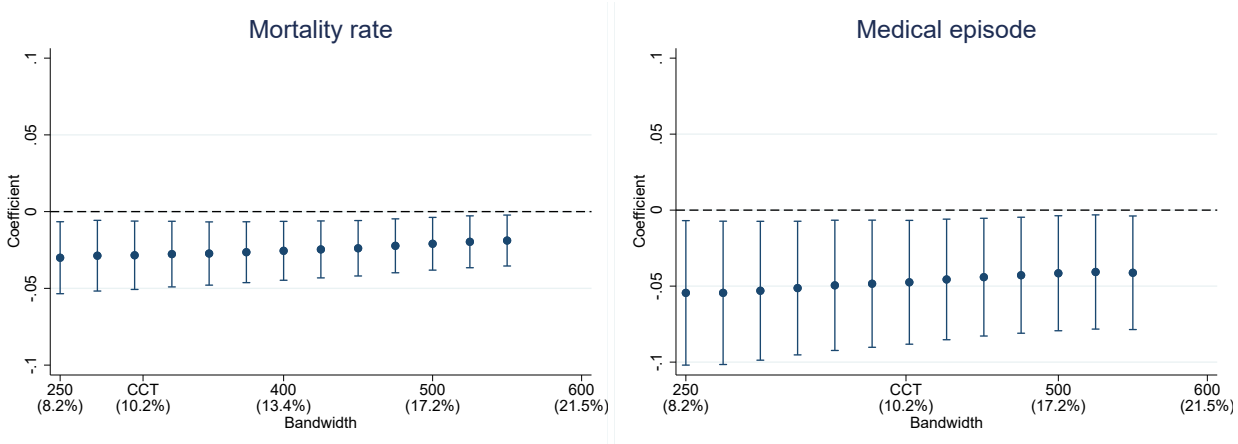
Notes: This figure presents the share of survivors in the treatment and control groups (500 score-point bandwidth) at each point in time following the first application. Survival rates are computed using a Cox proportional hazard model, adjusted by the deviation of the score from the cut-off and using triangular weights to give higher weight to the applicants closer to the cut-off.

Since the basic pension affects the probability of dying, we cannot estimate its causal effect on the days of hospitalization. Applicants on each side of the cut-off are not comparable, as those above the cut-off have fewer days available to be hospitalized due to their higher mortality rate. With this caveat, we still show the effect on the number of days that applicants spent in hospital, from the date of application to the last day that we are able to observe them (four years after applying, or the moment of death). Even though treatment group applicants have more potential days for hospitalization, the point estimates in Column (1) of Table IV suggest that, if anything, they spend fewer days in hospital, although the effect is not statistically significant.

To summarize treatment effects on health outcomes and circumvent the survival bias, we follow the medical literature and use as an outcome variable a dummy indicator equal to 1 if the applicant has either been hospitalized or died (*medical episode*) in the four years after applying (this is called 'primary outcome' in the medical literature, see [Pitt et al., 2014; Eikelboom et al., 2017]). Column (1) of Table IV shows that treated applicants are 5.0 pp. (p-value=0.024) less likely to experience a medical episode in the four years after applying.

Sensitivity and placebo checks on the direct effects

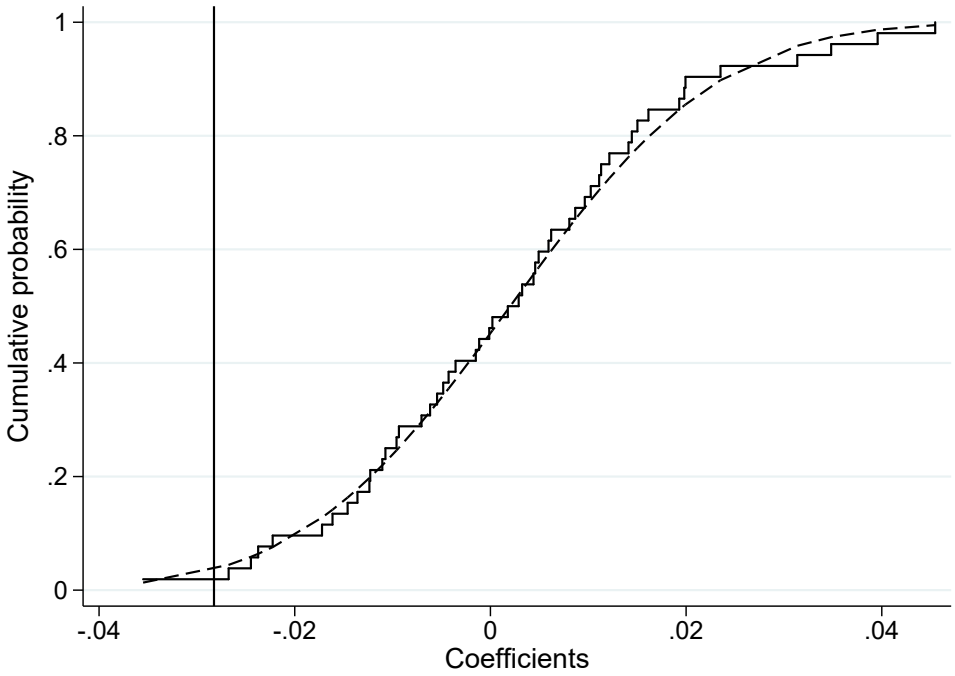
Figure V: Robustness of results for mortality and medical episodes using different bandwidths



Notes: Each graph shows the point estimate and the standard error of non-parametric RD estimations when using different bandwidths. The x-axis labels report the number of score points in each side of the bandwidth and, in parentheses, the percentage of total applicants that fall in the bandwidth. CCT is the optimal bandwidth using the approach proposed by Calonico et al. [2014].

Appendix Table C6 shows that the causal effect of the basic pension on mortality and medical episodes remains whether we use logistic regressions, non-parametric estimations, different sets of controls, or polynomials of order two in $Score_h$. Figure V also shows that the results do not change when we use different bandwidths around the cut-off.

Figure VI: Reduced-form effect of being below the cut-off on mortality: placebo estimates



Notes: This graph shows the cumulative distribution of reduced-form estimates on mortality, from placebo regressions in which the cut-off is set in different parts of the pension score distribution. Estimates are computed using Equation 2. Cut-offs are located every 25 points, starting from 306 (the Calonico et al.'s optimal bandwidth) up to 1606 score points, to make sure that we have observations in all points of the bandwidth. Remember that the cut-off is set at 1206 pension score points and the lowest pension score is zero. Conversely, placebo cut-offs are set between -900 and 400 pension score points from the cut-off. The solid line displays the empirical cumulative distribution of estimates and the dashed line displays fitted values of the cumulative distribution. The vertical line shows the coefficient estimated with our optimal bandwidth baseline specification.

Additionally, we implement the randomization inference method proposed by Cattaneo et al. [2015] on the mortality estimate. This method randomly varies which observations are assigned to treatment and control in a window around the threshold where treatment status is as good as randomly assigned. After running this permutation test based on difference in means, we reject the null hypothesis of no mortality effect with a p-value < 0.001. We also set placebo thresholds along the score distribution at intervals of 25 score-points and perform reduced form estimates at

every placebo threshold.[9] Figure VI compares these estimates and shows that the probability of obtaining a mortality estimate smaller than ours is as small as 0.0192. This result suggests that our estimated effect is not a random discontinuity that is likely to be observed in other parts of the score distribution.

Discussion on the mortality effect

We estimate an ITT income-mortality elasticity of -0.17: the basic pension reduces recipients' mortality by 30 percent (0.021/0.07) and increases their income by 180 percent.[10] Figure VII shows that the confidence interval of our estimate encompasses the majority of the income-mortality elasticity estimates obtained from previous papers.[11] Our confidence interval overlaps with the confidence intervals of all the negative estimates, including the one by Salm [2011] for the 1912 reform and the one by Cheng et al. [2016]. These include estimates for different countries and different historical periods, such as Russia and Mexico in the late 1990s [Jensen and Richter, 2003; Barham and Rowberry, 2013], the United States in the 1900s [Salm, 2011] and women in the United States in the 1970s [Snyder and Evans, 2006]. The positive estimates by Snyder and Evans [2006] for men and by Feeney [2018] are notable exceptions.

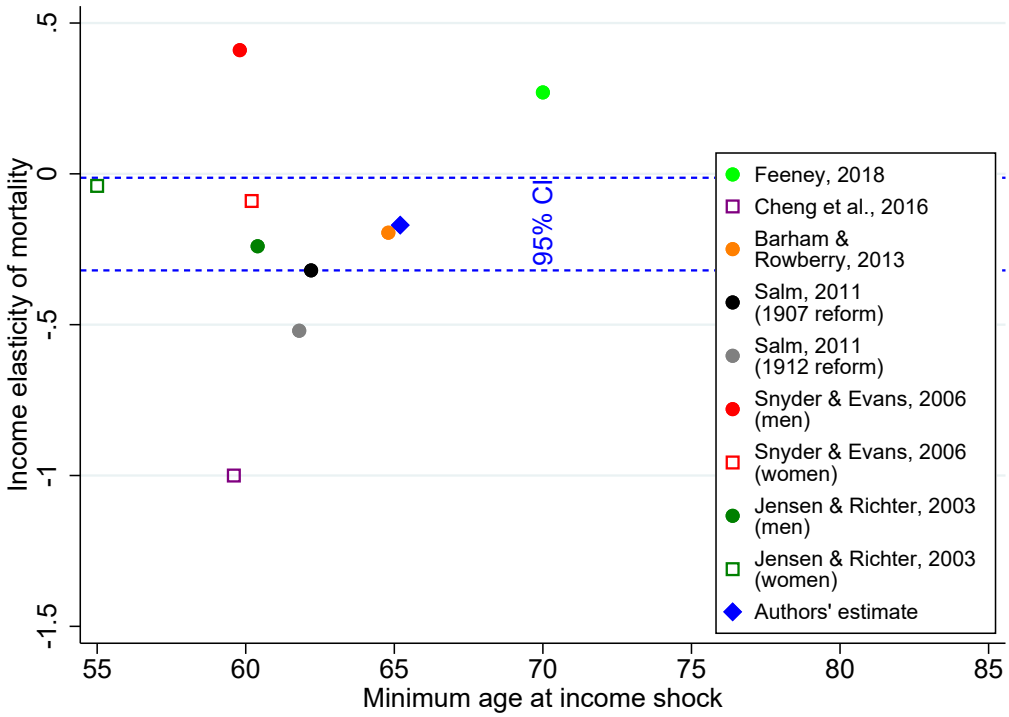
Snyder and Evans [2006] estimate that a notch in US social security payments for the cohorts 1916-1917, which reduced the later cohort's income by 4 percent on average, significantly *reduced* men's mortality rates in comparison to the wealthier cohort. They justify this result by showing that the poorer cohort retired *later*, reducing their social isolation and improving their health outcomes. Feeney [2017, 2018] exploits the age eligibility cut-off and the staggered introduction of a Mexican non-contributory pension across small rural towns, finding that this pension increases recipients' transition to retirement and mortality rates.

[9] Cut-offs are located at intervals of 25 points, starting from 306 (the Calonico et al.'s optimal bandwidth) until 1606 pension score points, to make sure that we have observations in all points of the bandwidth. Recall that the cut-off is set at 1206 pension score points and the lowest pension score is zero. This means that placebo cut-offs are set between -900 and 400 pension score points from the cut-off. The highest cut-off is located at 1606 pension score points because the data becomes limited in higher pension score points: many score points higher than 1606 have no applicants.

[10] The basic pension increases recipients' income by 79,488 Chilean pesos in 2012 (see Table C4), from a baseline of 44,209 Chilean pesos for control applicants at the cut-off (see Table C1). In our conversations with the PI, they mentioned that the income that recipients have before applying comes mainly from capital income and governmental transfers.

[11] As the majority of estimates in the literature are based on an individual measure of income [Cheng et al., 2016; Barham and Rowberry, 2013; Salm, 2011; Snyder and Evans, 2006], we use the applicant's income to compute the income-mortality elasticity. We use the ITT estimate for consistency with the majority of the estimates in the literature.

Figure VII: Estimates of income-mortality elasticity of elderly



Notes: This graph plots point estimates of income-mortality elasticity on the minimum age at which the income shock commenced. Empty squares indicate insignificant estimates. The dashed lines indicate the 95 percent confidence interval of our estimate. The elasticities in the other papers were computed using different measures of baseline income: Feeney [2018] household income; Cheng et al. [2016] average per capita net income among potential beneficiaries; Barham and Rowberry [2013] average beneficiary income in rural areas; Salm [2011] average monthly earnings for non-farm employees; [Jensen and Richter, 2003] household income; [Snyder and Evans, 2006] individual income. Where possible, estimates were separated by gender. The graph does not aim to represent the universe of papers that study the impact of income on elderly mortality. In several studies, it is not possible to calculate the income-mortality elasticity, because either baseline mortality or income are not reported.

The opposite sign of our estimate can be explained by differences in recipients' characteristics. To be eligible, basic pension applicants cannot have a history of formal employment. Survey data described in Table C12 shows that only 2.63 percent of the elderly population without a contributory pension and less than 5 percent of the elderly population without any pension reported some form of labor income.[12] While most Chilean basic pension recipients appear to be former stay-at-home mothers, for whom the pension induced very limited labor supply effects, a high fraction of recipients in Feeney [2017] and Snyder and Evans [2006] were workers induced to retire because of the pension increase.[13] Fitzpatrick and Moore [2018] showed that the transition to retirement

[12]This income comes mainly from informal, part-time jobs.

[13]Gelber et al. [2016] studies the same pension notch as Snyder and Evans [2006] and also provides evidence of

causes a significant jump in mortality due to the fall in labor supply, independently of whether income is affected. There is also evidence that transition to retirement is associated with changes in consumption patterns and lifestyles [Fitzpatrick and Moore, 2018; Zantinge et al., 2013; Browning and Meghir, 1991], along with social isolation [Snyder and Evans, 2006], and all of these factors are positively associated with mortality. Thus, differences in 'pre-pension' labor market participation levels could explain in part the opposite sign of Snyder and Evans [2006] and Feeney [2017, 2018] estimates. Our estimate can isolate the negative mortality effect of the permanent income increase from the positive mortality effect of the increase in retirement.

There are several ways in which the Chilean basic pension may have reduced recipients' mortality. Previous papers have shown that an income shock can increase expenditures on goods and services that improve the health of income recipients, such as vitamin-rich food [Bartali et al., 2006; Cederholm et al., 1995; Ortega et al., 1997; Fogel, 2004; Salm, 2011] and costly transport to attend medical check-ups regularly [Dahlgren and Whitehead, 1991; Jensen and Richter, 2003; Aguila et al., 2015]. Other possible explanations, such as purchase of private health insurance or medical treatments, should take into account that 95 percent of basic pension holders were enrolled in public health insurance [Ministerio de Desarrollo Social, 2011, 2015] and that medicines and medical treatments in Chile are free of charge for all non-rare diseases. Given the lack of administrative data on expenditure, we prefer to remain agnostic on the issue and we leave this avenue to future work.

5.2 The heterogeneous effects of receiving a pension on applicants

Table V shows the effect of the basic pension on different sub-groups of applicants. Following common practice in the medical literature on aging and mortality (e.g. Garre-Olmo et al. [2013]; Hawton et al. [2011]), we start exploring the heterogeneous effects according to the household structure of the applicants. Panel A of this table shows that treated applicants living alone or with elderly household members (i.e. without a working-age household member) are strongly affected by the receipt of the basic pension, with a significant reduction in their mortality rate of 5.3 pp. (p-value=0.008). Conversely, Panel B suggests that those living with at least one working-age household member remain unaffected by the receipt of the basic pension, with an insignificant reduction in their mortality rate of 0.01 pp. (p-value=0.954). The difference between the coeffi-

elderly labor supply responses to the pension increase, even though Gelber et al. [2016] does not find any significant impact on mortality.

Table V: Applicant's health outcomes over four years from application: household structure and gender

Variables	2sls (1)	S.E. 2sls (2)	RD Coef. (3)	S.E. (4)	P-value (5)	BW (6)	N (7)	Control (8)
Panel A: applicants not living with a working-age household member								
Mortality rate	-0.053	(0.019)	-0.045	(0.016)	0.006	500	3,647	0.094
Days hospitalized	-2.658	(0.764)	-2.250	(0.658)	0.001	500	3,647	5.386
Medical episode	-0.110	(0.042)	-0.093	(0.036)	0.008	500	3,647	0.352
Panel B: applicants living with working-age household members								
Mortality rate	-0.001	(0.018)	-0.001	(0.014)	0.953	500	4,852	0.049
Days hospitalized	0.796	(1.316)	0.635	(1.061)	0.545	500	4,852	4.124
Medical episode	0.000	(0.040)	-0.000	(0.032)	0.998	500	4,852	0.318
Panel C: female applicants								
Mortality rate	-0.024	(0.010)	-0.020	(0.008)	0.017	500	7,403	0.063
Days hospitalized	-0.847	(0.749)	-0.703	(0.629)	0.258	500	7,403	4.681
Medical episode	-0.053	(0.024)	-0.044	(0.020)	0.028	500	7,403	0.328
Panel D: male applicants								
Mortality rate	-0.053	(0.052)	-0.039	(0.039)	0.306	500	1,096	0.129
Days hospitalized	-0.478	(2.304)	-0.354	(1.726)	0.836	500	1,096	4.877
Medical episode	-0.044	(0.110)	-0.033	(0.083)	0.689	500	1,096	0.382

Notes: This table reports results, within four years from the date of the first application, from regressions of several dependent variables on a treatment dummy indicator and deviation of the pension score from the cut-off. Column (1) reports the treatment coefficient adjusted by the first stage and Column (2) reports its standard error clustered at the province level. Column (3) reports the treatment indicator coefficient and Column (4) reports its standard error clustered at the province level. Column (5) reports the p-value of the adjusted treatment coefficient reported in Column (1). Column (6) reports the range of pension score points from the cut-off and Column (7) reports the number of observations in the regression. Column (8) reports the constant of the ITT regression, showing the variable mean for control applicants at the cut-off.

cients in the two groups is statistically significant.[14] The same pattern appears when looking at the number of days of hospitalization and the probability of having a medical episode. Here, treatment group applicants living without a working-age household member spent 2.6 fewer days in hospital and are 11 pp. less likely to experience a medical episode (with p-values of 0.001 and 0.012, respectively). These results suggest that the group of treated applicants most strongly affected by the basic pension were not only living longer, but also enjoying better health, at least in terms of fewer days spent hospitalized.

These findings are also robust to the use of different specifications (see Appendix Tables C7 and C8) and remain significant at the 5 percent level when adjusting p-values by the number of hypotheses that we tested [Romano and Wolf, 2005a,b]. Not surprisingly, an analysis of survival rates shows that applicants living without a working-age relative are the main drivers of this dynamic effect across the whole sample, whereas applicants living with working-age relatives see virtually no improvement over time (Appendix Figure D9).

As shown in Panel C and D of Table V, we find no evidence of heterogeneous effects across gender. Males constitute a small fraction of our sample and we do not find any statistically significant difference with respect to the treatment effects on females.

Which diseases drive the effects?

In order to gain insight into which diseases drive the observed effects, Table VI disaggregates medical episodes by cause. We look at the sub-group of applicants whose health outcomes are most strongly affected - applicants living without a working-age relative - and find that the effects were driven by a reduction in the probability of experiencing a circulatory or respiratory medical episode.

Circulatory and respiratory diseases are, respectively, the first and the third leading cause of deaths around the world [World Health Organization, 2011; European Respiratory Society, 2017]. A focus on the population that is targeted by the policy shows that they are particularly susceptible to these diseases. According to survey evidence [Ministerio de Desarrollo Social, 2011], 47 percent of elderly pension recipients in 2011 had a chronic condition that is considered a risk factor

[14] There is no evidence of score manipulation within any of these subsamples of applicants: test statistics for the McCrary test are -0.486 and -0.976 for applicants living with and without a working-age relative, respectively (Figure D8). Moreover, the subsamples appear to be locally comparable at baseline: none of the 10 available covariates is significant for applicants living with working-age relatives and only 1 out of 10 is significant for applicants living without a working-age relative (Table C5).

for circulatory or respiratory diseases, such as hypertension, diabetes or severe asthma. Then, it is not surprising that these are the types of diseases that are most affected by the basic pension.[15]

Table VI: Medical episodes by cause over four years from application

Variables	2sls (1)	S.E. 2sls (2)	RD Coef. (3)	S.E. (4)	P-value (5)	BW (6)	N (7)	Control (8)
Panel A: applicants								
Circulatory	-0.015	(0.010)	-0.012	(0.008)	0.139	500	8,499	0.054
Respiratory	-0.008	(0.007)	-0.006	(0.006)	0.261	500	8,499	0.015
Tumour	-0.007	(0.011)	-0.006	(0.009)	0.512	500	8,499	0.033
Digestive or nutrional	-0.014	(0.013)	-0.012	(0.011)	0.263	500	8,499	0.058
Panel B: applicants not living with a working-age household member								
Circulatory	-0.047	(0.016)	-0.040	(0.013)	0.002	500	3,647	0.075
Respiratory	-0.022	(0.008)	-0.018	(0.007)	0.006	500	3,647	0.021
Tumour	-0.016	(0.011)	-0.014	(0.009)	0.138	500	3,647	0.035
Digestive or nutrional	-0.009	(0.024)	-0.008	(0.020)	0.695	500	3,647	0.054

Notes: This table reports results, within four years from the date of the first application, from regressions of several dependent variables on a treatment dummy indicator and deviation of the pension score from the cut-off. Column (1) reports the treatment coefficient adjusted by the first stage and Column (2) reports its standard error clustered at the province level. Column (3) reports the treatment indicator coefficient and Column (4) reports its standard error clustered at the province level. Column (5) reports the p-value of the adjusted treatment coefficient reported in Column (1). Column (6) reports the range of pension score points from the cut-off and Column (7) reports the number of observations in the regression. Column (8) reports the constant of the ITT regression, showing the variable mean for control applicants at the cut-off.

5.3 The effect of having a household member receiving a basic pension

Panel A of Table VII shows that elderly household members were more likely to die than applicants (the average mortality rate of control group elderly relatives at the cut-off is 12.5 percent), and this seems to be unaffected by having a relative who receives the basic pension.

Panel B of Table VII reveals that working-age relatives of basic pension recipients are 3.6 pp. (p-value$<$0.001) more likely to have a newborn child nine months after applying or later. As our data only identifies mothers and not fathers of newborn children, in Panel C we conducted the same analysis focusing on fertility-age women (16-40 years of age) and estimate that they are 12.4 pp. (p-value=0.002) more likely to have a newborn nine months after applying or later. The ITT

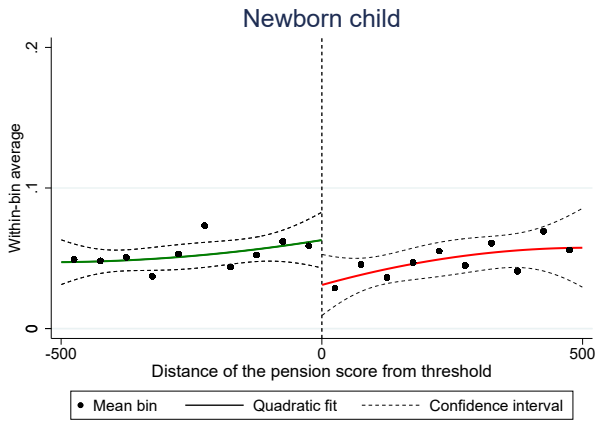
[15]The decrease in respiratory episodes amongst applicants does not appear to be driven by an increase in the use of vaccinations. As we can see in Appendix Table C11, we do not find any significant effect of the basic pension on the number of vaccinations received for influenza or pneumonia in the four years after applying, for any of the sub-groups.

effect of the pension is a 9.1 pp. increase in the probability of having a newborn from a baseline probability of 13.0 pp. These estimates remain highly significant when adjusting our p-values for multiple hypothesis testing, with an adjusted p-value < 0.01 [Romano and Wolf, 2005a,b]. Although the basic pension leads to a significant increase in births, we do not find evidence that it affects the health of the newborn child (Appendix Table C9).

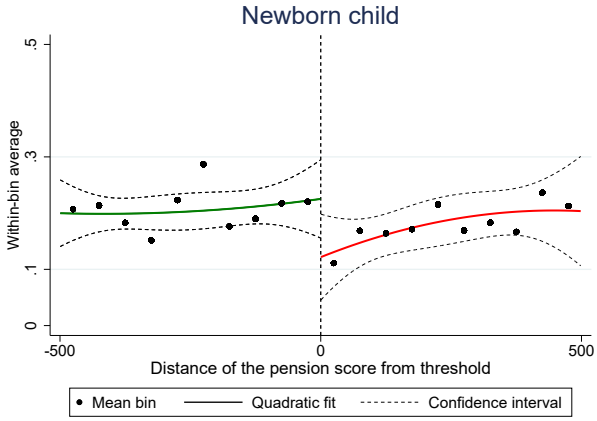
Figure VIII: Effect of the basic pension on mortality and fertility of household members

(A) Elderly household members

(B) Working-age household members



(C) Female household members of fertility age



Notes: Each graph shows the average value of the corresponding variable conditional on the distance of the score from the cut-off. The circles are averages across 50-point bins on either side of the threshold, while the solid and dashed lines represent the predicted values and associated confidence interval, respectively.

Figure IX shows the timing of childbirths for women of fertility age, between six months before and four years after the first application. Treated and control women in fertility age have a similar fraction of newborn children until 9 months after the application, with a slightly higher fertility rate for control group women. 1.2 years after the application, the two lines intersect and

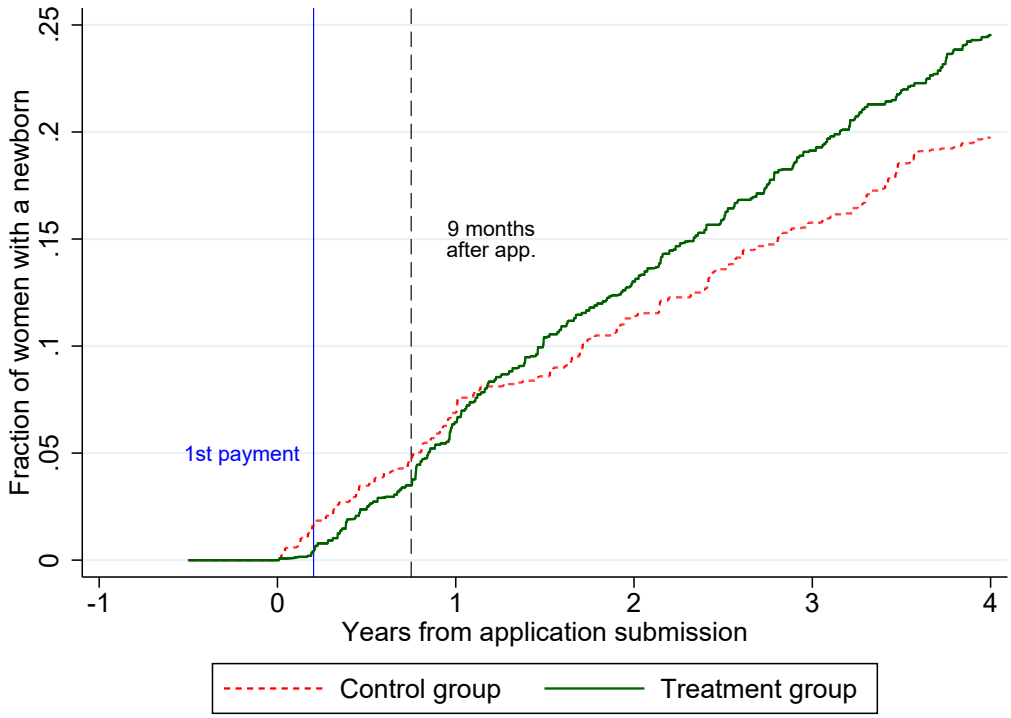
Table VII: Health outcomes over four years from application: household members by age

Variables	2sls (1)	S.E. 2sls (2)	RD Coef. (3)	S.E. (4)	P-value (5)	BW (6)	N (7)	Control (8)
Panel A: elderly household members								
Mortality rate	0.000	(0.016)	0.000	(0.013)	0.979	500	5,722	0.125
Days hospitalized	0.527	(1.231)	0.443	(1.045)	0.669	500	5,722	5.302
Medical episode	0.041	(0.035)	0.034	(0.030)	0.248	500	5,722	0.376
Panel B: working-age household members								
Days hospitalized	-0.313	(0.627)	-0.242	(0.493)	0.618	500	8,047	2.033
Newborn child	0.036	(0.009)	0.028	(0.007)	0.000	500	8,047	0.033
Panel C: female household members of fertility age (16-40)								
Days hospitalized	-0.190	(0.750)	-0.137	(0.547)	0.800	500	2,058	1.712
Newborn child	0.126	(0.039)	0.091	(0.028)	0.001	500	2,058	0.130

Notes: This table reports results, within four years from the date of the first application, from regressions of several dependent variables on a treatment dummy indicator and deviation of the pension score from the cut-off. Column (1) reports the treatment coefficient adjusted by the first stage and Column (2) reports its standard error clustered at the province level. Column (3) reports the treatment indicator coefficient and Column (4) reports its standard error clustered at the province level. Column (5) reports the p-value of the adjusted treatment coefficient reported in Column (1). Column (6) reports the range of pension score points from the cut-off and Column (7) reports the number of observations in the regression. Column (8) reports the constant of the ITT regression, showing the variable mean for control applicants at the cut-off.

the treatment effect on fertility starts accumulating over time. The fraction of women of fertility age who have a newborn is not small in this time span: almost a quarter of treated women and a fifth of control women had a child four years after applications are submitted.

Figure IX: Share of women of fertility age having a newborn between six months before applying and four years from date of application, adjusted by the deviation of the pension score from the cut-off.



Notes: This figure presents the share of women of fertility age that have a newborn in the treatment and control groups (500 score-point bandwidth), at each point in time between six months before applying and four years from the date of application. Shares are computed using a Cox proportional hazard model, adjusted for the deviation of the score from the cut-off and using triangular weights to give higher weight to observations closer to the cut-off.

Sensitivity and placebo checks on the spillover effects

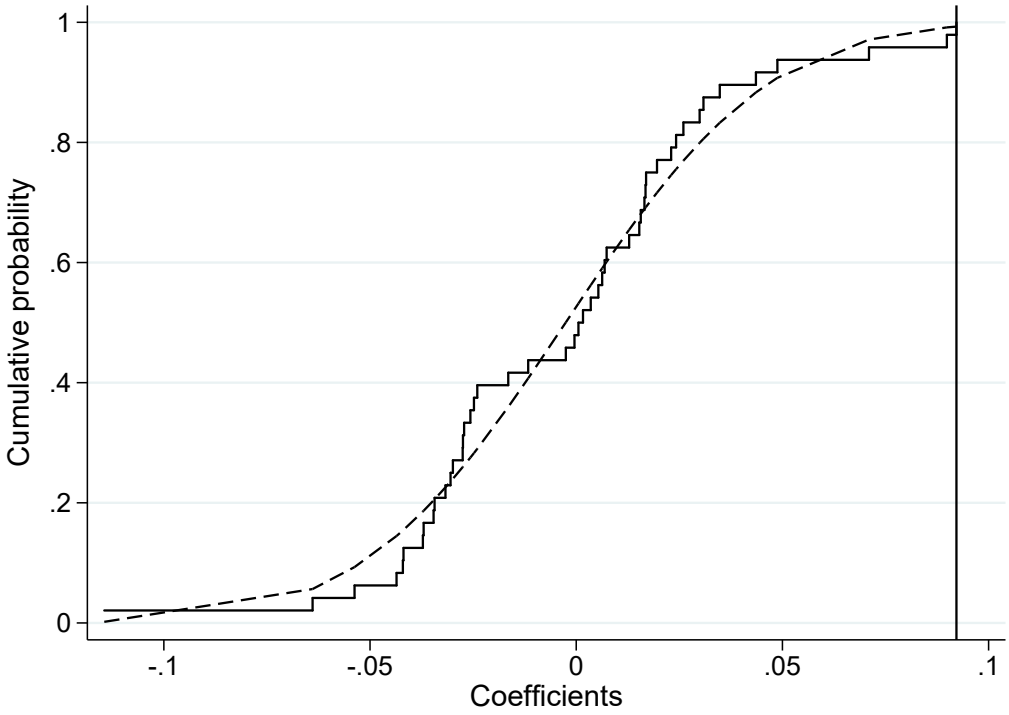
Table III shows that there is no imbalance in the probability of having a newborn before applying between the treatment and control groups. If we extend the analysis of the outcome up to 9 months after the application, we still find no evidence of imbalance between working-age (or women of fertility age) household members above and below the cut-off.

Appendix Table C10 shows that the results for elderly and working-age household members do not change when we use logistic regressions, non-parametric estimations, the optimal bandwidth

approach proposed by Calonico et al. [2014], all available controls, or when we control for a polynomial of order 2 in $Score_h$. This also ensures that the null effect on elderly household members is not driven by the slight imbalance in this group shown in Section 4.3.

Additionally, we implement the randomization inference method proposed by Cattaneo et al. [2015] on the fertility estimate and reject the null hypothesis of no fertility effect with a p-value < 0.001. We also set placebo thresholds along the score distribution, at intervals of 25 score-points, and perform reduced form estimates. Figure X compares our estimate with the distribution of placebo estimates and shows that no estimate is higher than ours. This suggests that our estimated effect on fertility is not a random discontinuity that is likely to be observed in other parts of the score distribution.

Figure X: Reduced-form effect of being below the cut-off on fertility: placebo estimates



Notes: This graph shows the cumulative distribution of reduced-form estimates on fertility, from placebo regressions in which the cut-off is set in different parts of the pension score distribution. Estimates are computed using Equation 2. Cut-offs are located every 25 points, starting from 456 (the Calonico et al.'s optimal bandwidth on fertility) and up to 1606 score points, to make sure that we have observations in all points of the bandwidth. The lowest pension score is zero and the cut-off is set at 1206 pension score points. Then, placebo cut-offs are set between -750 and 400 pension score points from the cut-off. The solid line displays the empirical cumulative distribution of estimates, while the dashed line displays fitted values of the cumulative distribution. The vertical line shows the coefficient estimated with our optimal bandwidth baseline specification.

Discussion on the spillover effect on fertility

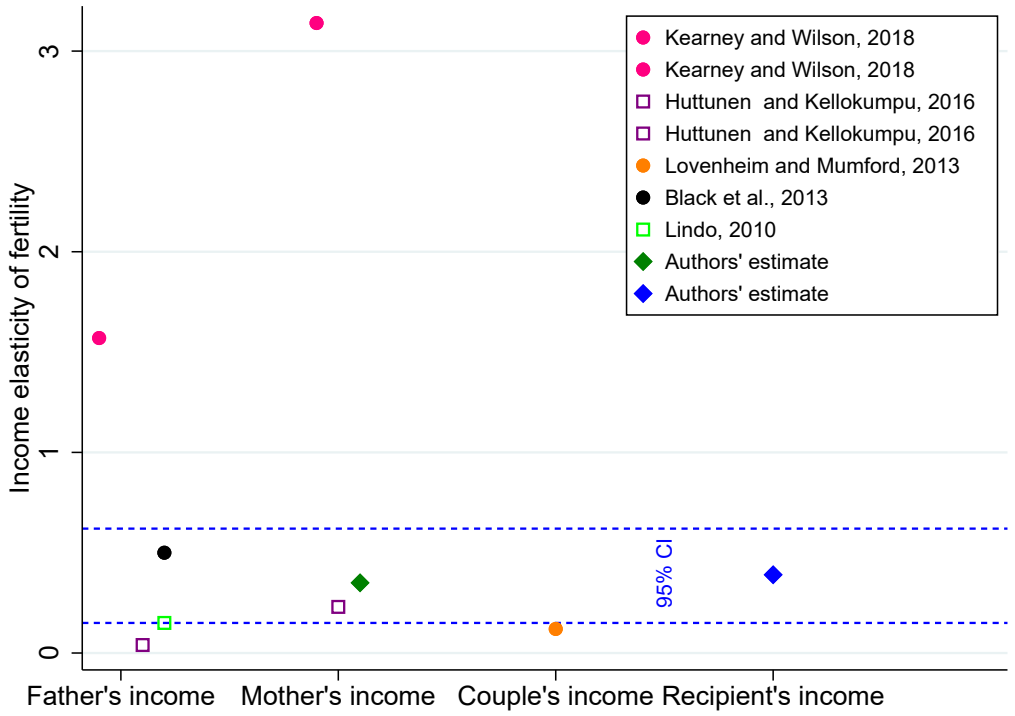
Most of the literature estimates income-fertility elasticities by dividing the ITT percentage change in newborns for women in fertility age over the percentage income change for the recipients of income. In our case, the recipients of income are the applicants, and this calculation yields an income-fertility elasticity of 0.39. Alternatively, if we use the mother's income rather than recipient's income, the income-fertility elasticity is 0.35.[16] Figure XI shows that previous causal estimates of income-fertility elasticity are also positive, which is in line with the predictions of Becker's [1960] neoclassical model of fertility.[17] Our estimate is roughly in the middle of the range, but there is a considerable dispersion of fertility-income elasticities across studies.

One explanation for the diverse pattern of estimates is that the nature of the income shock is very diverse across studies: mother's or father's job displacements in Lindo [2010] and Huttunen and Kellokumpu [2016]; boosts in house prices in Lovenheim and Mumford [2013]; economic booms in Black et al. [2013] and Kearney and Wilson [2018]; and the basic pension for elderly relatives in our case. Different shocks may also induce different impacts on household dynamics. For instance, job displacements might affect the probability of divorce and change women's career choices, while house price increases might be perceived as transitory income shocks with weaker effects on couples' decision to have a child, which is a permanent decision. Additionally, these studies are conducted in different countries, with different public provision of childcare, which could affect the relative 'price' of childbearing. For instance, Huttunen and Kellokumpu [2016] focuses on Finland which has a relatively generous welfare state compared to Chile and the US, the countries studied in our paper and the papers by Lindo [2010]; Black et al. [2013]; Lovenheim and Mumford [2013] and Kearney and Wilson [2018].

[16] Women of fertility age just above the cut-off have 0.091 more newborn children than their counterparts just below the cut-off, who have 0.13 newborn children. As the basic pension increases recipients' income by 180 percent, the recipient's income-fertility elasticity is 0.39. For the estimate of mother's income-fertility elasticity, we assumed perfect income pooling. In households with a woman of fertility age, the pension increases income per-capita by 20,347 Chilean pesos. As the mother's income at the cut-off is 10,221 Chilean pesos, the mother's income-fertility elasticity is 0.35.

[17] Since goods with no substitutes are generally considered normal, children should be 'normal goods' and their 'consumption' should increase with income. Our results, along with other recent empirical studies presented in Figure XI, help to explain the long-term puzzle of the negative cross-sectional correlation between income and fertility that is present in many parts of the world (see Jones and Tertilt [2008]).

Figure XI: Estimated income-fertility elasticity across different empirical studies



Notes: This graph plots point estimates of income-fertility elasticity in different empirical studies. Empty squares indicate insignificant estimates. The dashed lines indicate the 95 percent confidence intervals of our estimates. The elasticities in the other papers are computed using income shocks on different household members: Black et al. [2013] and Lindo [2010] estimate income-fertility elasticity using husband's income; Kearney and Wilson [2018] and Huttunen and Kellokumpu [2016] estimate mother's income-fertility elasticity and husband's income-fertility elasticity; and Lovenheim and Mumford [2013] estimate a fertility elasticity with respect to the house price. The graph does not aim to represent the universe of papers that study the impact of income on fertility. In several studies, it is not possible to calculate the income-fertility elasticity, because either baseline fertility or income are not reported.

The significant *spillover* effect on the fertility rate of working-age household members, combined with the insignificant *direct* effect on recipients living with them, could be the result of intra-household transfers of income. On the one hand, working-age household members may have reduced their transfers of income to applicants after receiving the pension, and thus retaining the necessary resources to raise a child. This would be consistent with previous evidence finding that social security benefits 'crowd out' 20-30 percent of private transfers from younger generations to the elderly [Cox and Jimenez, 1992; Jensen, 2003]. On the other hand, recipients may transfer part of the pension to working-age household members, as documented in previous studies [Duflo, 2000, 2003; Ardington et al., 2009]. This hypothesis would have to be reconciled with survey evidence showing that 82 percent of pension recipients do not share any money with their relatives

or friends, and only 4 percent share more than one-fifth of their pension with others [Ministerio Trabajo y Previsión Social, 2017]. Alternatively, fertility-age women may also have exited the labor force, using the income shock to increase the parental time available for childcare.[18] We do not have access to data on labor supply or intra-household transfers of income after the pension application to disentangle the exact economic household dynamics behind the *spillover* effects.

6 Concluding remarks

In this paper, we have explored the impact of a permanent increase of income for the elderly poor on their mortality and days of hospitalizations, as well as the spillover effects on their household members. By comparing basic pension applicants and their household members in a narrow window around the eligibility threshold, we disentangled the effects of the income increase in a regression discontinuity framework.

The permanent increase in income causes a reduction in basic pension recipients' mortality rates, within four years after they apply for the pension. This effect is concentrated on recipients who live alone or with another elderly person and appears to be driven by a decrease in circulatory and respiratory diseases. The main policy implication of our analysis is the confirmation that health inequalities in the elderly population are driven in part by contemporaneous income inequalities, and the resulting conclusion that increasing income at a late stage in life can improve the health outcomes of recipients.

We also observe that the basic pension does not have a direct effect on recipients living with a working-age household member, but that it does have a spillover effect on these working-age household members. Working-age household members of basic pension recipients are more likely to have a newborn child nine months or later following the application. Our results show that the effects of a non-contributory pension reach beyond the recipients to other household members. These are important illustrations to aid in the optimal design of social pension policies, as the spillover effect can account for a significant share of the overall benefits of a pension.

[18] Childcare is not universal in Chile. Around one-third of children between zero and four years of age attend a childcare center, and most of these centers are open only until noon. Additionally, it may be that pension recipients were the ones exiting the labor force to provide childcare. This appears less likely, since the fraction of pension recipients in the labor force seems very limited, as illustrated above.

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For Online Publication

Appendix A The pension score

The pension score was created with the sole purpose of determining basic pension recipients and has no further use for any other public agency or government benefit. This score is calculated as follows:

$$\text{Pension score}_g = \frac{\sum_{i}^{n_g}\{\ \text{Y}_{i,g} + \text{YP}_{i,g}\}}{\text{IN}_g} * F \tag{3}$$

Where:

- $Y_{i,g}$ is the labor income for person i in household group g.
  - For elderly household members, the National Tax Service provides this information. In cases where Tax Service records do not show any income from a particular person, the PI uses the self-reported measure collected from the *social security score*.
  - For working-age household members, labor income is imputed using a variation of the Mincer equation (also referred to by its Spanish name, "capacidad de generar ingreso" or CGI), which includes gender, level of education, town of residence, number and age of children, among other variables. This number is estimated by the Ministry of Planning and the equation is not known to the public. In this way, the government tries to prevent score manipulations, for example by working-age household members not reporting their full income or leaving their employment.
- $YP_{i,g}$ is income from other pensions, government transfers, financial assets and any other income source not considered in $Y_{i,g}$ for person i in household group g. The National Tax Service, the MP, banks and the private companies administering the pension funds provide this information. If these institutions do not show any record for a particular person, the PI uses the self-reported measure collected from the *social security score*.

- IN_g is the household size of household g, adjusted by the level of disability of each household member. This index is computed as the sum of people in the household, with household members above the age of 65 and those in the national register of disabled persons adding an extra 0.4 and 1.3 points to this index, respectively.

- n_g is the number of people in the household group g.

- F is a transformation factor used to convert the results to the scale of the pension score. This factor is not publicly available and we do not have access to it.

For 2012 applicants, labor income from household members and income from assets represent on average 40 and 60 percent of the numerator of the pension score, respectively. This shows that wealth in the form of other pensions or financial assets seems to be the most relevant factor in the pension score for the average applicant, with labor income being relatively less important. For applicants who submitted an application in 2011 or 2012, the pension runs between 0 and 43,103 score points. The cut-off has been 1206 score points since July 2011.

A.1 Pension payments

Monthly income from the basic pension has been adjusted yearly at a level slightly above the inflation rate except in 2009, which saw an increase above the inflation rate. In 2008, recipients started receiving monthly payments of 60,000 Chilean pesos (around US$114), which increased to 75,000 pesos (US$140) in 2009. In subsequent years, the basic pension has increased by 2,000-4,000 Chilean pesos every year, reaching 93,543 Chilean pesos in the final year of the study, 2016.

Basic pension payments can be received by bank transfer or by being collected in person, with an ID card, in a bank or PI office. In our sample, 96 percent of recipients collect their pension in person. This is not surprising, as it is common among poor elderly Chileans to operate outside the financial system. This indicates that the pension payments are effectively being received by applicants.

Basic pension payments cease if the recipient spends more than 90 days abroad in a single calendar year. The person can apply again, but they will need to prove 270 days of continuous residency in Chile in the year before applying. Payments also cease if the recipient does not collect any pension money within six months. In this case, recipients of the basic pension have another six months to request that the PI restore their payments. If this is not done, the basic pension expires

and people in this category can apply again for a basic pension without any restriction. Finally, payments immediately cease when the pension recipient dies.

A.2 Serial applicants

Figure I shows that a small number of applicants below the cut-off did not receive the basic pension. This is explained by reasons unrelated to the pension score (i.e: not redeeming the pension in time). This figure also shows that some applicants above the cut-off obtained a basic pension within four years. This is fully explained by non-recipients who submitted a subsequent application (henceforth referred to as *serial applicants*) that was successful.

To analyze the characteristics of serial applicants, we regress an indicator for whether the person is a serial applicant against baseline covariates. Column (1) of Table C2 presents a series of bivariate regressions in which each baseline characteristic is entered separately, while columns (2), (3), and (4) show estimations that regress on multiple covariates simultaneously. This table shows that applicants above the cut-off who are older and have a higher social security score are less likely to be serial applicants, while those in a larger household are more likely to apply more than once. This could be because: 1) older applicants might perceive a lower present value of the basic pension income (they expect to live for a shorter time); and, 2) wealthier people believe they are less likely to obtain the pension. In contrast, people in larger families might be more likely to see changes in their household composition or income. They may believe that these changes will affect their pension score which encourages them to reapply. In Table C3, we analyze the characteristics of serial applicants who eventually obtain the basic pension. We show that serial applicants with a higher social security score are less likely to eventually obtain the basic pension for the reasons mentioned above. Living with an elderly relative also reduces the probability of obtaining the basic pension later, likely due to elderly relatives having the least volatile source of income: a contributory pension.

Appendix B Set of controls used on estimation robustness.

We test the robustness of our results by replicating them on several specifications. For the particular specification in which we use a polynomial of order 1 in score and other controls, we perform the regressions using the following control variables:

- Individual and household covariates: month-year of the first application fixed effect, age of application fixed effect, gender, social security score, and number of applicants in the household. We also use the following household characteristics prior to applying: dummy for whether the applicant lives with an elderly household member, dummy for whether the applicant lives with a working-age relative, dummy for whether the applicant lives with a person below 16 years of age, and household size.

- Health covariates six months before applying: days of hospitalization, dummy indicator for whether the applicant had been given a pneumonia vaccination, and dummy indicator for whether the applicant had been given an influenza vaccination.

- Geographical covariates: health service fixed effects, the number of health facilities per square kilometer, municipal income per capita, whether the town is rural or urban, and whether or not there is a hospital in the town.

Appendix C Tables

Table C1: Evolution of basic pension coverage

Period	Coverage	Monthly payment in Chilean pesos	Monthly payment in US dollars
From July 1st, 2008 to June 30th, 2009	40 percent	60,000	113.24
From July 1st, 2009 to August 31st, 2009	45 percent	75,000	141.55
From September 1st, 2009 to June 30th, 2010	50 percent	75,000	134.84
From July 1st, 2010 to June 30th, 2011	55 percent	75,840	139.37
From July 1st, 2011	60 percent	78,449	168.30
From July 1st, 2012	60 percent	80,528	160.76
From July 1st, 2013	60 percent	82,058	162.56
From July 1st, 2014	60 percent	85,964	155.67
From July 1st, 2015	60 percent	89,764	140.41
From July 1st, 2016	60 percent	93,543	141.98

Notes: This table shows the evolution of the basic pension cut-off and monthly payment amounts from 2008 onwards. Dates, cut-off points, and payment amounts in Chilean pesos are reported by the Chilean Pension Institute. Payment in US dollars is computed using the amount in Chilean pesos divided by the conversion rate on the day in which the amount became effective.

Table C2: The effect of baseline covariates on the probability of applying multiple times

	(1)	(2)	(3)	(4)
Female	-0.034	0.031	0.031	0.026
	(0.016)	(0.016)	(0.017)	(0.015)
Age (years)	-0.012	-0.009	-0.009	-0.006
	(0.001)	(0.001)	(0.001)	(0.001)
Social security score	-0.023	-0.021	-0.022	-0.019
	(0.001)	(0.001)	(0.001)	(0.001)
Days hospitalized	-0.001	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.001)
Received influenza vaccination	0.050	0.069	0.070	0.018
	(0.011)	(0.011)	(0.011)	(0.011)
Received pneumonia vaccination	-0.034	-0.097	-0.098	-0.005
	(0.024)	(0.024)	(0.024)	(0.021)
Household size	0.014		0.021	0.023
	(0.005)		(0.007)	(0.006)
Elderly household member	-0.055		-0.017	-0.012
	(0.012)		(0.014)	(0.012)
Working-age household member	0.037		-0.010	-0.021
	(0.010)		(0.016)	(0.014)
Live with child under 16	0.074		0.004	-0.045
	(0.052)		(0.051)	(0.048)
FIXED EFFECTS	NO	NO	NO	YES
N	6,423	6,423	6,423	6,423

Notes: Using the sample of all applicants above the cut-off, this table reports results from OLS regressions of a binary indicator equal to 1 if the individual applied for the basic pension more than once (and 0 otherwise) on several covariates. Column (1) reports coefficients of bivariate regressions. Columns (2), (3) and (4) report coefficients of multivariate regressions on the specified variables. Fixed effects are at the month-of-application and the health-district level. Standard errors are clustered at the province level. For ease of interpretation, the social security score is rescaled (divided by 1,000).

Table C3: The effect of baseline covariates on the probability of receiving the pension four years after applying, for applicants above the cut-off

	(1)	(2)	(3)	(4)
Female	-0.165	-0.099	-0.084	-0.056
	(0.040)	(0.041)	(0.041)	(0.041)
Age (years)	-0.014	-0.011	-0.010	-0.007
	(0.003)	(0.004)	(0.004)	(0.004)
Social security score	-0.030	-0.026	-0.025	-0.026
	(0.003)	(0.003)	(0.003)	(0.003)
Days hospitalized	0.001	0.002	0.002	0.002
	(0.005)	(0.005)	(0.005)	(0.005)
Received influenza vaccination	0.025	0.050	0.050	-0.042
	(0.027)	(0.027)	(0.027)	(0.030)
Received pneumonia vaccination	-0.001	-0.028	-0.035	0.030
	(0.067)	(0.067)	(0.066)	(0.067)
Household size	-0.008		0.026	0.032
	(0.012)		(0.018)	(0.018)
Elderly household member	-0.156		-0.125	-0.109
	(0.029)		(0.034)	(0.033)
Working-age household member	0.018		-0.060	-0.054
	(0.027)		(0.041)	(0.041)
Live with child under 16	-0.051		-0.094	-0.103
	(0.118)		(0.117)	(0.120)
FIXED EFFECTS	NO	NO	NO	YES
N	1365	1365	1365	1365

Notes: Using the sample of all applicants above the cut-off, this table reports results from OLS regressions of a dummy indicator equal to 1 if the applicant obtains the basic pension four years after the first application (and 0 otherwise) on several covariates. Column (1) reports coefficients of bivariate regressions. Columns (2), (3) and (4) report coefficients of multivariate regressions on the specified variables. Fixed effects are at the month-of-application and health-district level. Standard errors are clustered at the province level. For ease of interpretation, the social security score is rescaled (divided by 1,000).

Table C4: Balancing tests on other covariates (2012 only)

Variables	RD Coef. (1)	S.E. (2)	t stat (3)	P-value (4)	BW (5)	N (6)	Control (7)
Total household income	0.300	(10.208)	0.029	0.977	500	4,072	650.0
Imputed income	-24.942	(12.043)	-2.071	0.044	500	4,072	93.23
Labor income	28.497	(36.620)	0.778	0.440	500	4,072	246.0
All incomes from assets	-28.197	(36.467)	-0.773	0.443	500	4,072	404.0
Labor income factor	-0.014	(0.024)	-0.576	0.567	500	4,072	1.939
Needs index (IN)	-0.034	(0.021)	-1.609	0.114	500	4,072	2.022
Net working salary	-3.991	(19.995)	-0.200	0.843	500	4,072	187.5
Other labor income	36.106	(30.905)	1.168	0.248	500	4,072	20.06
Net pension income	5.875	(18.698)	0.314	0.755	500	4,072	356.3
Avg. no. of students	-0.021	(0.016)	-1.275	0.208	500	4,072	0.070
Applicants' inc. (CLP)	-1,581	(5,771)	-0.274	0.785	500	4,072	44,209
Elderly house. membs.' inc. (CLP)	-7,551	(11,611)	-0.65	0.516	500	2,775	256,310
Work.-age house. membs.' inc. (CLP)	-2,468	(16,788)	-0.15	0.883	500	2,312	141,924
Fertility age woman's inc. (CLP)	549	(7,083)	0.08	0.938	500	828	10,221

Notes: This table reports results from OLS regressions of pre-determined variables on a treatment dummy indicator and deviation of the pension score from the cut-off. All estimations are computed using averages at household level due to data limitations (Section 3). Columns (1), (2), (3), and (4) report the treatment indicator coefficient, its standard error clustered at the province, t-statistic, and p-value, respectively. Columns (5) and (6) report the range of pension score points from the cut-off and the number of observations in the regression, respectively. Column (7) reports the constant of this regression, showing the variable mean for control applicants at the cut-off. All variables reporting some form of income are expressed in US dollars, unless that Chilean pesos (CLP) is specified.

Table C5: Balancing tests by household structure

Variables	RD Coef. (1)	S.E. (2)	t stat (3)	P-value (4)	BW (5)	N (6)	Control (7)
Panel A: applicants not living with a working-age household members							
Female	-0.014	(0.020)	-0.693	0.491	500	3,647	0.871
Age (years)	-0.680	(0.457)	-1.488	0.143	500	3,647	69.00
Days hospitalized	-0.513	(0.216)	-2.379	0.021	500	3,647	0.617
Influenza vaccination	-0.011	(0.028)	-0.387	0.701	500	3,647	0.360
Pneumonia vaccination	0.025	(0.016)	1.513	0.137	500	3,647	0.033
Household size	-0.016	(0.020)	-0.840	0.405	500	3,647	1.915
Social security score	-48.817	(207.017)	-0.236	0.815	500	3,647	9640.
Elderly household member	-0.022	(0.019)	-1.180	0.244	500	3,647	0.892
Live with child under 16	-0.004	(0.004)	-1.036	0.305	500	3,647	0.004
Municipal income	5.761	(5.048)	1.141	0.259	500	3,640	141.8
Panel B: applicants living with working-age household members							
Female	-0.017	(0.021)	-0.780	0.439	500	4,852	0.906
Age (years)	-0.116	(0.314)	-0.369	0.713	500	4,852	66.38
Days hospitalized	0.185	(0.236)	0.781	0.439	500	4,852	0.324
Influenza vaccination	-0.036	(0.027)	-1.342	0.186	500	4,852	0.355
Pneumonia vaccination	0.010	(0.014)	0.681	0.499	500	4,852	0.052
Household size	0.008	(0.060)	0.136	0.892	500	4,852	3.227
Social security score	167.250	(255.827)	0.654	0.516	500	4,852	9823.
Elderly household member	0.043	(0.026)	1.646	0.106	500	4,852	0.528
Live with child under 16	0.007	(0.006)	1.045	0.301	500	4,852	0.007
Municipal income	-9.301	(5.746)	-1.619	0.112	500	4,843	150.9

Notes: This table reports results from OLS regressions of pre-determined variables on a treatment dummy indicator and deviation of the pension score from the cut-off. Columns (1), (2), (3), and (4) report the treatment indicator coefficient, its standard error clustered at the province level, t-statistic, and p-value, respectively. Columns (5) and (6) report the range of pension score points from the cut-off and the number of observations in the regression, respectively. Column (7) reports the constant of this regression, showing the variable mean for control applicants at the cut-off. Health covariates are defined 6 months before applying.

Table C6: Applicants' health outcomes in four years from the first application using logit, non-parametric estimations, optimal bandwidth, controls, and quadratic functional form in $Score_h$

Variables	Regression (1)	RD Coef. (2)	S.E. (3)	P-value (4)	BW (5)	N (6)
Mortality rate	Logit	-0.020	(0.009)	0.029	500	8,499
Mortality rate	Non-parametric	-0.021	(0.010)	0.045	500	8,499
Mortality rate	Optimal bandwidth	-0.028	(0.013)	0.027	306	5,048
Mortality rate	Controls	-0.019	(0.010)	0.059	500	8,499
Mortality rate	Quadratic	-0.033	(0.015)	0.024	500	8,499
Medical episode	Logit	-0.041	(0.018)	0.018	500	8,499
Medical episode	Non-parametric	-0.042	(0.023)	0.071	500	8,499
Medical episode	Optimal bandwidth	-0.048	(0.021)	0.021	398	6,605
Medical episode	Controls	-0.038	(0.017)	0.025	500	8,499
Medical episode	Quadratic	-0.057	(0.028)	0.043	500	8,499

Notes: This table reports results, within four years from the date of the first application, from regressions of several dependent variables on a treatment dummy indicator and deviation of the pension score from the cut-off using equation 2. Column (1) indicates the specification used. *Logit* reports estimations using a logistic regression. *Non-parametric* reports non-parametric estimations using kernel local linear regressions. *Optimal bandwidth* estimates treatment effects using the optimal bandwidth proposed by Calonico et al. [2014]. *Controls* employs our preferred specification, polynomial of order 1 in $Score_h$, as well as 17 other controls listed in Appendix Section B. *Quadratic* uses polynomial of order 2 in $Score_h$. Column (2) reports the treatment indicator coefficient and Column (3) reports the standard error clustered at the province level. Column (4) reports the p-value of the treatment coefficient. Column (5) indicates the range of pension score points from the cut-off and Column (6) reports the number of observations in the regression.

Table C7: Health outcomes, over four years from application, for applicants not living with working-age household members using logit, non-parametric estimations, optimal bandwidth, controls, and quadratic functional form in $Score_h$

Variables	Regression (1)	RD Coef. (2)	S.E. (3)	P-value (4)	BW (5)	N (6)
Mortality rate	Logit	-0.047	(0.018)	0.003	500	3,647
Mortality rate	Non-parametric	-0.045	(0.019)	0.021	500	3,647
Mortality rate	Optimal bandwidth	-0.051	(0.019)	0.006	374	2,704
Mortality rate	Controls	-0.040	(0.015)	0.011	500	3,647
Mortality rate	Quadratic	-0.063	(0.025)	0.012	500	3,647
Days hospitalized	Logit	-0.074	(0.037)	0.050	500	3,647
Days hospitalized	Non-parametric	-2.250	(0.721)	0.002	500	3,647
Days hospitalized	Optimal bandwidth	-2.780	(0.741)	0.000	288	2,073
Days hospitalized	Controls	-1.645	(0.580)	0.007	500	3,647
Days hospitalized	Quadratic	-2.762	(0.846)	0.001	500	3,647
Medical episode	Logit	-0.091	(0.034)	0.009	500	3,647
Medical episode	Non-parametric	-0.093	(0.034)	0.007	500	3,647
Medical episode	Optimal bandwidth	-0.124	(0.053)	0.020	294	2,124
Medical episode	Controls	-0.085	(0.039)	0.035	500	3,647
Medical episode	Quadratic	-0.136	(0.061)	0.026	500	3,647

Notes: This table reports results, within four years from the date of the first application, from regressions of several dependent variables on a treatment dummy indicator and deviation of the pension score from the cut-off using equation 2. Column (1) indicates the specification used. *Logit* reports estimations using a logistic regression. *Non-parametric* reports non-parametric estimations using kernel local linear regressions. *Optimal bandwidth* estimates treatment effects using the optimal bandwidth proposed by Calonico et al. [2014]. *Controls* employs our preferred specification, polynomial of order 1 in $Score_h$, as well as 17 other controls listed in Appendix Section B. *Quadratic* uses polynomial of order 2 in $Score_h$. Column (2) reports the treatment indicator coefficient and Column (3) reports the standard error clustered at the province level. Column (4) reports the p-value of the treatment coefficient. Column (5) indicates the range of pension score points from the cut-off and Column (6) reports the number of observations in the regression.

Table C8: Applicants' health outcomes, over four years from application, for applicants living with working-age household members using logit, non-parametric estimations, optimal bandwidth, controls, and quadratic functional form in $Score_h$

Variables	Regression (1)	RD Coef. (2)	S.E. (3)	P-value (4)	BW (5)	N (6)
Mortality rate	Logit	-0.001	(0.014)	0.947	500	4,852
Mortality rate	Non-parametric	-0.001	(0.013)	0.949	500	4,852
Mortality rate	Optimal bandwidth	-0.006	(0.017)	0.718	364	3,382
Mortality rate	Controls	-0.003	(0.010)	0.738	500	4,852
Mortality rate	Quadratic	-0.009	(0.021)	0.689	500	4,852
Days hospitalized	Logit	-0.010	(0.032)	0.767	500	4,852
Days hospitalized	Non-parametric	0.635	(0.928)	0.494	500	4,852
Days hospitalized	Optimal bandwidth	0.623	(0.995)	0.531	533	5,242
Days hospitalized	Controls	0.617	(1.077)	0.569	500	4,852
Days hospitalized	Quadratic	0.906	(1.830)	0.620	500	4,852
Medical episode	Logit	0.000	(0.032)	0.992	500	4,852
Medical episode	Non-parametric	0.000	(0.035)	0.998	500	4,852
Medical episode	Optimal bandwidth	0.000	(0.032)	0.997	506	4,924
Medical episode	Controls	-0.001	(0.037)	0.989	500	4,852
Medical episode	Quadratic	0.006	(0.049)	0.909	500	4,852

Notes: This table reports results, within four years from the date of the first application, from regressions of several dependent variables on a treatment dummy indicator and deviation of the pension score from the cut-off using equation 2. Column (1) indicates the specification used. *Logit* reports estimations using a logistic regression. *Non-parametric* reports non-parametric estimations using kernel local linear regressions. *Optimal bandwidth* estimates treatment effects using the optimal bandwidth proposed by Calonico et al. [2014]. *Controls* employs our preferred specification, polynomial of order 1 in $Score_h$, as well as 17 other controls listed in Appendix Section B. *Quadratic* uses polynomial of order 2 in $Score_h$. Column (2) reports the treatment indicator coefficient and Column (3) reports the standard error clustered at the province level. Column (4) reports the p-value of the treatment coefficient. Column (5) indicates the range of pension score points from the cut-off and Column (6) reports the number of observations in the regression.

Table C9: Health conditions of newborn children at birth

Variables	2sls (1)	S.E. 2sls (2)	RD Coef. (3)	S.E. (4)	P-value (5)	BW (6)	N (7)	Control (8)
Weeks of pregnancy	0.234	(0.533)	0.169	(0.389)	0.660	500	527	38.43
Weight	0.097	(0.125)	0.070	(0.090)	0.437	500	525	3.354
Height	-0.454	(0.530)	-0.327	(0.386)	0.392	500	526	49.62

Notes: This table reports results, within four years from the date of the first application, from regressions of several dependent variables on a treatment dummy indicator and deviation of the pension score from the cut-off. Column (1) reports the treatment coefficient adjusted by the first stage and Column (2) reports its standard error clustered at the province level. Column (3) reports the treatment indicator coefficient and Column (4) reports its standard error clustered at the province level. Column (5) reports the p-value of the adjusted treatment coefficient reported in Column (1). Column (6) reports the range of pension score points from the cut-off and Column (7) reports the number of observations in the regression. Column (8) reports the constant of the ITT regression, showing the variable mean for control applicants at the cut-off.

Table C10: Health outcomes of family members, by age, over four years from application using logit, non-parametric estimations, optimal bandwidth, controls, and quadratic functional form in $Score_h$

Variables	Regression (1)	RD Coef. (2)	S.E. (3)	P-value (4)	BW (5)	N (6)
Panel A: elderly household members						
Mortality rate	Logit	0.000	(0.014)	0.975	500	5,722
Mortality rate	Non-parametric	0.000	(0.015)	0.981	500	5,722
Mortality rate	Optimal bandwidth	-0.001	(0.016)	0.933	402	4,596
Mortality rate	Controls	0.010	(0.013)	0.414	500	5,722
Mortality rate	Quadratic	-0.001	(0.021)	0.956	500	5,722
Medical episode	Logit	0.035	(0.030)	0.251	500	5,722
Medical episode	Non-parametric	0.034	(0.027)	0.208	500	5,722
Medical episode	Optimal bandwidth	0.038	(0.039)	0.336	407	4,657
Medical episode	Controls	0.045	(0.032)	0.162	500	5,722
Medical episode	Quadratic	0.052	(0.058)	0.370	500	5,722
Panel B: working-age household members						
Days hospitalized	Logit	0.010	(0.019)	0.623	500	8,047
Days hospitalized	Non-parametric	-0.242	(0.660)	0.713	500	8,047
Days hospitalized	Optimal bandwidth	0.008	(0.679)	0.991	289	4,328
Days hospitalized	Controls	-0.010	(0.618)	0.987	500	8,047
Days hospitalized	Quadratic	-0.172	(0.898)	0.848	500	8,047
Newborn child	Logit	0.030	(0.008)	0.000	500	8,047
Newborn child	Non-parametric	0.028	(0.007)	0.000	500	8,047
Newborn child	Optimal bandwidth	0.029	(0.008)	0.000	451	7,169
Newborn child	Controls	0.017	(0.008)	0.041	500	8,047
Newborn child	Quadratic	0.032	(0.011)	0.003	500	8,047

Notes: This table reports results, within four years from the date of the first application, from regressions of several dependent variables on a treatment dummy indicator and deviation of the pension score from the cut-off using equation 2. Column (1) indicates the specification used. *Logit* reports estimations using a logistic regression. *Non-parametric* reports non-parametric estimations using kernel local linear regressions. *Optimal bandwidth* estimates treatment effects using the optimal bandwidth proposed by Calonico et al. [2014]. *Controls* employs our preferred specification, polynomial of order 1 in $Score_h$, as well as 17 other controls listed in Appendix Section B. *Quadratic* uses polynomial of order 2 in $Score_h$. Column (2) reports the treatment indicator coefficient and Column (3) reports the standard error clustered at the province level. Column (4) reports the p-value of the treatment coefficient. Column (5) indicates the range of pension score points from the cut-off and Column (6) reports the number of observations in the regression.

Table C11: Vaccinations received in the four years after applying for applicants and applicants by household structure

Variables	2sls (1)	S.E. 2sls (2)	RD Coef. (3)	S.E. (4)	P-value (5)	BW (6)	N (7)	Control (8)
Panel A: applicants								
Influenza (per year)	0.003	(0.020)	0.002	(0.016)	0.878	500	8,499	0.398
Pneumonia	0.010	(0.028)	0.009	(0.023)	0.711	500	8,499	0.306
Panel B: applicants not living with working-age household members								
Influenza (per year)	0.010	(0.022)	0.009	(0.019)	0.645	500	3,647	0.402
Pneumonia	-0.007	(0.026)	-0.006	(0.022)	0.794	500	3,647	0.301
Panel C: applicants living with a working-age household members								
Influenza (per year)	-0.003	(0.027)	-0.002	(0.022)	0.925	500	4,852	0.395
Pneumonia	0.027	(0.042)	0.021	(0.034)	0.523	500	4,852	0.311

Notes: This table reports results, within four years from the date of the first application, from regressions of several dependent variables on a treatment dummy indicator and deviation of the pension score from the cut-off. Column (1) reports the treatment coefficient adjusted by the first stage and Column (2) reports its standard error clustered at the province level. Column (3) reports the treatment indicator coefficient and Column (4) reports its standard error clustered at the province level. Column (5) reports the p-value of the adjusted treatment coefficient reported in Column (1). Column (6) reports the range of pension score points from the cut-off and Column (7) reports the number of observations in the regression. Column (8) reports the constant of the ITT regression, showing the variable mean for control applicants at the cut-off.

Table C12: Characteristics of Chileans who are aged 65 or over and do not have a contributory pension

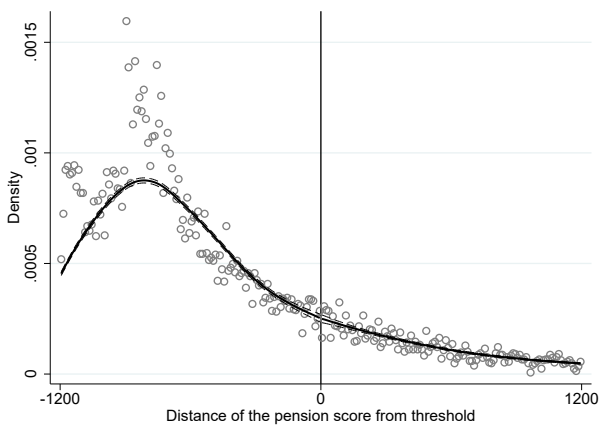
	All	Basic pension recipients	Basic pension non-recipients
	(1)	(2)	(3)
Female	0.720	0.721	0.718
	(0.449)	(0.448)	(0.450)
Age	73.55	73.94	72.83
	(6.706)	(6.614)	(6.811)
Household size	2.358	2.345	2.383
	(1.099)	(1.114)	(1.070)
Elderly household member	0.579	0.580	0.579
	(0.494)	(0.494)	(0.494)
Working-age household member	0.461	0.436	0.507
	(0.499)	(0.496)	(0.500)
Child household member	0.0755	0.0772	0.0723
	(0.264)	(0.267)	(0.259)
Metropolitan area	0.307	0.295	0.327
	(0.461)	(0.456)	(0.469)
Urban town	0.770	0.722	0.855
	(0.421)	(0.448)	(0.352)
Employed	0.0263	0.0156	0.0457
	(0.160)	(0.124)	(0.209)
Food from health service	0.380	0.434	0.285
	(0.486)	(0.496)	(0.451)
Public health insurance	0.946	0.977	0.892
	(0.225)	(0.151)	(0.311)
Self-reported health score (std)	0.0209	-0.0454	0.140
	(1.024)	(1.005)	(1.045)
Received a basic pension	0.643	1	0
	(0.479)	(0)	(0)

Notes: Using data from the 2011 Chilean household survey [Ministerio de Desarrollo Social, 2011], this table reports the means and standard deviations (in parentheses) of several covariates for the Chilean population without a contributory pension in 2011. Column (1) reports statistics for the whole population, Column (2) reports statistics for elderly people with a basic pension and Column (3) reports statistics for elderly people without a basic pension.

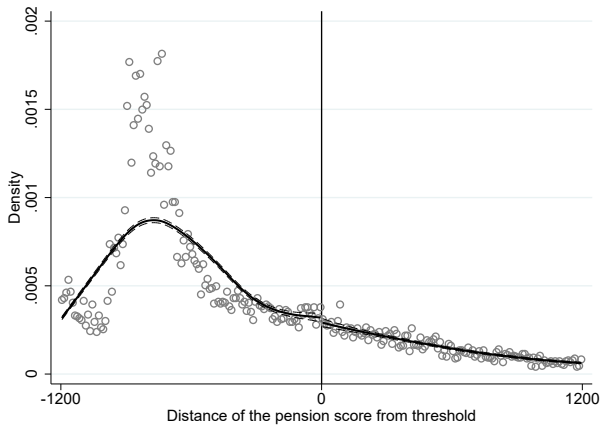
Appendix D Figures

Figure D1: McCrary tests of working-age and elderly household members

(A) Working-age household members

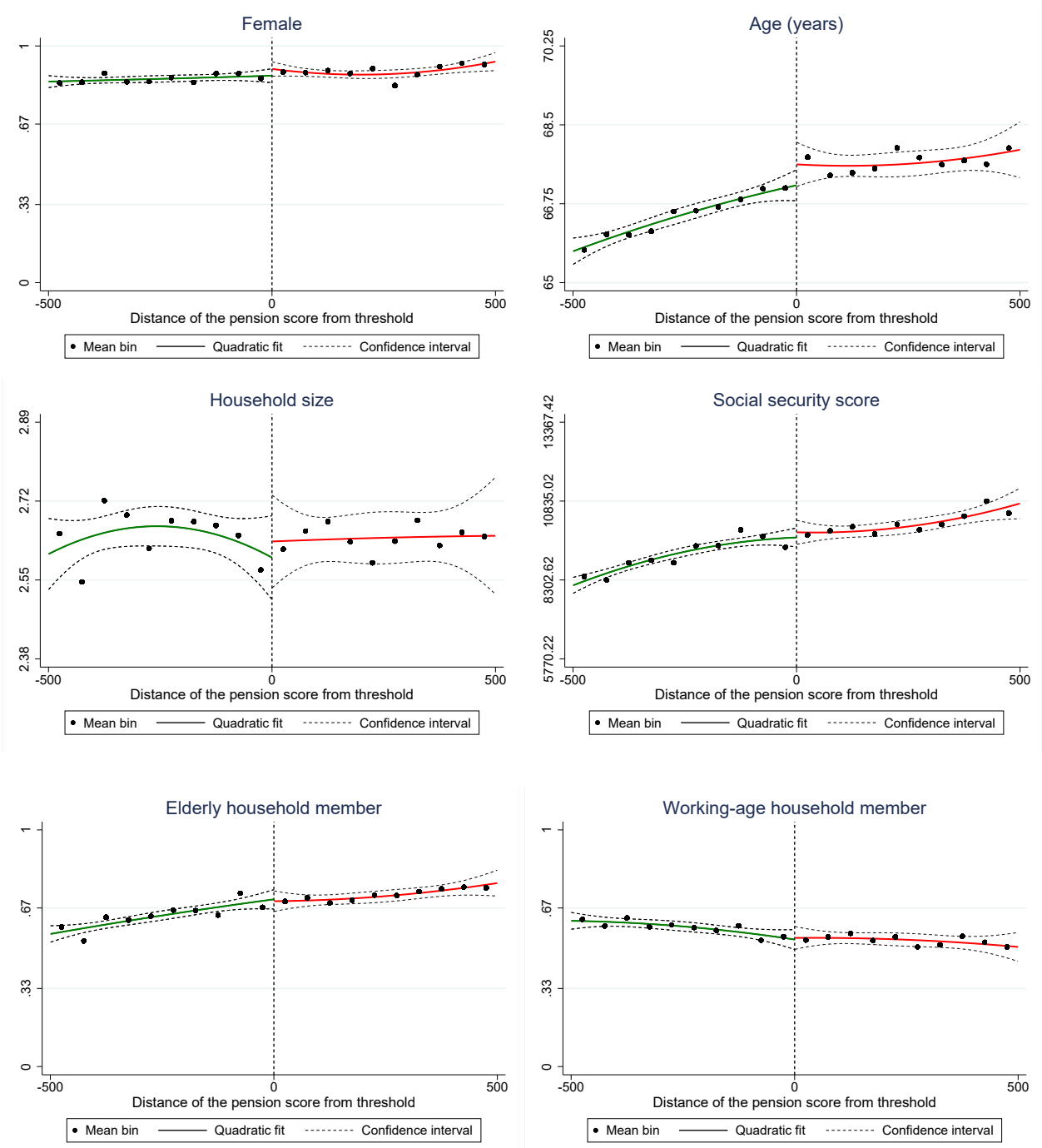


(B) Elderly household members



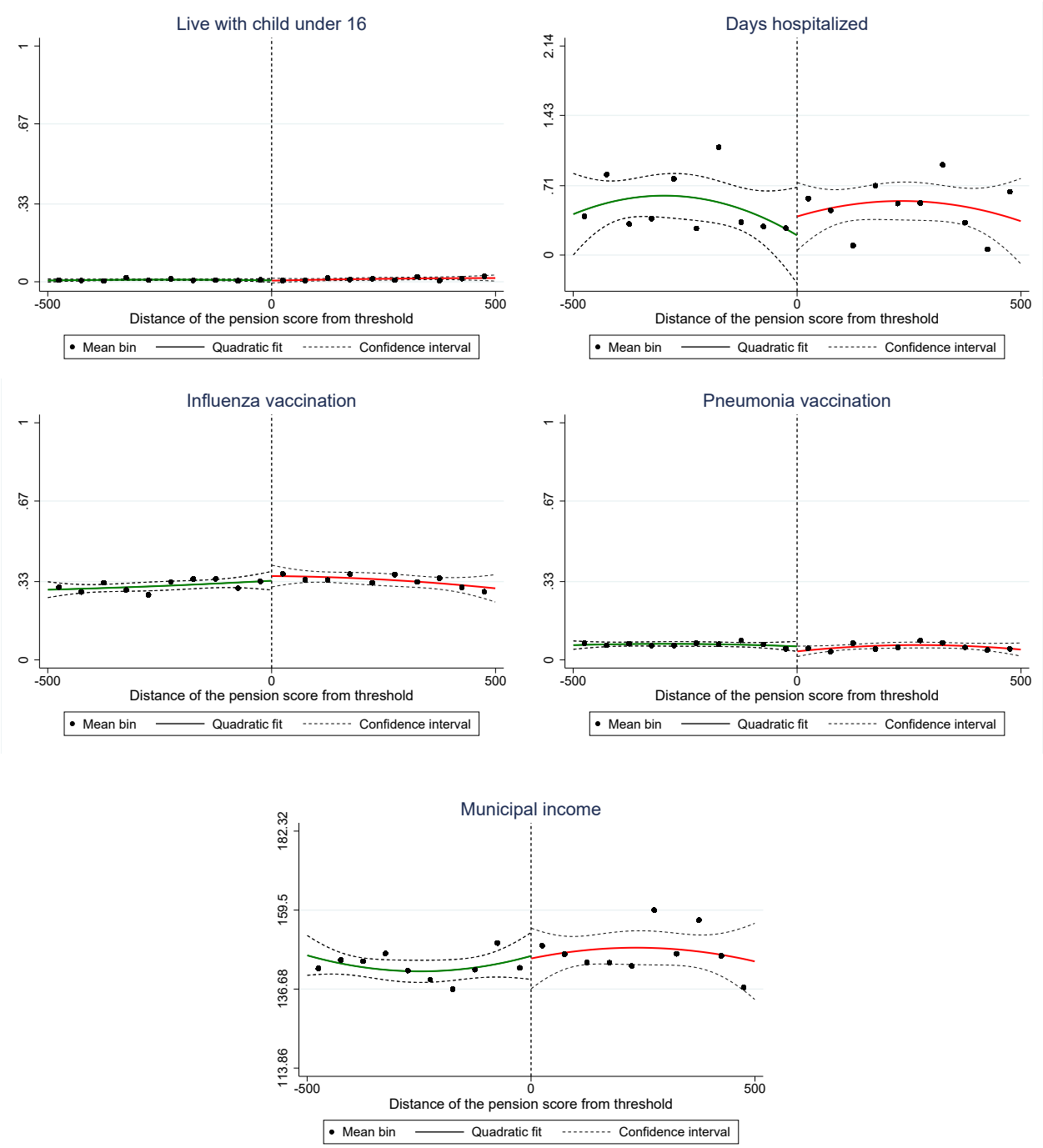
Notes: These figures show the density of individuals in 10 score-point bins. The solid line plots fitted values from a local linear regressions of density on pension score deviations from the cut-off, estimated separately on both sides of the cut-off. The thin lines represent the 95% confidence intervals.

Figure D2: Covariate RD plots, applicants



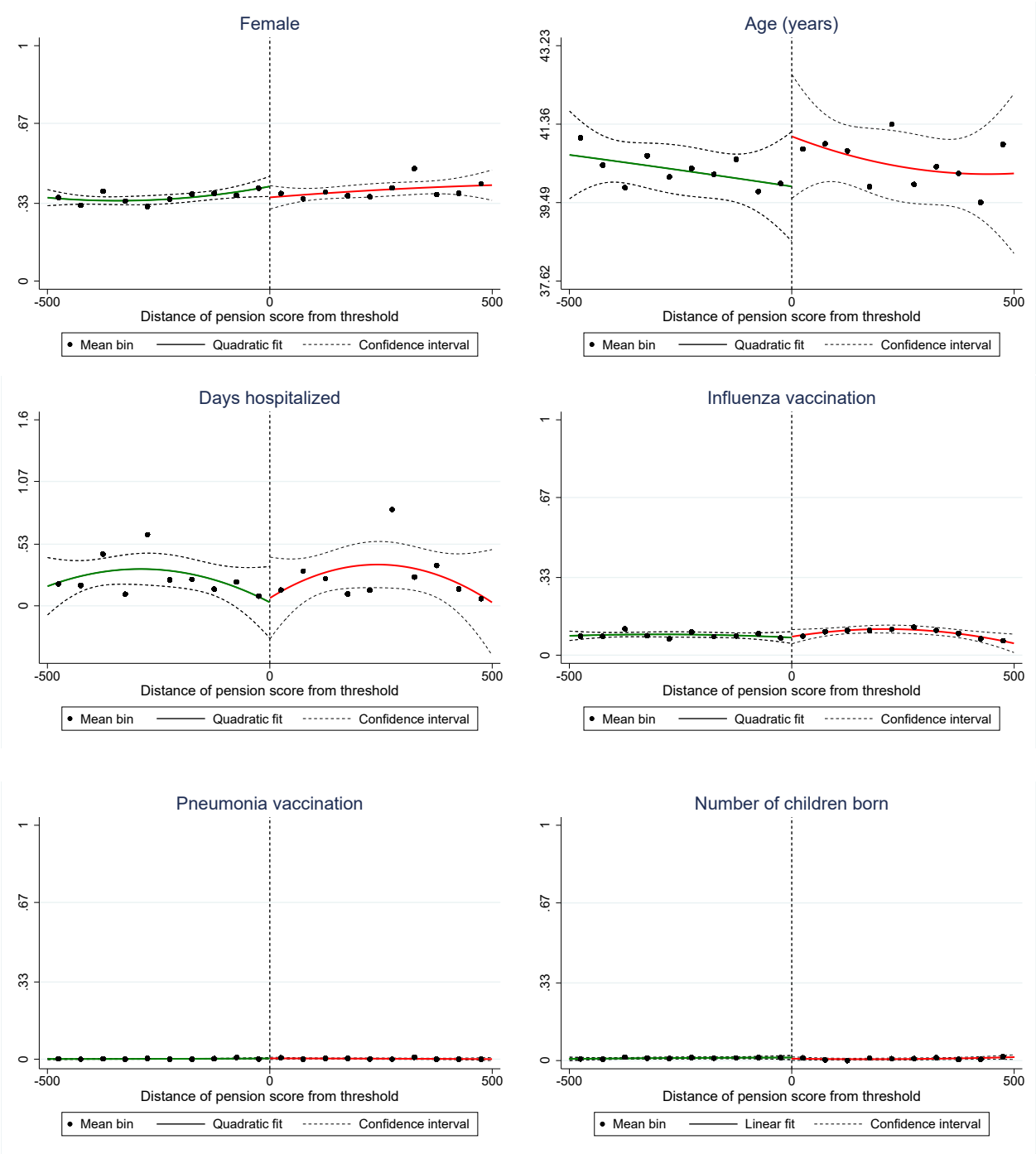
Notes: Each graph shows the average value of the corresponding covariate conditional on the distance of the score from the cut-off. The circles are averages across 50-point bins on either side of the threshold, while the solid and dashed lines represent the predicted values and associated confidence interval, respectively.

Figure D3: Covariate RD plots, applicants



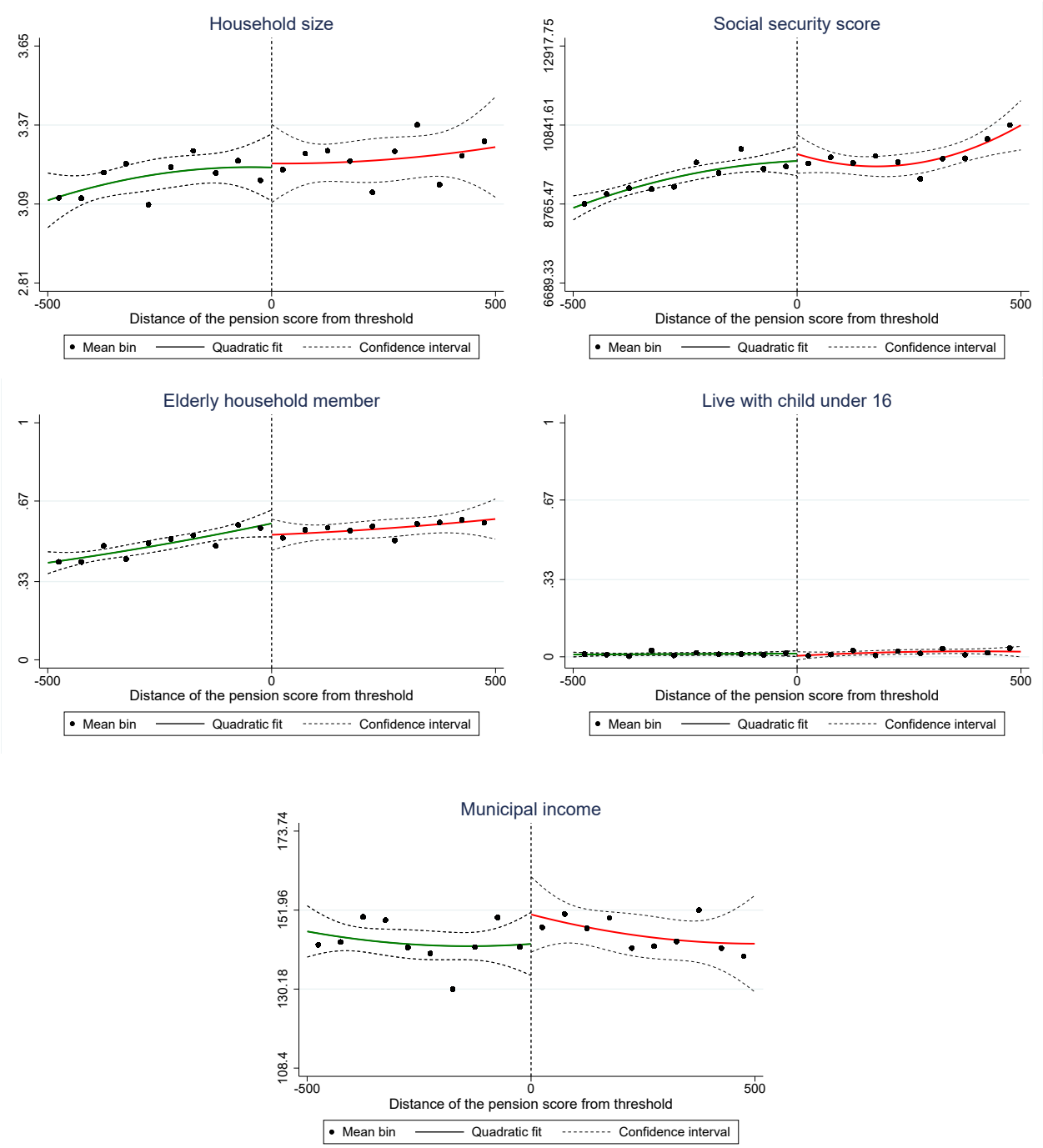
Notes: Each graph shows the average value of the corresponding covariate conditional on the distance of the score from the cut-off. The circles are averages across 50-point bins on either side of the threshold, while the solid and dashed lines represent the predicted values and associated confidence interval, respectively.

Figure D4: Covariate RD plots, working-age household members



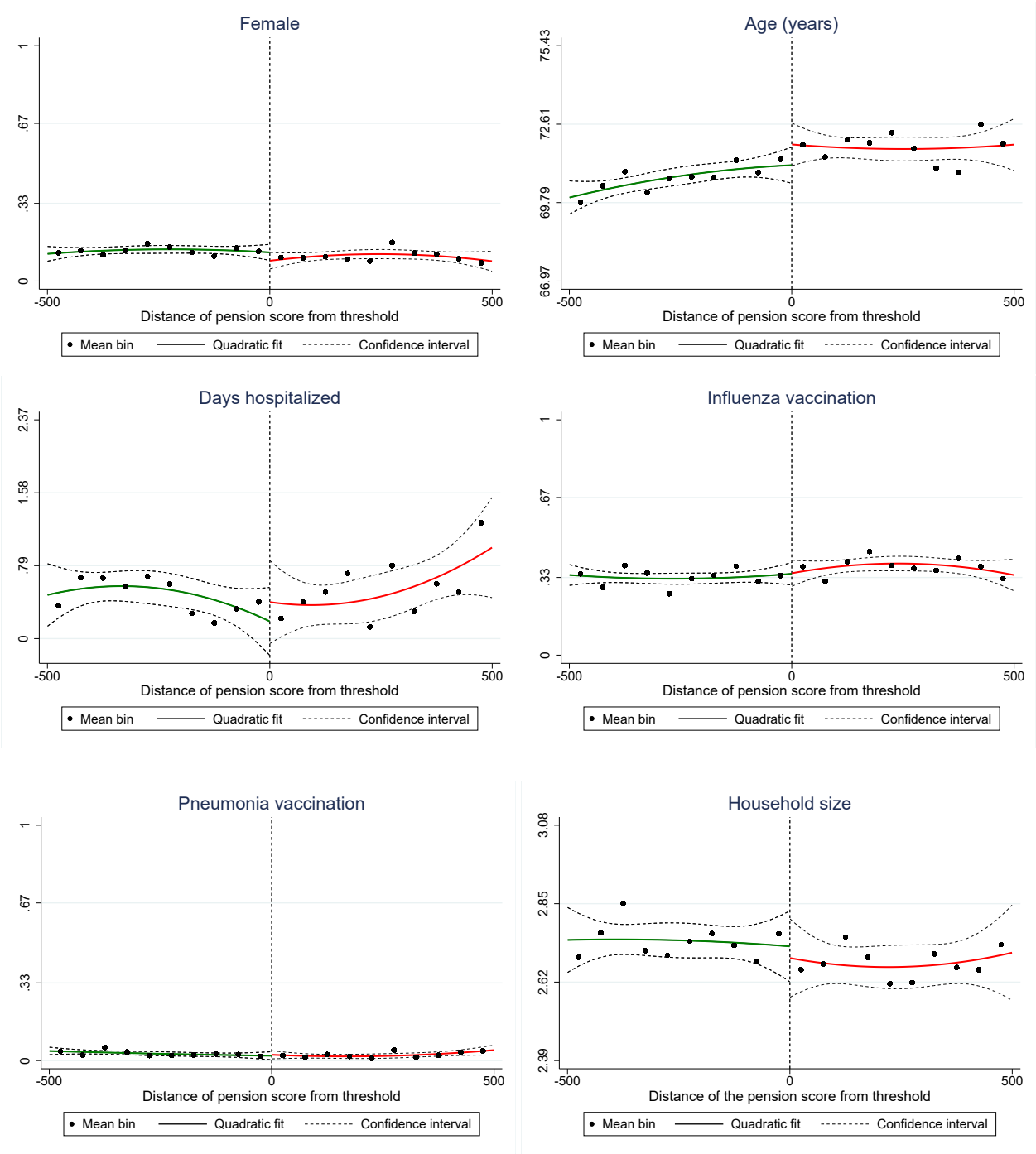
Notes: Each graph shows the average value of the corresponding covariate conditional on the distance of the score from the cut-off. The circles are averages across 50-point bins on either side of the threshold, while the solid and dashed lines represent the predicted values and confidence interval, respectively.

Figure D5: Covariate RD plots, working-age household members



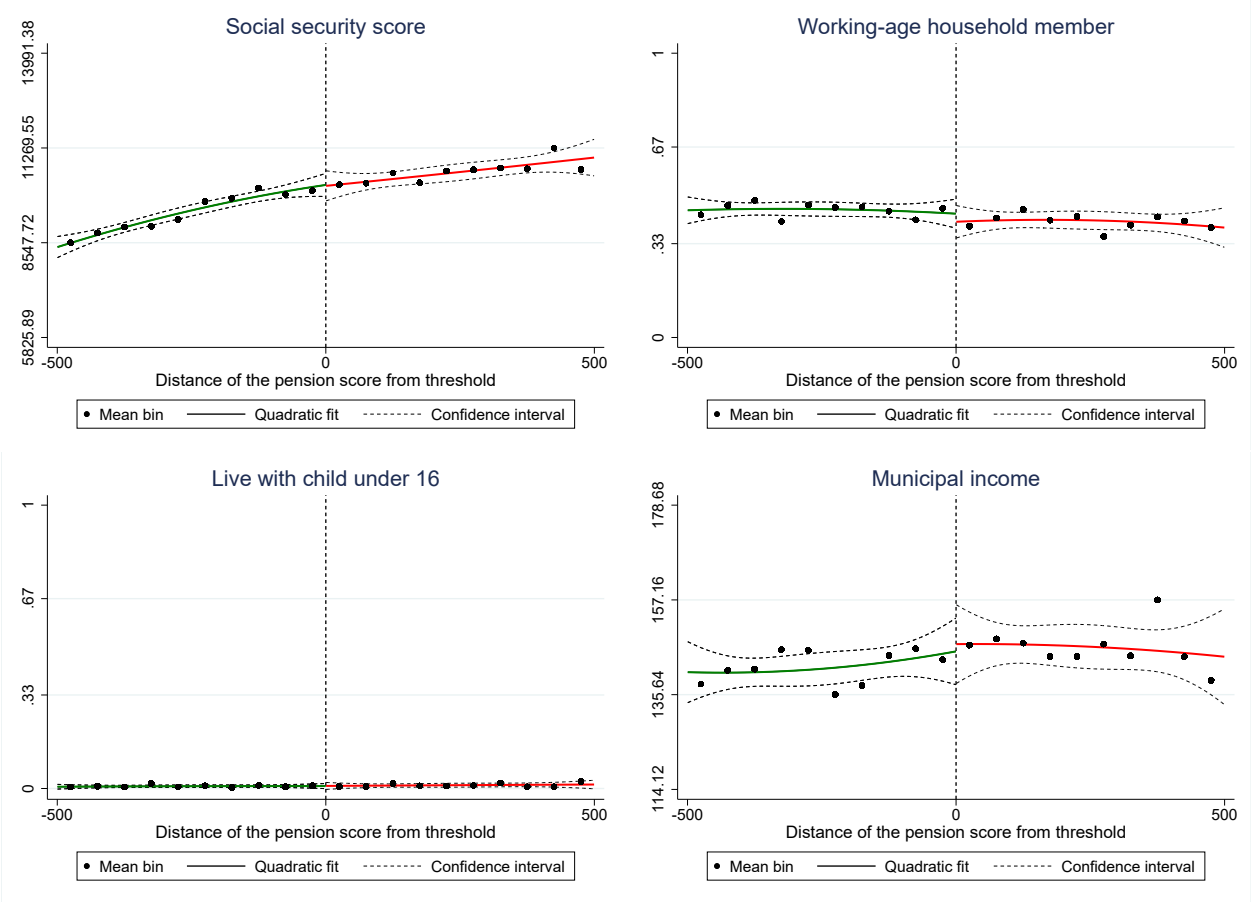
Notes: Each graph shows the average value of the corresponding covariate conditional on the distance of the score from the cut-off. The circles are averages across 50-point bins on either side of the threshold, while the solid and dashed lines represent the predicted values and confidence interval, respectively.

Figure D6: Covariate RD plots, elderly household members



Notes: Each graph shows the average value of the corresponding covariate conditional on the distance of the score from the cut-off. The circles are averages across 50-point bins on either side of the threshold, while the solid and dashed lines represent the predicted values and associated confidence interval, respectively.

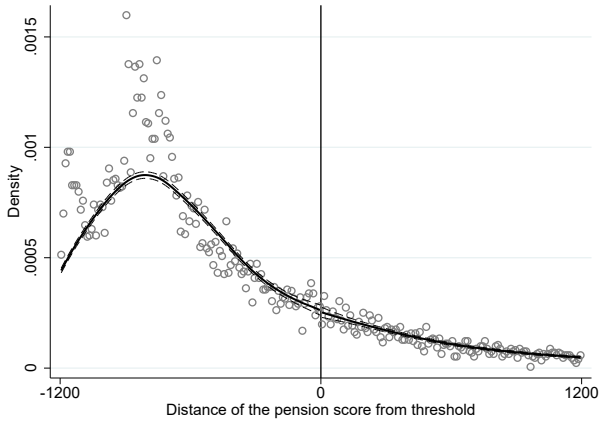
Figure D7: Covariate RD plots, elderly household members



Notes: Each graph shows the average value of the corresponding covariate conditional on the distance of the score from the cut-off. The circles are averages across 50-point bins on either side of the threshold, while the solid and dashed lines represent the predicted values and associated confidence interval, respectively.

Figure D8: McCrary tests by household structure

(A) Applicants living with working-age household members

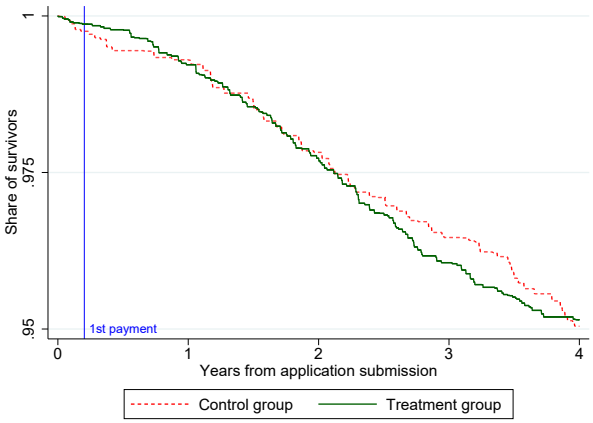


(B) Applicants not living with a working-age household member

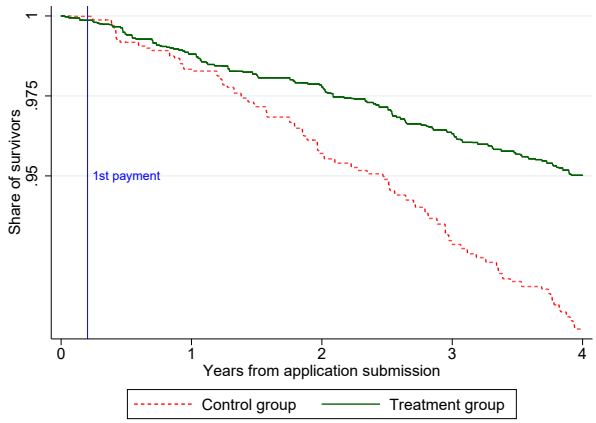
Notes: These figures show the density of individuals in 10 score-point bins. The solid line plots fitted values from local linear regressions of density on pension score deviations from the cut-off, separately estimated on both sides of the cut-off. The thin lines represent the 95% confidence intervals.

Figure D9: Share of surviving applicants by household structure within four years of application, adjusted by score deviations from the cut-off.

(A) Applicants living with working-age household members



(B) Applicants not living a working-age household member



Notes: This figure presents the share of survivors in the treatment and control groups at each point in time after the first application, by household structure. Survival rates are computed using the Cox proportional hazard model, adjusted by score deviations from the cut-off and using triangular weights to give more weight to the applicants closer to the cut-off.