Online Appendix

Health effects of increasing income for the elderly: evidence from a Chilean pension program

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APPENDIX A The pension score

The pension score was created solely to determine basic pension recipients and has no further use for other public agencies. This score is calculated as follows:

$$\text{(A1)} \qquad Pension\ score_g = \frac{\sum_{i}^{n_g} \{ Y_{i,g} + YP_{i,g} \}}{IN_g} \times F$$

Where:

- $Y_{i,g}$ is the labor income for person i in household group g.
  - For elderly household members, the National Revenue Service provides this information. In cases where Revenue Service records do not show any income from a particular person, the Pension Institute 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, 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 avoids score manipulations 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 Revenue Service, the Ministry of Planing, banks and the private companies administering the pension funds provide this information. If these institutions do not show any record for a person, the

Pension Institute 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 is not available to us.

For 2012 applicants, labor income from household members and income from assets represent on average 40% and 60% 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 score runs between 0 and 43,103 score points. To determine the 60^{th} percentile for the Chilean population in 2011, the Pension Institute 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 60^{th} 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 60^{th} percentile was estimated at 1,206 pension score points.

Overall, the majority of the elderly population who did not receive a contributory pension applied to receive a basic pension. In 2011, 64.3% 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 G10 shows the characteristics of the elderly population without contributory pensions in 2011.

Pension payments

Monthly income from the basic pension has been adjusted yearly at a level that is around the inflation rate, except in 2009, when the increase was well above the inflation rate. Appendix Figure A1 shows the evolution of the cut-off and pension payments, along with their dates of changes. This figure also shows the years for which we have data.

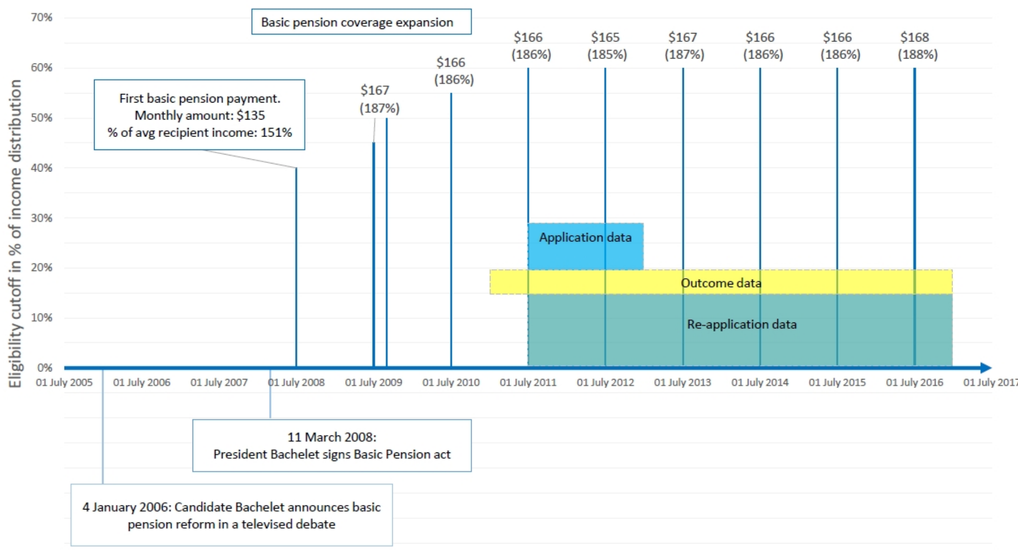


Figure A1. : Timeline of the basic pension reform

Notes: This figure shows the evolution of the basic pension reform, the expansion of its coverage and monthly payment amounts from 2008 onwards. Dates, eligibility cut-off points, and payment amounts are reported by the Chilean Pension Institute. Payments are in 2012 US dollars. To obtain payments in 2012 US dollar, we transformed the nominal value of the payments into 2012 Chilean pesos using the consumer price index and converted this amount into US dollars using the 2012 exchange rate. In parentheses, we report payments as percentages of the average recipient's income at the cut-off in 2012. The 'outcome data' horizontal bar represents the timeframe for which we have outcome data (January 2011 to December 2016). The 'application data' horizontal bar represents the timeframe in which we analyze the first applications of the applicants (July 2011 to December 2012). The 're-application data' horizontal bar represents the timeframe for which we have data on applications for the applicants that re-applied after a first application (July 2011 to December 2016).

Basic pension payments can be received by bank transfer or collected in person with an ID card. In our sample, 96% of recipients collect their pension in person. 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 Pension Institute 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.

Less than 0.05% 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).

APPENDIX B Anticipating behavior

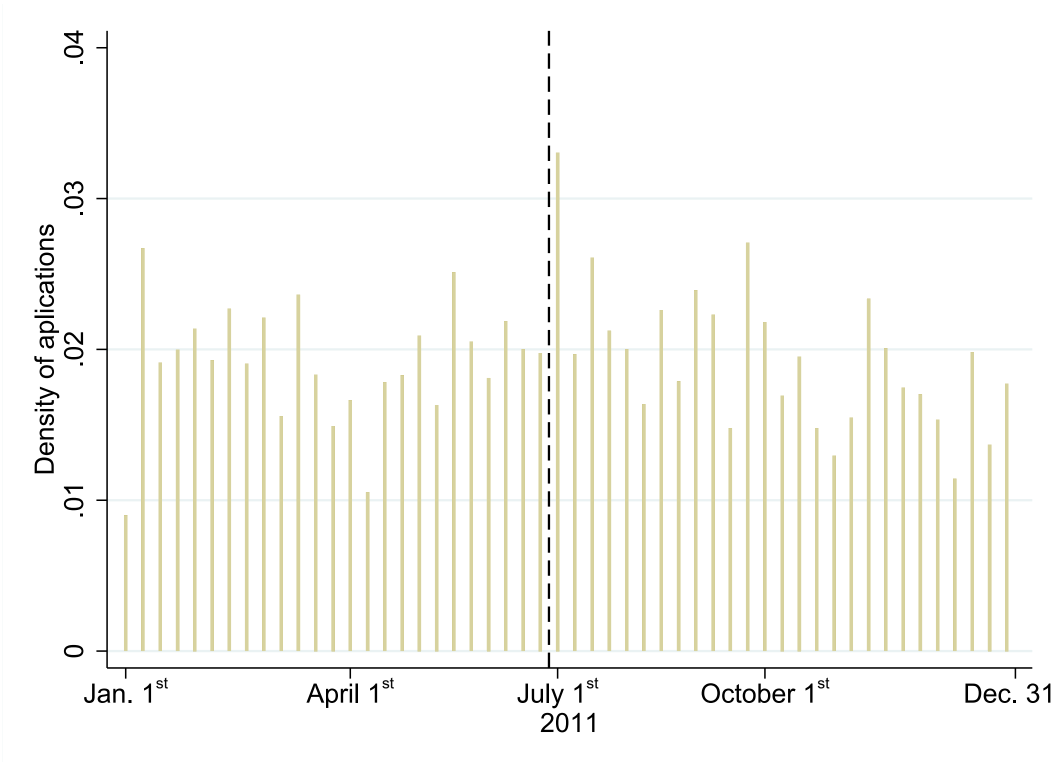


Figure B1. : Weekly density of applications over 2011

Notes: This figure shows the weekly density of applicants (both recipients and non-recipients) in 2011. The dashed vertical line represents the change in the pension score cut-off on July 1st, 2011.

The cut-off changes from covering 55% to covering 60% of the pension score distribution on July 1st, 2011 (Appendix Figure A1). This may have incentivized people to wait until this date to apply, in order to increase their probability of receiving a pension. Appendix Figure B1 shows an increase in the density of applications in the week beginning on July 1st, 2011, which is statistically significant according to the density test by (Cattaneo, Jansson and Ma, 2019). However, this increase appears to be transitory and disappears immediately after the first week of July. The absence of a strong anticipating behaviour can be rationalized by considering that the cut-off increase was not large, the monetary cost of applying is zero and individuals can apply multiple times without a penalty. Thus the increase in the number of applicants in the week beginning on July 1^{st} is arguably due to people stalling their application for only a short time or re-applying, and does not appear to affect the external validity of the main results. Our point estimates remain significant and of similar magnitude when we exclude applicants that applied in the first week of July 2011 (results are available upon request).

APPENDIX C Serial applicants

Figure 1 shows that few applicants below the cut-off did not receive the basic pension. This is explained by reasons unrelated to the pension score (e.g. not redeeming the pension in time). This figure also shows that a relevant number of 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 Appendix Table C1 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.

Table C1—: The effect of baseline covariates on the probability of applying multiple times

	(1)	(2)	(3)	(4)
Female	-0.076	-0.001	0.001	0.004
	(0.020)	(0.021)	(0.021)	(0.020)
Age (years)	-0.023	-0.019	-0.018	-0.016
	(0.001)	(0.001)	(0.001)	(0.001)
Social security score	-0.031	-0.026	-0.027	-0.025
	(0.001)	(0.001)	(0.002)	(0.002)
Days hospitalised	0.000	0.003	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Received influenza vaccination	0.017	0.034	0.037	0.014
	(0.013)	(0.013)	(0.013)	(0.014)
Received pneumonia vaccination	0.067	-0.001	-0.005	0.024
	(0.029)	(0.030)	(0.030)	(0.030)
Household size	0.022		0.021	0.023
	(0.006)		(0.010)	(0.010)
Elderly cohabitant	-0.116		-0.032	-0.030
	(0.014)		(0.017)	(0.017)
Working-age cohabitant	0.089		0.023	0.021
	(0.012)		(0.019)	(0.019)
Live with child under 16	0.106		0.009	-0.017
	(0.063)		(0.060)	(0.062)
Fertility age women	0.073		-0.027	-0.027
	(0.016)		(0.019)	(0.019)
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 submitted at least another application within 4 years from 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 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).

APPENDIX D Set of controls used in the robustness estimations

We test the robustness of our results by replicating them on several specifications. For the 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 fixed effects.

- Health covariates six months before applying: percentage of 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 there is a hospital in the town.

APPENDIX E Sensitivity and placebo checks on the direct health effects

Appendix Table G11 shows that the causal effect of the basic pension on mortality and medical episodes remains qualitatively unchanged whether we use logistic regressions, non-parametric estimations, different sets of controls, or polynomials of order two in $Score_h$. When we include all controls, the p-values are slightly higher but remain small. Figure E1 also shows that the results do not change when we use different bandwidths around the cut-off, suggesting also that our results are not driven by observations far away from the cut-off.

Additionally, we implement the randomization inference method proposed by (Cattaneo, Frandsen and Titiunik, 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. Figure E2 compares these estimates and shows that the probability of obtaining a mortality estimate smaller than ours is as small as 0.0384. 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.

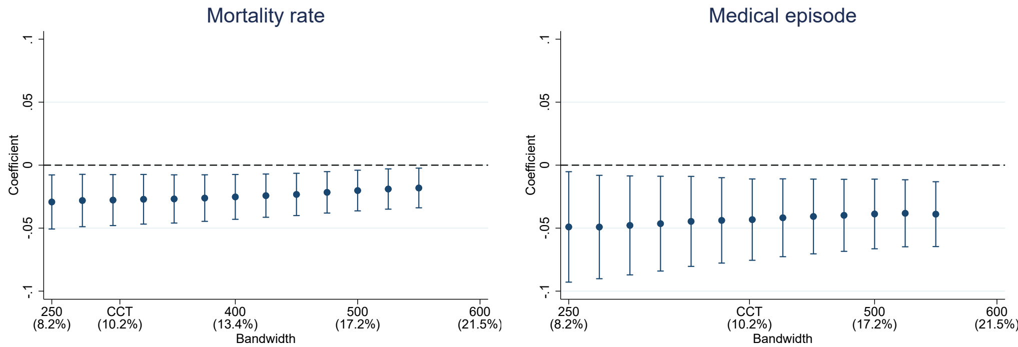


Figure E1. : Robustness of results for mortality and medical episodes using different bandwidths

Notes: Each graph shows the point estimate and the standard error of the ITT effect of the basic pension on applicants' mortality and medical episodes, using different bandwidths and all controls specified in regression Equation (1). 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, Cattaneo and Titiunik, 2014).

Finally, according to the power calculation method suggested by (Gelman and Carlin, 2014), our mortality estimate appears to be well powered. Previous estimates in the literature find that the median income effect size on elderly mortality is 2.2 pp. and the average effect size is 2.7 pp. (Jensen and Richter, 2003; Snyder and Evans, 2006; Salm, 2011; Barham and Rowberry, 2013; Cheng et al., 2016; Feeney, 2018).[1] In our power estimations, we use our standard error for the mortality effect (0.97 pp.) and a statistical significance threshold of 0.05 (Gelman and Carlin, 2014). Using these numbers, we obtain a power of 0.62 for the median average effect size (0.8 for the mean effect size). This is reassuring considering that problems with the exaggeration ratio (expectation of the absolute value of the estimate divided by the effect size) 'start to arise when power is less than 0.5, and problems with the Type S error rate [probability that the estimate has an incorrect sign if significant] start to arise when power is less than 0.1' ((Gelman and Carlin, 2014), p.643).

[1]The literature finds these mortality effect sizes using different income shocks, in different populations and historical periods. Keeping this caveat in mind, we prefer to use the face value of these estimates rather than adjusting them using an arbitrary criterion.

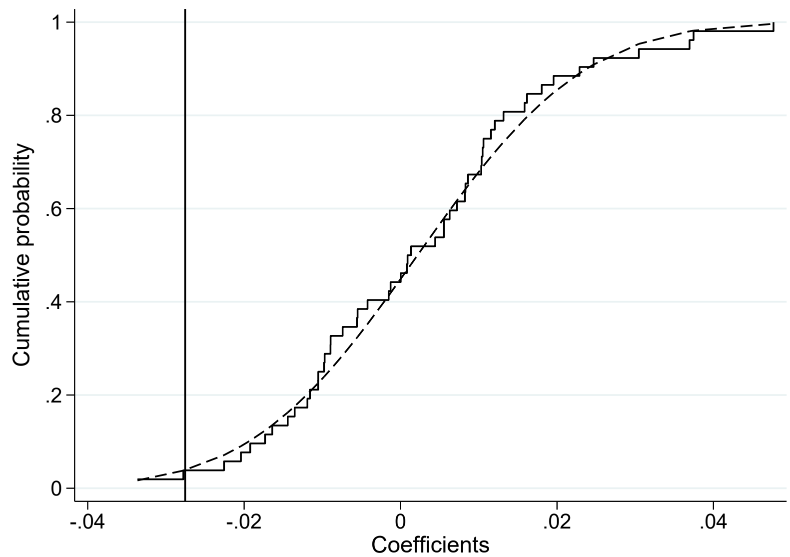


Figure E2. : Reduced-form effect of being below the cut-off on mortality: placebo estimates

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 the regression in Equation (1). Cut-offs are located every 25 points, starting from 306 (Calonico, Cattaneo and Titiunik's (2014) optimal bandwidth) up to 1606 score points, to make sure that we have observations in all points of the bandwidth. The cut-off is set at 1206 pension score points and the lowest pension score is zero. Therefore, 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.

APPENDIX F Spillover effects on applicants' household members

A Spillover results

This section provides 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 in a regression discontinuity design.

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. Therefore, to analyze spillover effects, we 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.

Table F1—: Health outcomes over four years from application: household members by age

Variables	TOT (1)	S.E. TOT (2)	ITT (3)	S.E. ITT (4)	P-value (5)	BW (6)	N (7)	Control (8)
Panel A: working-age household members								
% days hospitalized	0.012	(0.035)	0.012	(0.021)	0.575	500	8,047	0.100
Newborn child	0.024	(0.010)	0.017	(0.008)	0.035	500	8,047	0.033
Panel B: female household members of fertility age (16-40)								
% days hospitalized	0.007	(0.043)	-0.005	(0.033)	0.872	500	2,058	0.116
Newborn child	0.098	(0.036)	0.067	(0.028)	0.023	500	2,058	0.130
Panel C: elderly household members								
Mortality rate	0.012	(0.016)	0.011	(0.013)	0.397	500	5,722	0.125
% days hospitalized	0.060	(0.084)	0.026	(0.055)	0.635	500	5,722	0.274
Medical episode	0.061	(0.038)	0.045	(0.032)	0.164	500	5,722	0.376

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, deviation of the pension score from the cut-off, and the control variables specified in Equation (1). Column (1) reports the *treatment on the treated* coefficient as in Equation (4) and Column (2) reports its standard error computed using the delta method. Column (3) reports the *intent-to-treat* coefficient and Column (4) reports its standard error clustered at the province level. Column (5) reports the p-value of the ITT coefficient reported in Column (3). 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.

Panel A of Appendix Table F1 shows that working-age relatives of basic pension recipients do not see a change in the percentage of days spent in hospital. This is not surprising, considering that working-age relatives are young (40 years old on average) and are rarely hospitalized.[2] Panel C of this table shows that elderly household members were more likely to die than applicants (their average mortality rate, in column (7), is 12.5 percent), but this seems to be unaffected by having a relative who receives the basic pension.

Section IV.C shows that the household structure is a relevant determinant of the effect of the basic pension on recipients. One of the potential reasons is that families with a working-age household member pool income to different extents. To provide further evidence on the presence of intra-household transfers of income, we explore whether the fertility of working relatives living with recipients increases when pension payments begin. (Becker, 1960) suggests that children are normal goods, so their 'consumption' should increase when more income is available to

[2]Covariates seem to change smoothly at the cut-off for working-age and elderly household members. Panel A of Table G12 shows that 1 out of the 11 available covariates is significant for working-age household members. Panel B of Table G12 shows that 2 out of the 10 available covariates are statistically significant among elderly household members. Appendix Table G13 shows that adding covariates as controls does not change the results. Appendix Figure H11 also shows no discontinuity in the density of applicants' working-age household members (t-statistic of -0.013 and p-value of 0.999) or elderly household members (t-statistic of -1.576 and p-value of 0.115) at the cut-off.

parents. Panel A of Table F1 reveals that working-age relatives are 2.4pp. more likely to have a newborn child nine months after the pension application or later. As our data only identifies mothers and not fathers of newborn children, Panel B repeats the analysis focusing on fertility-age women (16-40 years of age) and estimate that they are 9.8 pp. more likely to have a newborn nine months after the application or later.[3] The ITT effect of the pension is a 6.7pp. increase (p-value=0.023) on the probability of having a newborn from a baseline probability of 13.0pp. Appendix Section F.B shows that fertility results remain statistically significant to a variety of robustness checks and are also in line with previous estimates in the literature.[4]

Our fertility results complement previous findings on 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, Case and Hosegood, 2009). The presence of spillover effects suggests that the benefits of pension policies could extend beyond the welfare of direct recipients and affect the life choices of younger generations.

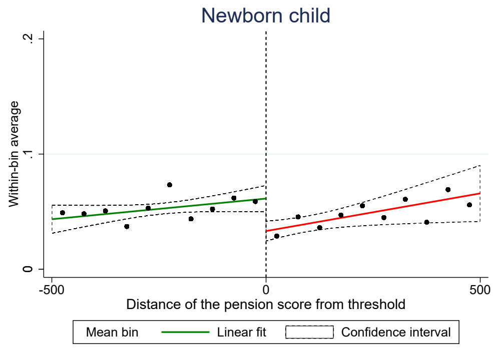
The significant *spillover* effect on the fertility rate of working-age household members, combined with the insignificant *direct* effect on recipients living with them, could be the result of intra-household transfers of income. As mentioned above, fertility is expected to increase when more income is available to parents (Becker, 1960).[5] On the one hand, working-age household members may have reduced their net transfers of income to applicants (current or expected future ones) after applicants started receiving the pension, and thus retained the necessary resources to raise a child. This would be consistent with previous evidence finding that social security benefits 'crowd out' 20%-30% of private transfers from younger generations to the elderly (Cox and Jimenez, 1992; Jensen, 2003), and the fact that a large fraction of recipients living with working-age relatives expect to finance their retirement with transfers from their children (see Section IV.C). 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, Case and Hosegood, 2009). This hypothesis would need to be reconciled with survey evidence showing that 82% of pension recipients do not share any money with their relatives or friends, and only 4% share more than one-fifth of their pension with others (Ministerio Trabajo y Previsión Social, 2017).

[3] Appendix Figure H12 shows no discontinuity in the density of applicants' fertility-age female household members (t-statistic of -1.131 and p-value of 0.258). Appendix Table G14 shows that there is no imbalance out of 9 available covariates for female household members of fertility age.

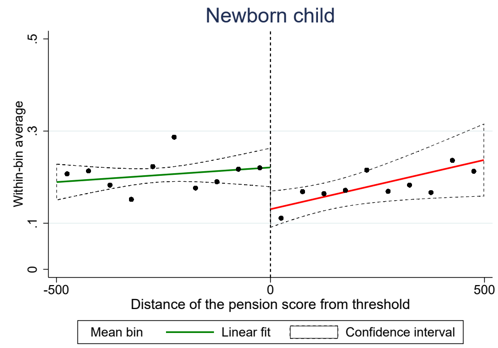
[4] According to our data, 49.9% of days spent in hospital by women of fertility age are due to pregnancy, childbirth and the puerperium. Hospitalizations for these reasons observe a significant increase if a family member receives a basic pension, in accordance with the positive effect on childbirth numbers. However, if we include days of hospitalization due to other causes, the estimation becomes less precise and we do not detect any significant effect. Results are available upon request.

[5] Alternatively, we could have considered working-age household relatives' consumption of other goods, such as food. Our administrative data does not contain consumption of these kinds of goods, and the EPS survey only contains household consumption without separating by household members.

(a) Working-age household members



(b) Female household members of fertility age



(c) Elderly household members

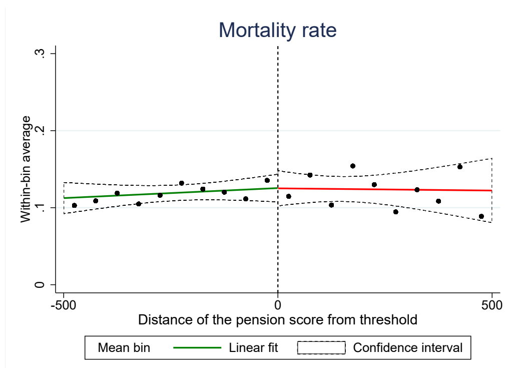


Figure F1. : Effect of the basic pension on mortality and fertility of household members

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.

Alternatively, receipt of the pension could reduce the cost of raising a child (for example, financially autonomous healthy grandmothers may be more able to accompany children to and from school) and increase fertility, as highlighted in the previous literature (D'Addio and d'Ercole, 2006; Kalwij, 2010; Liu et al., 2018). Even though we cannot separate the causes of our fertility results – an increase in income versus a decrease in the costs of child-raising – the latter does seem less relevant in our context, given that most pension recipients do not have any job to quit that might grant them more free time to provide support for their grandchildren (arguably the main cause of the reduction in child-raising costs).

B Robustness of fertility results

This section explores the robustness and timing of the spillover effects on fertility and situates them in the context of the literature. Tables G12 and G14 show 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 Tables G13 and G15 show that the results for working-age, female fertility-age, and elderly household members do not change when we use logistic regressions, non-parametric estimations, the optimal bandwidth approach proposed by (Calonico, Cattaneo and Titiunik, 2014), or different sets of controls, nor 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.

Figure F2, shows that the fertility result remains positive and significant when using different bandwidths. Additionally, we implement the randomization inference method proposed by (Cattaneo, Frandsen and Titiunik, 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 F3 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. Finally, fertility estimates remain significant when adjusting our p-values for multiple hypothesis testing, with an adjusted p-value = 0.03 (Romano and Wolf, 2005*a*,*b*).

Figure F4 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 the treatment effect on fertility starts accumulating over time.[6] 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.

[6] In Appendix Figure H13 we can see that the impact on fertility is not significant in the first year after the application, but it becomes evident since the second year after the application.

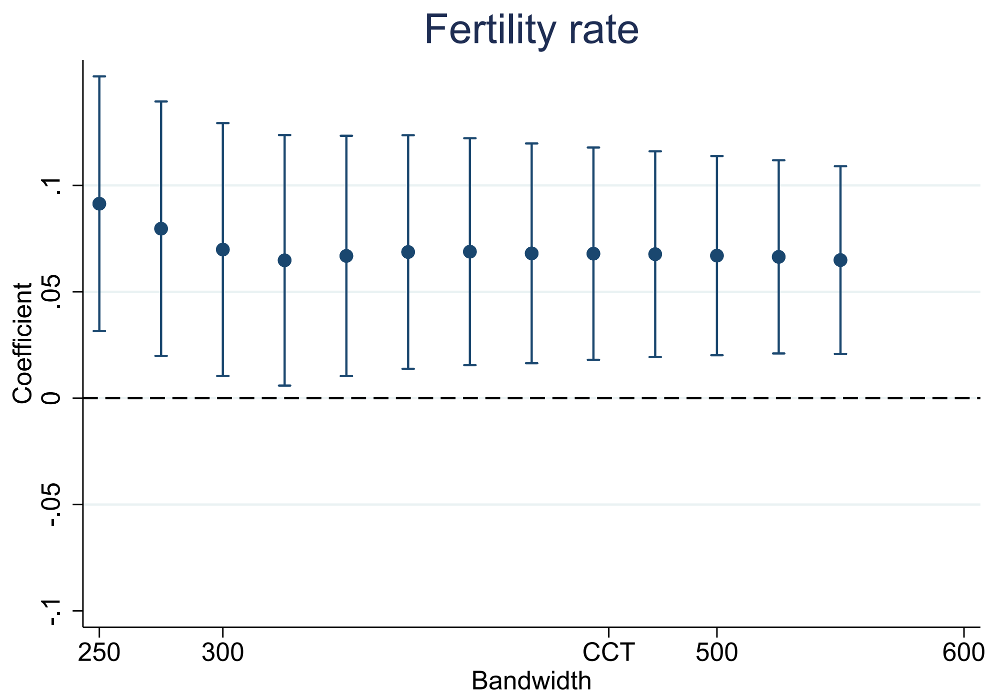


Figure F2. : Robustness of results for fertility using different bandwidths

Notes: This graph shows the point estimate and the standard error of the ITT effect of the basic pension on having a newborn child in the period from 9 months to 4 years after application for applicants' female household members of fertility age, using different bandwidths and all controls specified in regression Equation (1). The x-axis labels report the number of score points on each side of the bandwidth. CCT is the optimal bandwidth using the approach proposed by (Calonico, Cattaneo and Titiunik, 2014).

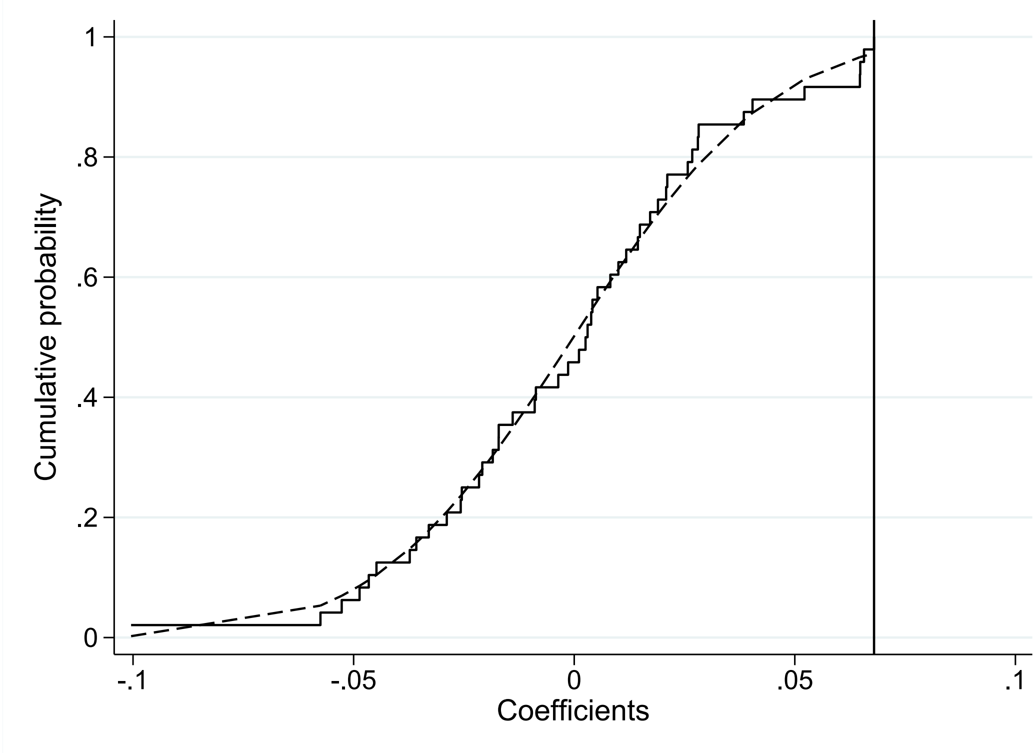


Figure F3. : Reduced-form effect of being below the cut-off on fertility: placebo estimates

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 regression Equation (1). Cut-offs are located every 25 score points, ranging from 456 (Calonico, Cattaneo and Titiunik's (2014) optimal bandwidth on fertility) to 1606, to ensure 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.

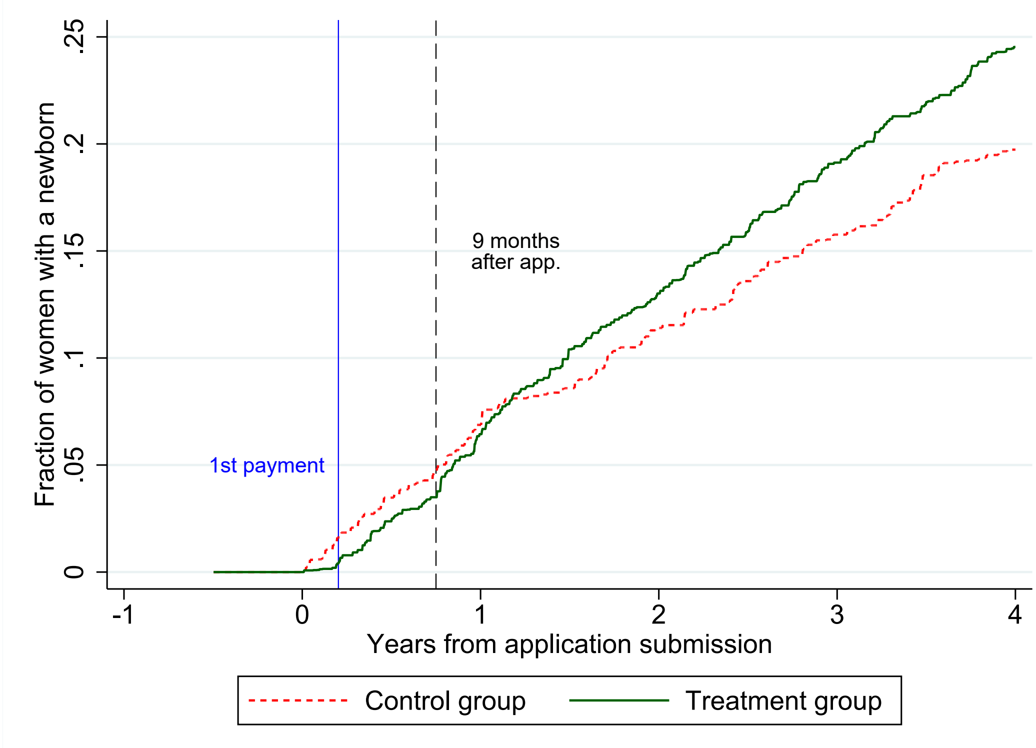


Figure F4. : Share of women of fertility age having a newborn between six months before applying and four years from date of application, adjusted by the deviation of the pension score from the cut-off.

Notes: This figure presents the share of women of fertility age that have a newborn in the treatment and control groups at each point in time following the first application. Shares are equal to $1 - \hat{S}(t)$, with $\hat{S}(t)$ being the $k_0(t)$ term in the Cox proportional hazard model: $k(t) = k_0(t)\exp(\beta_1 Score_h)$, with t being the time following the first application. Shares are estimated separately for the treatment and control groups in the 500 score-point bandwidth and using triangular weights.

C Discussion on the spillover effect on fertility

Following most of the literature, we estimate the income-fertility elasticity by dividing the ITT percentage change in newborns for women of fertility age by the ITT 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 0.7. Alternatively, if we use the mother's income rather than recipient's income, the income-fertility elasticity is 0.76.[7] Figure F5 shows that

[7]The probability of having a newborn increases by 51% (0.067/0.130) for women of fertility age living with a pension recipient at the cut-off. As the basic pension increases recipients' income by 72.4 percent,

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.[8] Our estimate is roughly in the middle of the range, but there is a considerable dispersion of fertility-income elasticities across studies.

the recipient's income-fertility elasticity is 0.7. For the estimate of mothers' income-fertility elasticity, we assumed perfect income pooling. In households with a woman of fertility age, the pension increases average monthly income per-capita by USD 26 over the four years following the first application, from an average monthly income of USD 34 for control group applicants. This leads to a mother income-fertility elasticity of 0.76. As before, these estimates take into account the full trajectory of income and are done using only first applicants from 2012.

[8]Children are generally considered 'normal goods' and their 'consumption' should increase with income. Our results, along with other recent empirical studies presented in Figure F5, 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)).

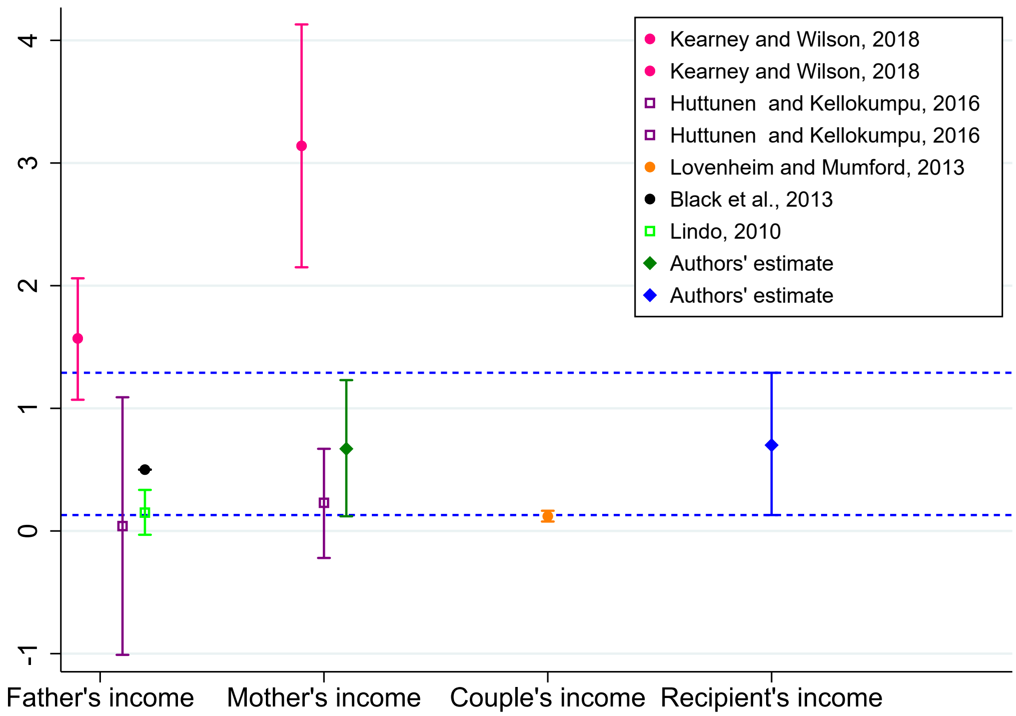


Figure F5. : Estimated income-fertility elasticity across different empirical studies

Notes: This graph plots point estimates and confidence intervals of income-fertility elasticity in different empirical studies. Empty squares indicate insignificant estimates. The dashed lines indicate the 95% 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. In several studies, it is not possible to calculate the income-fertility elasticity, because either baseline fertility or income are not reported. The confidence interval for (Black et al., 2013) is unavailable as the standard errors are not reported.

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).

APPENDIX G Additional tables

Table G1—: Characteristics of applicants, and their household members, at the moment of application and within 500 score points around the threshold

	Applicants (1)	Working-age household members (2)	Elderly household members (3)
Female	0.871	0.363	0.12
Age (years)	66.851	40.364	71.074
Social security score	9385.748	9576.395	9835.929
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
Child under 16	0.009	0.018	0.009
Days hospitalized	0.461	0.247	0.466
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	0.799		
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 for the 6 months before applicants submit their first application.

Table G2—: Balancing tests on other covariates (2012 only)

Variables	ITT Coef. (1)	S.E. (2)	t stat (3)	P-value (4)	BW (5)	N (6)	Control (7)
Panel A: household measures							
Total household income	0.833	(10.163)	0.082	0.935	500	4,066	649.7
Imputed income	-25.000	(12.083)	-2.069	0.044	500	4,066	93.40
Labor income	27.940	(36.573)	0.764	0.449	500	4,066	246.5
All incomes from assets	-27.11	(36.282)	-0.747	0.459	500	4,066	403.1
Labor income factor	-0.013	(0.024)	-0.562	0.577	500	4,066	1.939
Needs index (IN)	-0.032	(0.021)	-1.539	0.130	500	4,066	2.021
Net working salary	-4.596	(19.870)	-0.231	0.818	500	4,066	187.8
Other labor income	36.160	(30.979)	1.167	0.249	500	4,066	20.10
Net pension income	5.339	(18.848)	0.283	0.778	500	4,066	357.0
Avg. no. of students	-0.021	(0.016)	-1.258	0.214	500	4,066	0.070
Panel B: income of household members							
Applicants' income	-1.464	(11.615)	-0.126	0.900	500	4,066	89.37
Elderly relatives' inc.	-17.44	(21.819)	-0.799	0.428	500	2,769	525.2
Work.-age relatives' inc.	-4.775	(31.926)	-0.150	0.882	500	2,309	290.0
Fert. age woman's inc.	0.956	(12.432)	0.0770	0.939	500	828	20.90

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. 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 variable mean for control applicants at the cut-off. All income variables are expressed in 2012 US dollars.

Table G3—: Applicant's health outcomes over four years from application by gender

Variables	TOT (1)	S.E. TOT (2)	ITT (3)	S.E. ITT (4)	P-value (5)	BW (6)	N (7)	Control (8)
Panel A: female applicants								
Mortality rate	-0.028	(0.011)	-0.022	(0.008)	0.013	500	7,403	0.063
% days hospitalized	-0.034	(0.062)	-0.005	(0.048)	0.908	500	7,403	0.263
Medical episode	-0.068	(0.030)	-0.047	(0.021)	0.026	500	7,403	0.328
Panel B: male applicants								
Mortality rate	0.010	(0.052)	0.014	(0.037)	0.710	500	1,096	0.129
% days hospitalized	-0.144	(0.258)	-0.019	(0.138)	0.890	500	1,096	0.363
Medical episode	0.005	(0.117)	0.034	(0.079)	0.669	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, deviation of the pension score from the cut-off, and the control variables specified in Equation (1). Column (1) reports the *treatment on the treated* coefficient as in Equation (4) and Column (2) reports its standard error computed using the delta method. Column (3) reports the *intent-to-treat* coefficient and Column (4) reports its standard error clustered at the province level. Column (5) reports the p-value of the ITT coefficient reported in Column (3). 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 G4—: Balancing tests by household structure

Variables	ITT 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 relatives							
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	-0.270	(0.116)	-2.339	0.023	500	3,647	0.336
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	-48.82	(207.017)	-0.236	0.815	500	3,647	9640.
Elderly relative	-0.022	(0.019)	-1.180	0.244	500	3,647	0.892
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 relatives							
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	0.048	(0.099)	0.488	0.628	500	4,852	0.174
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	167.3	(255.827)	0.654	0.516	500	4,852	9823.
Elderly relative	0.043	(0.026)	1.646	0.106	500	4,852	0.528
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	151.0

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 variable mean for control applicants at the cut-off. Health covariates are computed for the 6 months before applying.

Table G5—: 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)	ITT Coef. (2)	S.E. ITT (3)	P-value (4)	BW (5)	N (6)
Mortality rate	No controls	-0.045	(0.016)	0.008	500	3,647
Mortality rate	Controls	-0.040	(0.015)	0.010	500	3,647
Mortality rate	Logit	-0.047	(0.015)	0.001	500	3,647
Mortality rate	Non-parametric	-0.045	(0.019)	0.021	500	3,647
Mortality rate	Optimal bandwidth	-0.050	(0.019)	0.010	374	2,704
Mortality rate	Quadratic	-0.065	(0.025)	0.013	500	3,647
Medical episode	No controls	-0.093	(0.036)	0.012	500	3,647
Medical episode	Controls	-0.086	(0.040)	0.036	500	3,647
Medical episode	Logit	-0.090	(0.037)	0.017	500	3,647
Medical episode	Non-parametric	-0.093	(0.034)	0.007	500	3,647
Medical episode	Optimal bandwidth	-0.116	(0.058)	0.053	294	2,124
Medical episode	Quadratic	-0.128	(0.066)	0.058	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, deviation of the pension score from the cut-off, and the control variables specified in Equation (1). Column (1) indicates the specification used. *No controls* reports estimates of a regression of the outcome variable on the treatment dummy indicator and deviation of the pension score from the cut-off, without further controls. *Controls* employs our preferred specification, polynomial of order 1 in $Score_h$, with the addition of the 17 other controls listed in Appendix Section D. *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, Cattaneo and Titiunik (2014). *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 G6—: 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)	ITT Coef. (2)	S.E. ITT (3)	P-value (4)	BW (5)	N (6)
Mortality rate	No controls	-0.001	(0.014)	0.954	500	4,852
Mortality rate	Controls	-0.004	(0.010)	0.679	500	4,852
Mortality rate	Logit	-0.002	(0.010)	0.810	500	4,852
Mortality rate	Non-parametric	-0.001	(0.013)	0.949	500	4,852
Mortality rate	Optimal bandwidth	-0.012	(0.012)	0.317	364	3,382
Mortality rate	Quadratic	-0.017	(0.017)	0.312	500	4,852
Medical episode	No controls	-0.000	(0.032)	0.998	500	4,852
Medical episode	Controls	0.001	(0.038)	0.985	500	4,852
Medical episode	Logit	0.000	(0.036)	0.994	500	4,852
Medical episode	Non-parametric	0.000	(0.035)	0.990	500	4,852
Medical episode	Optimal bandwidth	-0.000	(0.035)	0.997	506	4,924
Medical episode	Quadratic	0.008	(0.053)	0.874	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, deviation of the pension score from the cut-off, and the control variables specified in Equation (1). Column (1) indicates the specification used. *No controls* reports estimates of a regression of the outcome variable on the treatment dummy indicator and deviation of the pension score from the cut-off, without further controls. *Controls* employs our preferred specification, polynomial of order 1 in $Score_h$, with the addition of the 17 other controls listed in Appendix Section D. *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, Cattaneo and Titiunik (2014). *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 G7—: Medical episodes by cause over four years from application

Variables	TOT (1)	S.E. TOT (2)	ITT (3)	S.E. (4)	P-value (5)	BW (6)	N (7)	Control (8)
Panel A: applicants								
Circulatory	0.013	(0.016)	0.011	(0.012)	0.376	500	8,499	0.076
Respiratory	-0.030	(0.011)	-0.019	(0.008)	0.019	500	8,499	0.044
Tumour	-0.028	(0.015)	-0.021	(0.011)	0.067	500	8,499	0.054
Digestive or nutritional	-0.025	(0.016)	-0.020	(0.012)	0.097	500	8,499	0.098
Accidents	-0.002	(0.003)	-0.001	(0.002)	0.548	500	8,499	0.002
Panel B: applicants not living with a working-age household member								
Circulatory	-0.017	(0.026)	-0.011	(0.019)	0.544	500	3,647	0.099
Respiratory	-0.045	(0.012)	-0.031	(0.009)	0.001	500	3,647	0.050
Tumour	-0.048	(0.018)	-0.036	(0.014)	0.014	500	3,647	0.058
Digestive or nutritional	-0.009	(0.033)	-0.008	(0.026)	0.756	500	3,647	0.091
Accidents	0.002	(0.004)	0.001	(0.003)	0.600	500	3,647	0.001

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, deviation of the pension score from the cut-off, and the control variables specified in Equation (1). Column (1) reports the *treatment on the treated* coefficient as in Equation (4) and Column (2) reports its standard error computed using the delta method. Column (3) reports the *intent-to-treat* coefficient and Column (4) reports its standard error clustered at the province level. Column (5) reports the p-value of the ITT coefficient reported in Column (3). 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 G8—: Vaccinations received in the four years after applying for applicants and applicants by household structure

Variables	TOT (1)	S.E. TOT (2)	ITT (3)	S.E. ITT (4)	P-value (5)	BW (6)	N (7)	Control (8)
Panel A: applicants								
Influenza vaccine	0.010	(0.037)	-0.001	(0.025)	0.960	500	8,499	0.679
Pneumonia vaccine	0.027	(0.034)	0.009	(0.024)	0.721	500	8,499	0.306
Panel B: applicants not living with working-age household members								
Influenza vaccine	-0.001	(0.043)	-0.005	(0.031)	0.870	500	3,647	0.687
Pneumonia vaccine	0.008	(0.034)	-0.005	(0.025)	0.848	500	3,647	0.301
Panel C: applicants living with a working-age household members								
Influenza vaccine	0.012	(0.040)	-0.003	(0.026)	0.909	500	4,852	0.673
Pneumonia vaccine	0.040	(0.043)	0.019	(0.029)	0.510	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, deviation of the pension score from the cut-off, and the control variables specified in Equation (1). Column (1) reports the *treatment on the treated* coefficient as in Equation (4) and Column (2) reports its standard error computed using the delta method. Column (3) reports the *intent-to-treat* coefficient and Column (4) reports its standard error clustered at the province level. Column (5) reports the p-value of the ITT coefficient reported in Column (3). 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 G9—: Characteristics of basic pension applicants when aged between 60 and 64

Variables	Recipients (1)	Non-recipients (2)	Difference (3)	P-value (4)
Panel A: individual level variables				
Private health insurance	0.017	0.018	-0.001	0.991
Informal work	0.156	0.228	-0.072	0.252
Visited a GP	0.589	0.655	-0.066	0.331
Visited a health center	0.769	0.793	-0.024	0.695
Visits to health center	11.097	8.862	2.235	0.174
Bad Health	0.220	0.276	-0.056	0.432
Smoked, last month	0.163	0.163	0.000	0.998
Number of cigarettes, last month	32.413	54.102	-21.689	0.437
Drunk alcohol, last month	0.106	0.265	-0.159	0.026
Number of drinks, last month	0.884	1.673	-0.790	0.077
Panel B: household income and expenditure in 2012 US dollars				
Monthly income	475.663	552.012	-76.349	0.380
Total expenditure	356.933	446.101	-89.168	0.075
Food	192.412	227.491	-35.079	0.212
Clothes	17.713	19.192	-1.479	0.742
Utilities	90.335	128.805	-38.47	0.086
Transport	30.082	40.699	-10.617	0.226
Domestic services	0.686	2.182	-1.496	0.354
Drugs	26.804	23.549	3.255	0.643
Children's education	10.445	4.995	5.451	0.119

Notes: This table reports the mean of the listed covariates for basic pension applicants at age 60-64. Column (1) reports means for applicants who eventually obtained the pension. Column (2) reports means for applicants who did not obtain the pension. Column (3) reports the difference between columns (1) and (2). Column (4) reports the p-value of a test of means differences between column (1) and (2). 'Visited a health center' is a dummy variable for whether the individual had at least one appointment at a health center in the last two years. Income and expenditure variables are reported in 2012 US dollars. 'Total expenditure' refers to the sum of the expenditures reported in the table. Data is from the panel survey conducted in 2004, 2006, 2009, 2012, and 2015 by the Ministry of Labor.

Table G10—: Characteristics of Chileans who are aged 65 or over and do not have a contributory pension

	All (1)	Basic pension recipients (2)	Basic pension non-recipients (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)
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.

Table G11—: 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)	ITT Coef. (2)	S.E. ITT (3)	P-value (4)	BW (5)	N (6)
Mortality rate	No controls	-0.021	(0.010)	0.034	500	8,499
Mortality rate	Controls	-0.019	(0.010)	0.058	500	8,499
Mortality rate	Logit	-0.018	(0.009)	0.055	500	8,499
Mortality rate	Non-parametric	-0.021	(0.010)	0.045	500	8,499
Mortality rate	Optimal bandwidth	-0.028	(0.012)	0.029	306	5,048
Mortality rate	Quadratic	-0.035	(0.015)	0.021	500	8,499
Medical episode	No controls	-0.042	(0.018)	0.024	500	8,499
Medical episode	Controls	-0.037	(0.016)	0.029	500	8,499
Medical episode	Logit	-0.038	(0.016)	0.020	500	8,499
Medical episode	Non-parametric	-0.042	(0.023)	0.071	500	8,499
Medical episode	Optimal bandwidth	-0.043	(0.020)	0.033	398	6,605
Medical episode	Quadratic	-0.050	(0.027)	0.077	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, deviation of the pension score from the cut-off, and the control variables specified in Equation (1). Column (1) indicates the specification used. *No controls* reports estimates of a regression of the outcome variable on the treatment dummy indicator and deviation of the pension score from the cut-off, without further controls. *Controls* employs our preferred specification, polynomial of order 1 in $Score_h$, with the addition of the 17 other controls listed in Appendix Section D. *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, Cattaneo and Titiunik (2014). *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 G12—: Balancing tests for working-age and elderly relatives

Variables	ITT Coef. (1)	S.E. (2)	t-stat (3)	P-value (4)	BW (5)	N (6)	Control (7)
Panel A: working-age relatives							
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	-0.026	(0.033)	-0.794	0.431	500	8,047	0.094
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	9857
Elderly relative	0.047	(0.026)	1.767	0.084	500	4,836	0.525
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	150.1
Panel B: elderly relatives							
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	-0.022	(0.048)	-0.454	0.652	500	5,722	0.171
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	1.0e+
Working-age relative	0.027	(0.024)	1.147	0.257	500	5,566	0.412
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 variable mean for control applicants at the cut-off. Health covariates are computed for the 6 months before applying.

Table G13—: 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)	ITT Coef. (2)	S.E. ITT (3)	P-value (4)	BW (5)	N (6)
Panel A: working-age household members						
% days hospitalized	No controls	0.009	(0.023)	0.685	500	8,047
% days hospitalized	Controls	0.032	(0.030)	0.291	500	8,047
% days hospitalized	Logit	0.005	(0.019)	0.788	500	8,047
% days hospitalized	Non-parametric	0.009	(0.033)	0.781	500	8,047
% days hospitalized	Optimal bandwidth	0.014	(0.030)	0.649	260	3,889
% days hospitalized	Quadratic	0.028	(0.044)	0.528	500	8,047
Newborn child	No controls	0.028	(0.007)	0.000	500	8,047
Newborn child	Controls	0.016	(0.008)	0.050	500	8,047
Newborn child	Logit	0.057	(0.026)	0.034	500	8,047
Newborn child	Controls	0.016	(0.008)	0.050	500	8,047
Newborn child	Non-parametric	0.028	(0.007)	0.000	500	8,047
Newborn child	Optimal bandwidth	0.017	(0.008)	0.043	452	7,185
Newborn child	Quadratic	0.019	(0.010)	0.059	500	8,047
Panel B: elderly household members						
Mortality rate	No controls	0.000	(0.013)	0.979	500	5,722
Mortality rate	Controls	0.012	(0.013)	0.379	500	5,722
Mortality rate	Logit	0.011	(0.012)	0.371	500	5,722
Mortality rate	Non-parametric	0.000	(0.015)	0.981	500	5,722
Mortality rate	Optimal bandwidth	0.009	(0.015)	0.547	402	4,596
Mortality rate	Quadratic	0.008	(0.020)	0.672	500	5,722
Medical episode	No controls	0.034	(0.030)	0.256	500	5,722
Medical episode	Controls	0.047	(0.033)	0.158	500	5,722
Medical episode	Logit	0.045	(0.032)	0.155	500	5,722
Medical episode	Non-parametric	0.034	(0.027)	0.208	500	5,722
Medical episode	Optimal bandwidth	0.047	(0.042)	0.268	407	4,657
Medical episode	Quadratic	0.062	(0.062)	0.320	500	5,722

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, deviation of the pension score from the cut-off, and the control variables specified in Equation (1). Column (1) indicates the specification used. *No controls* reports estimates of a regression of the outcome variable on the treatment dummy indicator and deviation of the pension score from the cut-off, without further controls. *Controls* employs our preferred specification, polynomial of order 1 in $Score_h$, with the addition of the 17 other controls listed in Appendix Section D. *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, Cattaneo and Titiunik (2014). *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 G14—: Balancing tests for fertility-age female relatives

Variables	ITT Coef. (1)	S.E. (2)	t-stat (3)	P-value (4)	BW (5)	N (6)	Control (7)
Age (years)	-0.446	(0.466)	-0.958	0.343	500	2,058	29.58
% days hospitalized	0.000	(0.051)	0.006	0.995	500	2,058	0.103
Influenza vaccination	-0.013	(0.025)	-0.507	0.615	500	2,058	0.101
Newborn child	0.018	(0.018)	1.017	0.315	500	2,058	0.026
Household size	0.103	(0.175)	0.588	0.560	500	2,058	3.883
Social security score	396.901	(257.480)	1.541	0.130	500	2,058	9272.
Elderly relative	0.004	(0.057)	0.073	0.942	500	2,058	0.661
Child under 16	0.011	(0.016)	0.719	0.476	500	2,058	0.015
Municipal income	-17.838	(11.340)	-1.573	0.123	500	2,057	154.4

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 variable mean for control applicants at the cut-off. Health covariates are computed for the 6 months before applying.

Table G15—: Fertility rate of fertility-age female family members 9 months or later after application using non-parametric estimations, different controls, optimal bandwidth and quadratic functional form in $Score_h$

Variables	Regression (1)	ITT Coef. (2)	S.E. ITT (3)	P-value (4)	BW (5)	N (6)
Newborn child	No controls	0.091	(0.028)	0.002	500	2,058
Newborn child	Controls	0.052	(0.027)	0.062	500	2,058
Newborn child	Logit	0.068	(0.029)	0.020	500	2,058
Newborn child	Non-parametric	0.091	(0.029)	0.002	500	2,058
Newborn child	Optimal bandwidth	0.068	(0.030)	0.029	456	1,869
Newborn child	Quadratic	0.080	(0.034)	0.025	500	2,058

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, deviation of the pension score from the cut-off, and the control variables specified in Equation (1). Column (1) indicates the specification used. *No controls* reports estimates of a regression of the outcome variable on the treatment dummy indicator and deviation of the pension score from the cut-off, without further controls. *Controls* employs our preferred specification, polynomial of order 1 in $Score_h$, with the addition of the 17 other controls listed in Appendix Section D. *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, Cattaneo and Titiunik (2014). *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.

APPENDIX H Additional figures

Figure H1. : 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.

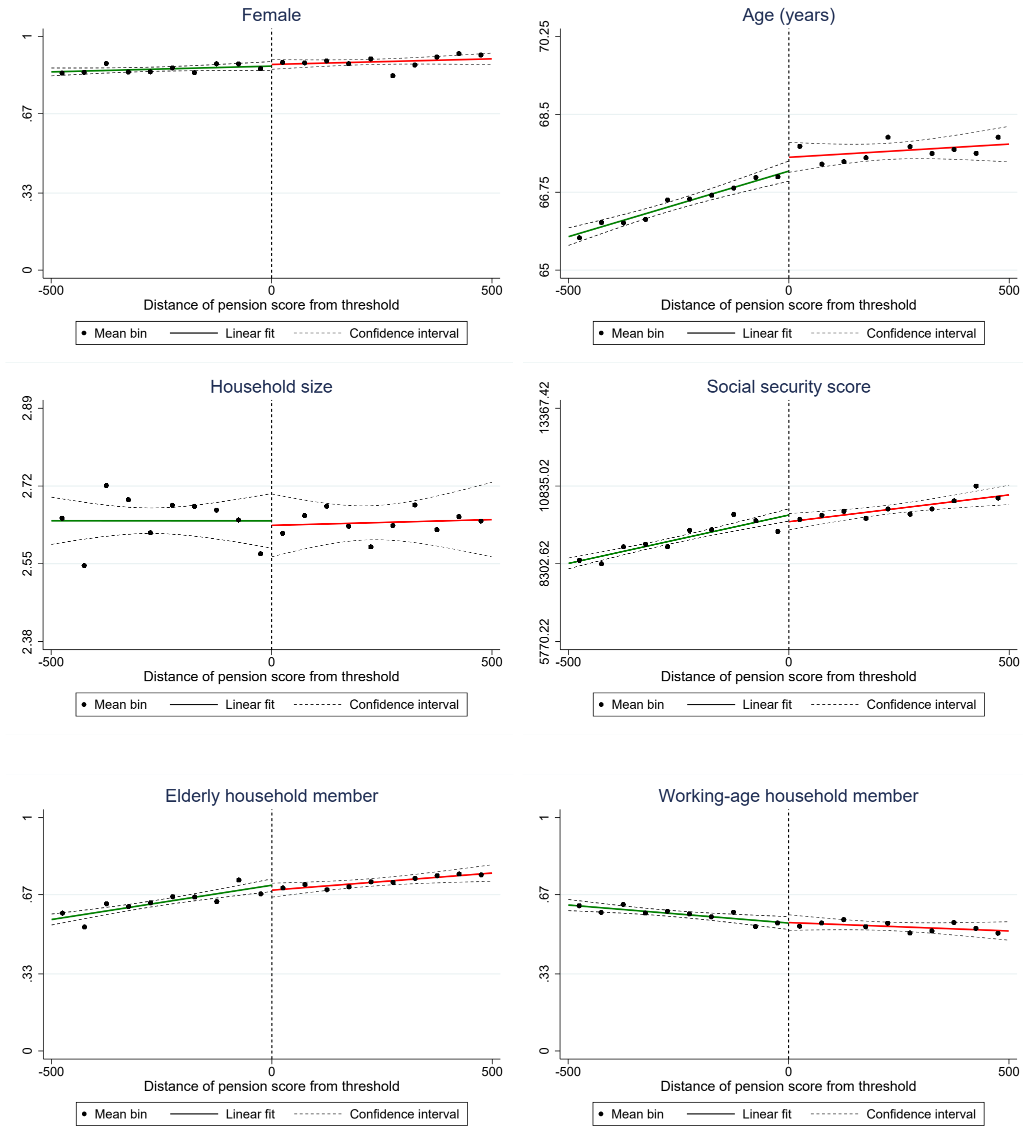


Figure H2. : Pre-determined covariates. RD plots, applicants

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.

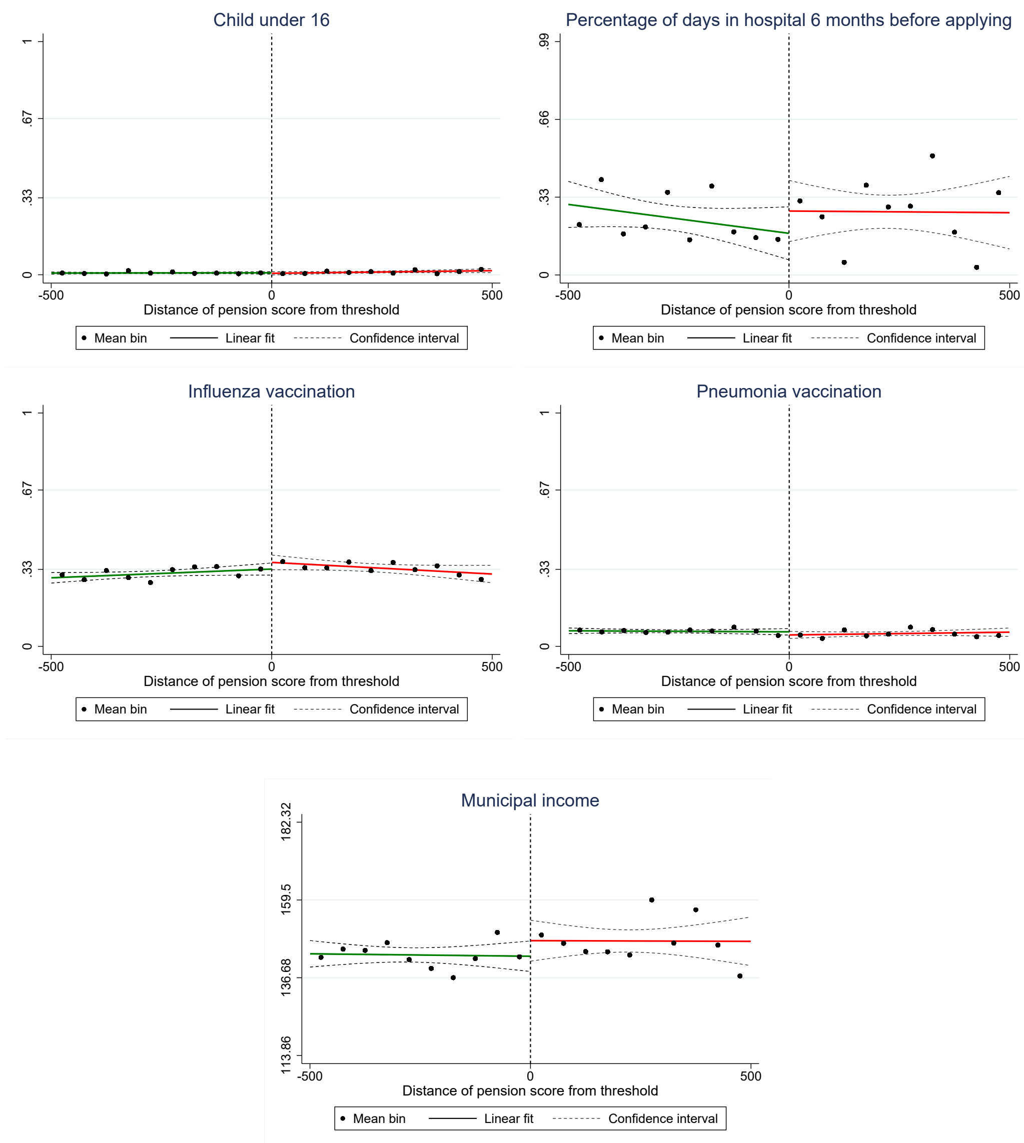


Figure H3. : Pre-determined covariates. RD plots, applicants

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.

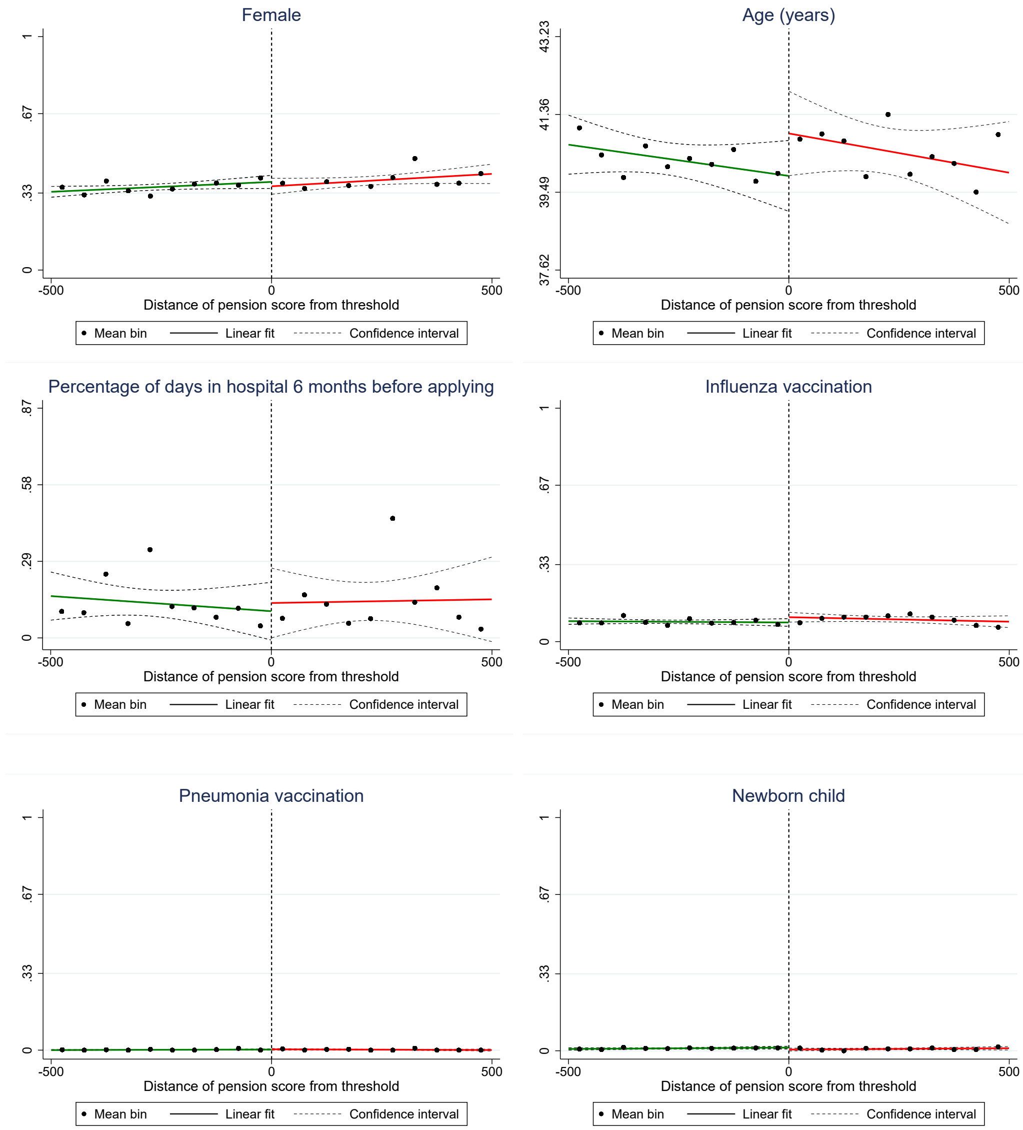


Figure H4. : Pre-determined covariates. RD plots, working-age household members

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.

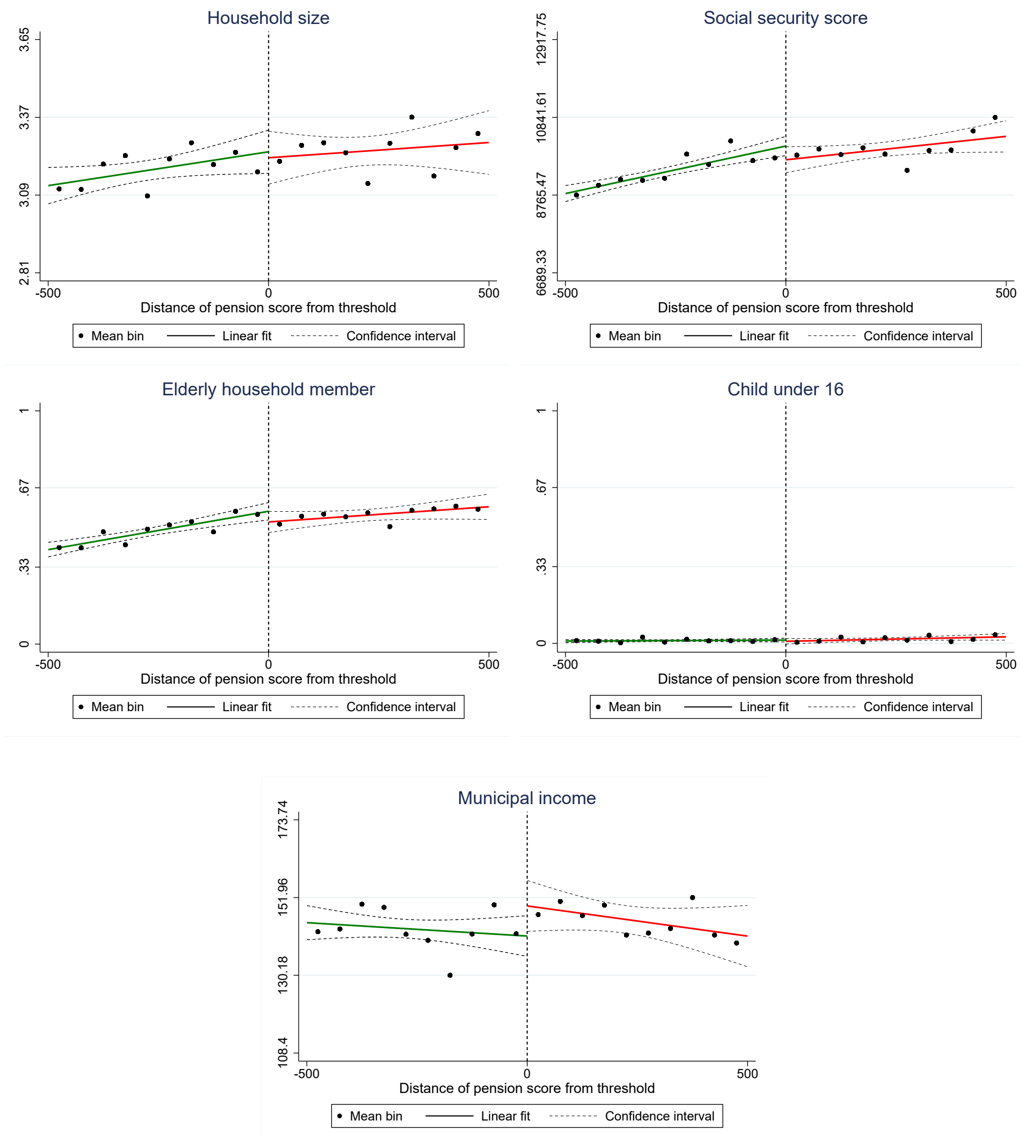


Figure H5. : Pre-determined covariates. RD plots, working-age household members

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.

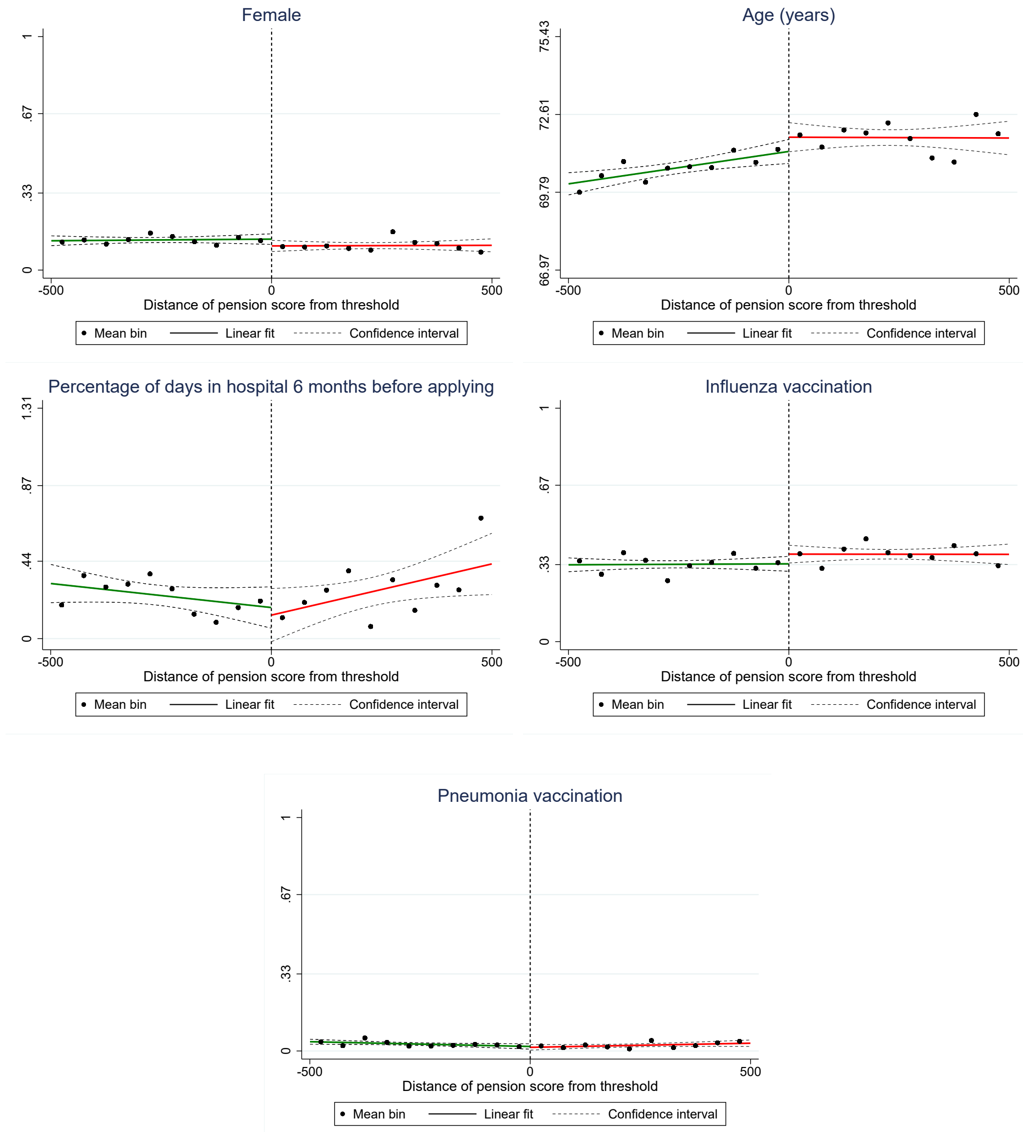


Figure H6. : Pre-determined covariates. RD plots, elderly household members

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.

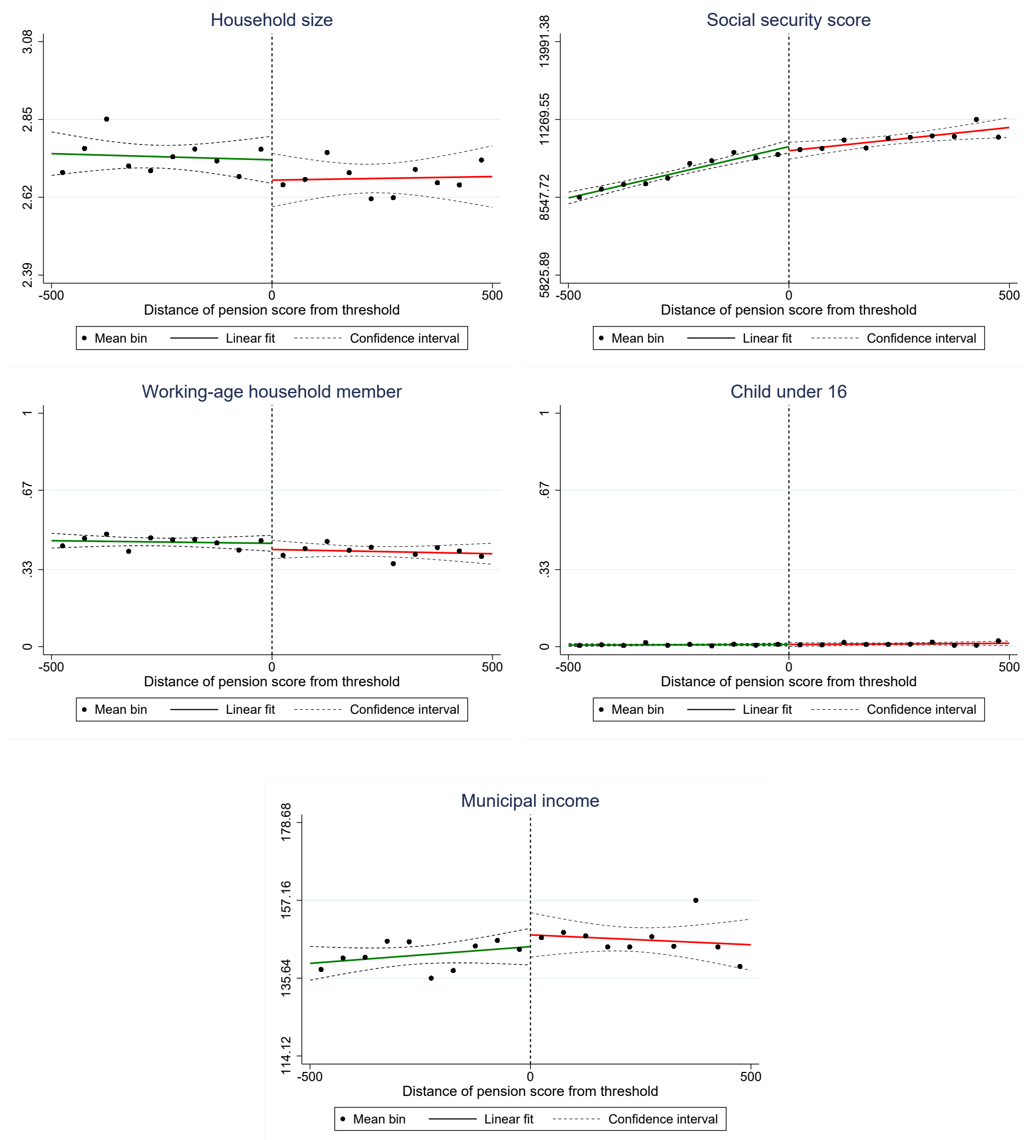


Figure H7. : Pre-determined covariates. RD plots, elderly household members

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.

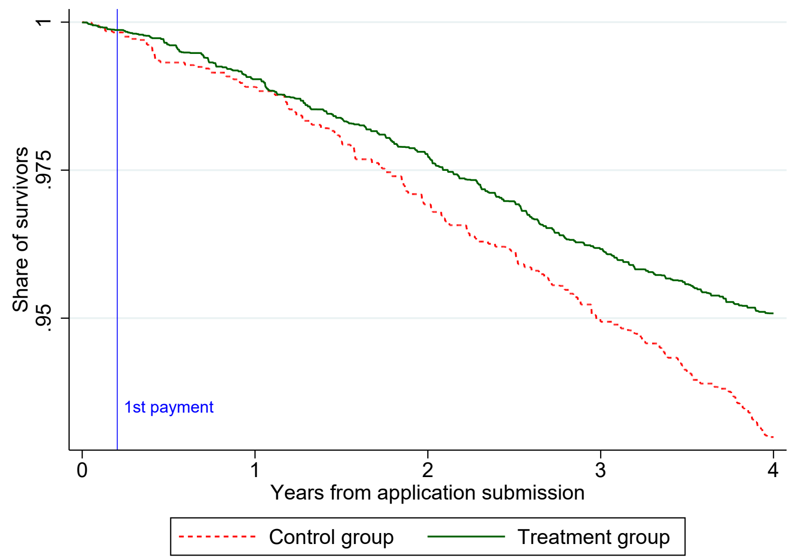


Figure H8. : Share of surviving applicants over 4 years from date of application, adjusted by the deviation of pension score from the cut-off.

Notes: This figure presents the share of survivors in the treatment and control groups at each point in time following the first application. Survival rates are equal to $1 - \hat{S}(t)$, with $\hat{S}(t)$ being the $k_0(t)$ term in the Cox proportional hazard model: $k(t) = k_0(t)\exp(\beta_1 Score_h)$, with t being the time elapsed after the first application. Survival rates are estimated separately for the treatment and control groups in the 500 score-point bandwidth and using triangular weights.

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

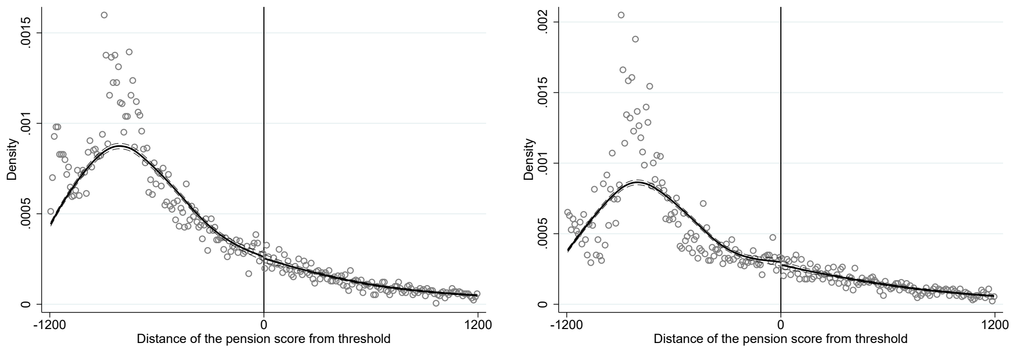


Figure H9. : McCrary tests by household structure

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.

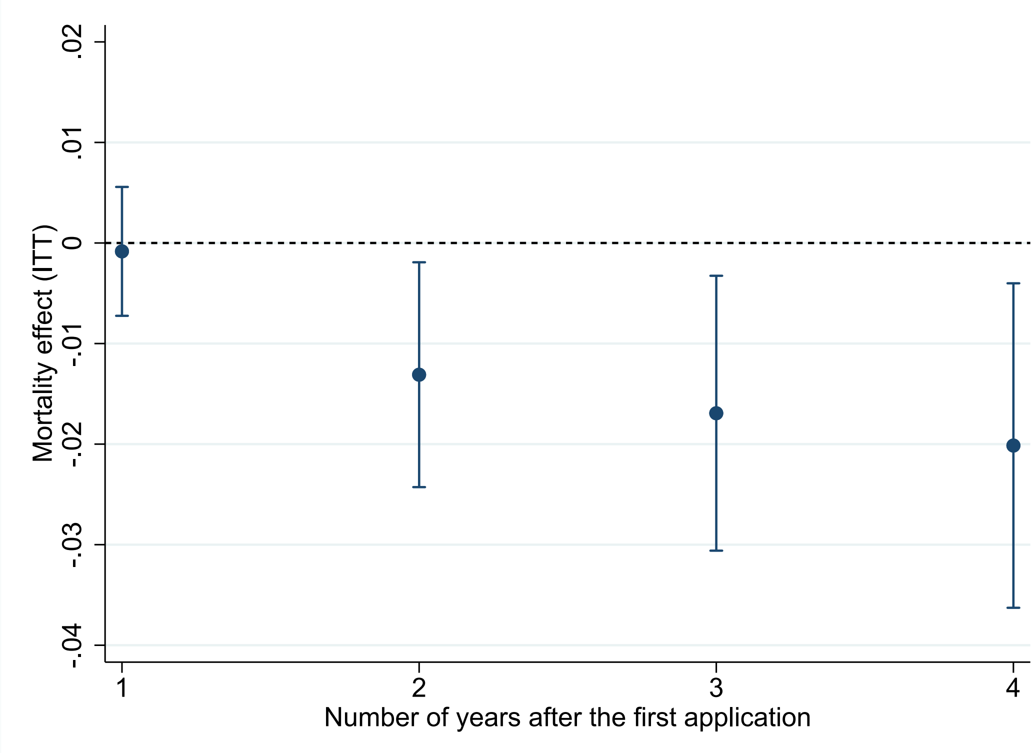


Figure H10. : Mortality by year

Notes: This graph represents the point estimate and 90% confidence intervals of the ITT effect of the basic pension on applicants' mortality in each of the four years observed after the first application.

(a) Working-age household members (b) Elderly household members

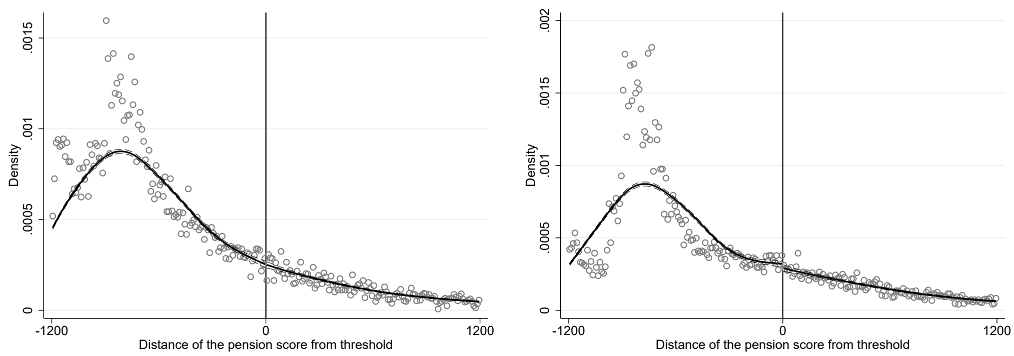


Figure H11. : McCrary tests of working-age and elderly household members

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.

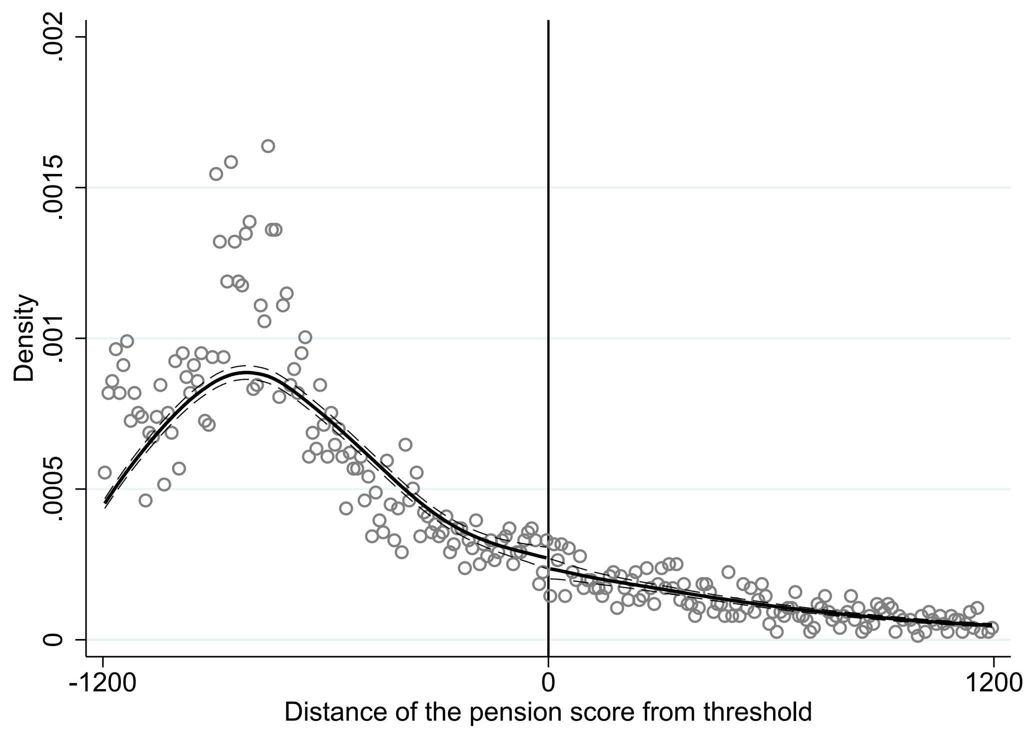


Figure H12. : McCrary test on female fertility-age household members

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.

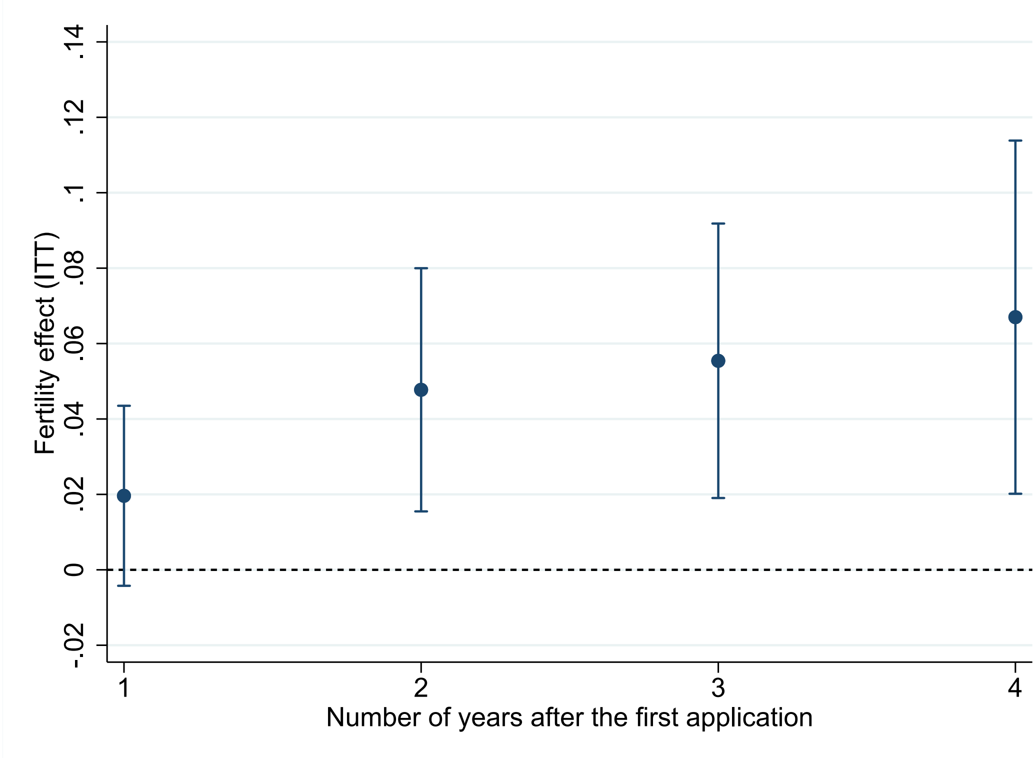


Figure H13. : Fertility by year

Notes: This graph represents the point estimate and 90% confidence intervals of the ITT effect of the basic pension on the probability of having a child for a female fertility-age family member of an applicant in each of the four years observed after the first application.

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