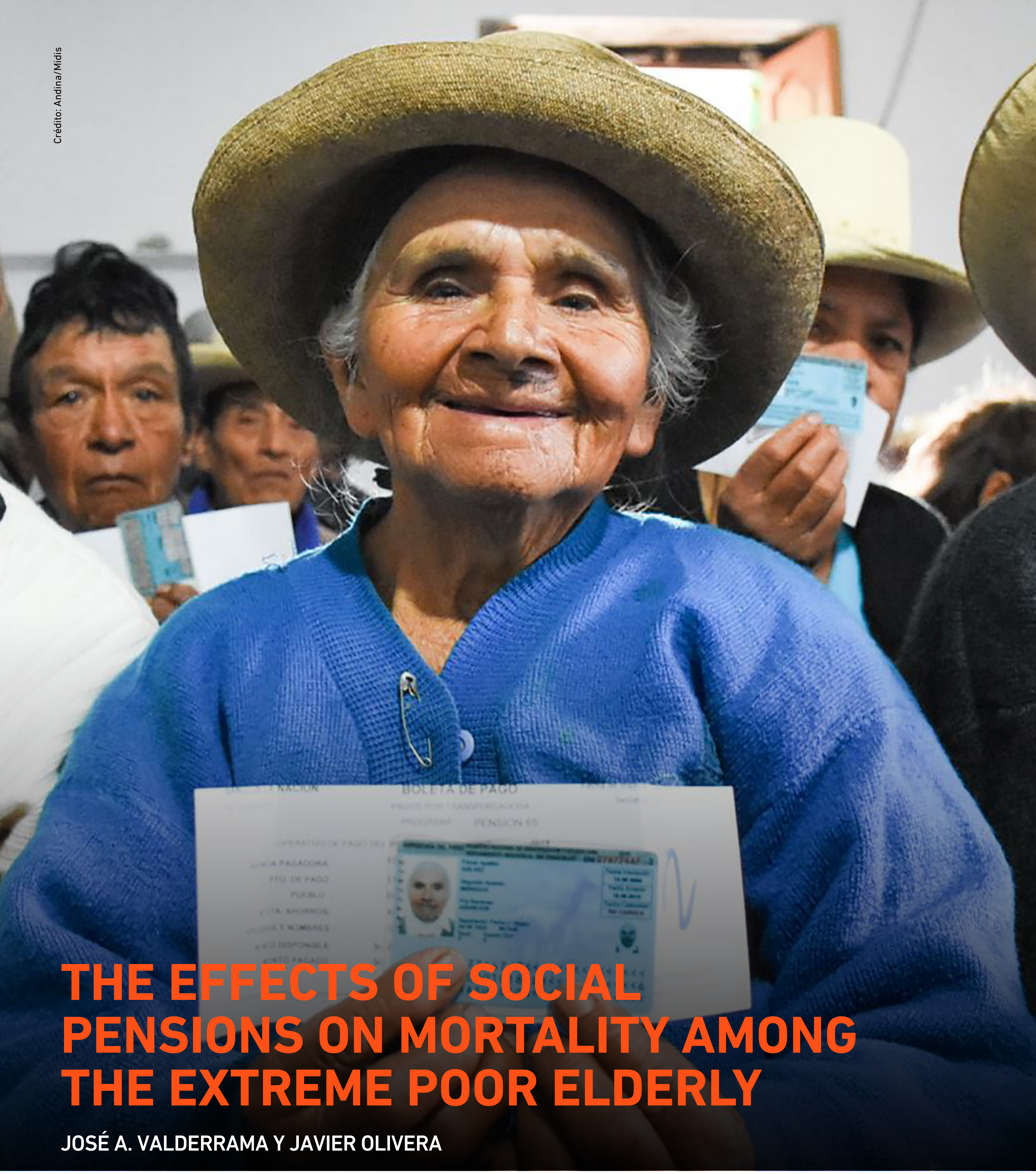

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THE EFFECTS OF SOCIAL PENSIONS ON MORTALITY AMONG THE EXTREME POOR ELDERLY

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The effects of social pensions on mortality among the extreme poor elderly*

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Abstract

We studied the effects that Peru's social pension programme, *Pensión 65,* had on mortality. The programme provides pensions to people aged 65 and older who do not have other pension benefits and are extreme poor. The analysis relies on survey data obtained at the baseline and matched to mortality records of 2012-2019. We exploited the discontinuity around the welfare index used by the programme to determine eligibility, and estimate intention-to-treat effects. We found that, after seven years, the programme could reduce mortality among eligible people by about 11.4 percentage points, implying an increase in life expectancy of about one year.

Keywords: non-contributory pensions, mortality, regression discontinuity, old-age poverty.
JEL-classification: H55, J14, I38.

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1 Introduction

Social security participation is low in developing countries, mostly due to the existence of large informal labour markets and the high predominance of precarious jobs in which pension and health contributions are not compulsory. As populations are rapidly becoming older in these countries, a popular solution for governments has been the establishment of social pension programmes providing pension transfers unrelated to histories of social security contributions. These schemes, also known as non-contributory pension (NCP) programmes, provide monetary transfers targeted at the elderly poor (although some are universal) who do not have contributory pensions and have reached retirement age. The transfer amounts tend to be small relative to the national average income or GDP per capita, but they are not trivial for the eligible elderly poor (Huang and Zhang, 2021).

There is an important body of literature studying the effects of social pensions in low and middle-income countries, although more attention has been paid to labour and economic outcomes and less to health and welfare domains. Some distinctive pension programmes that have been widely studied are those implemented in South Africa (Duflo, 2000; Case and Deaton, 2001; Duflo, 2003), Brazil (Barrientos et al., 2003; de Carvalho-Filho, 2008) and Mexico (Aguila et al., 2015; Juarez and Pfutze, 2015). As these pensions are granted late in life— that is, when people are more fragile and health deteriorates quickly—they could contribute to the survival of individuals via well-known income effects on life expectancy. Indeed, keeping people alive is an important outcome for public intervention, let alone that it is a truly objective health outcome at advanced ages.[1]

In this paper, we study the causal effects of Peru's non-contributory pension programme, *Pensión 65*, on elderly mortality. The programme provides a pension equivalent to 125 soles per month, equivalent to approximately 32 US dollars, or 13% of the official minimum wage in 2021. Although this amount may seem low, it could be important among the poor. For example, the transfer represents 62% of the national extreme poverty line in 2021 (or 33% of the national poverty line). We exploit a survey fielded in 2012, intentionally designed to apply a Regression Discontinuity Design (RDD) to uncover the causal effects of the programme. We match this to administrative records for the programme and mortality statistics from population registers for the 2012-2019 period.

Evidence regarding the effects of social pensions on mortality is limited and mixed. In developed economies, for example, Balan-Cohen (2008) found that the Old Age Assistance (OAA) programme in the US was associated with a sizeable decrease in male mortality over the age of 64 after 1940. By contrast, Stoian and Fishback (2010) found that this programme had no signifi

[1]In general, the positive association between income and health is well established in the literature (see, for instance Case et al., 2002; Deaton, 2002; Gerdtham and Johannesson, 2004; Smith, 2007; Smith and Goldman, 2007; Von Gaudecker and Scholz, 2007; Belloni et al., 2013), but the literature is less extensive when it comes to identifying causal effects of income on health (see, for instance Smith, 1998; Deaton and Paxson, 1998; Smith, 1999; Lenhart, 2019).

cant impact on American urban mortality rates before 1940. For Canada, Emery and Matheson (2012) found that a means-tested social pension programme had no impact on the mortality of people aged 65-69, but they did find that the universal social pension programme for people aged 70 and above (Old Age Security, OAS) reduced mortality by 4.2%.[2]

With regard to studies focusing on low or middle-income countries, Cheng et al. (2018) report very modest evidence for the long-term effects of China's New Rural Pension Scheme (NRPS) programme on mortality risk, whereas Huang and Zhang (2021) find a mortality-income elasticity of -0.38 for the same programme based on 1-year mortality. For Chile's social pension programme, *Pensión Básica*, Miglino et al. (2023) find an elasticity of -0.386 based on 4-year mortality. For Mexico's social programme, *Progresa*, Barham and Rowberry (2013) find an elasticity of -0.18 based on 1-year mortality for elderly individuals, while Jensen and Richter (2004) find an elasticity of -0.244 based on 2-year mortality for male pensioners aged 60 in Russia who suffered from pension arrears.

The *Pensión 65* programme gives a lifetime pension to people aged 65 and above who do not have any other pension benefits and reside in a household classified as extreme poor by the national targeting system, SISFOH. This classification is based on a continuous welfare index (the SISFOH score) given to households and compared with cutoff points determining three groups: extreme poor, non-extreme poor and non-poor. To estimate the causal effect of the programme on mortality, we exploit a discontinuity resulting from the eligibility rule of the SISFOH index on a sample of just eligible (extreme poor) and just ineligible (non-extreme poor) individuals, located each side of and very close to the eligibility threshold. We provide evidence rejecting the manipulation of the SISFOH score and argue that the eligibility condition is as if we were to randomly allocate treatment and control conditions locally around the threshold of eligibility. We estimate the intention-to-treat (ITT) effect of the programme and find that the 7-year mortality rate of eligible individuals is reduced by 11.4 percentage points, implying a substantial reduction of 56.7% with respect to the mortality rate of ineligible individuals at the eligibility threshold.

This result is robust to various checks, including the addition of pre-treatment health conditions, nutrition quality and objective markers such as anaemia, hypertension and anthropometric measurements associated with mortality risk. The mortality effect holds under different bandwidths, observation periods, model specifications (including the assessment of the hazard ratio of mortality rate in survival models), polynomial orders and various other robustness, falsification and validation tests. Relying on mortality parametric functions, we estimate that the programme could potentially increase the life expectancy of eligible individuals by about a year. This is a very important policy result for an income transfer programme. The cost-benefit analysis reveals that the cost for increasing life expectancy is well below (about 19-30%) the estimates of the value of a statistical life. Thus, the programme is cost effective.

[2]We can also point to the results of social pensions reducing mortality in South Africa by Mostert et al. (2022); and Arno et al. (2011), Galofré-Vilà et al. (2022), Engelhardt et al. (2022) in the US.

Furthermore, we compute a mortality-income elasticity of -0.486, which is higher than the value found other studies. We argue that this could be because our observation period for mortality (7-year rate) is longer than the periods used in other papers. In addition, we analyse very poor elderly people who have experienced multiple deprivations during their lifetime with inadequate access to healthcare, nutrition and education, all of which lead to a higher mortality risk at the start of the programme. Thus, the effect of the income transfer could be very important (and more elastic) in preventing death for the very poor.

Among the potential mechanisms behind the effect of the transfer on mortality, Bernal et al. (2022)— who use the follow-up of our survey in 2015— find that *Pensión 65* has impacts on reducing anaemia and increasing nutrition quality, food expenditures and healthcare utilisation, as well as improving mortality risk markers. As all these variables have well-known effects on mortality, we consider them as leading mechanisms for the effect of the transfer on mortality.

The remainder of this paper is organised as follows. Section 2 describes the NCP programme while Section 3 presents the data. Section 4 explains the empirical strategy, and Section 5 analyses and discusses the results, as well as examining policy impacts. Section 6 presents and discusses evidence for validation, falsification and robustness checks. Lastly, Section 7 concludes the study.

2 Non-contributory pensions in Peru

Pensión 65 is a government programme that provides social pensions to individuals aged 65 and above who do not have any other pension benefits and reside in a household classified as extreme poor by the national targeting system SISFOH. This scheme is part of a wave of new non-contributory pension (NCP) programmes launched in Latin America during recent years. *Pensión 65* provides a bi-monthly transfer of 250 soles to the recipients and facilitates registration in the public health system (*Seguro Integral de Salud, SIS)*, which covers health at no cost, although it can incur some out-of-pocket expenditure. In principle, all individuals classified as poor by SISFOH are eligible for SIS—that is, both the extreme poor and the non-extreme poor—but there is likely to be a relatively lower participation by the non-extreme poor in SIS.

The pension amount has not changed since the implementation of the programme at the end of 2011. While the transfer was equivalent to 47 US dollars in 2012, this represented 32 US dollars in 2021. Even though the transfer has lost about 31% of purchasing power, it can be a relatively important source of income for poor individuals. For example, by looking at the figures from Peru's National Institute of Statistics (INEI) for monetary poverty lines, we note the transfer represented 83% of the national extreme poverty line and 44% of the national poverty line in 2012; while in 2021 it represented 62% and 33%, respectively. In rural areas, these percentages were 98% and 59%, respectively. For 2012, the transfer represented 17% of the minimum wage, 14% of the national household income per capita in urban areas and 33% in rural areas.

The programme reached 568,599 recipients in 2021, representing about 19% of the population aged 65 and above and involving a cost of 0.10% of the GDP. These percentages have not changed substantially since 2015, the time at which the programme reached maturity with slightly over half a million recipients. The programme started enrolling individuals living in the poorest districts of six prioritised departments, and in 2012, the roll-out continued to include 14 departments where a previous small-scale and short-lived pilot NCP programme had been in place.[3]

As mentioned earlier, SISFOH (*Sistema de Focalización de Hogares* in Spanish) is the national targeting system in Peru. It maintains a national register of socio-economic conditions of households in order to assess whether a household could be eligible for social programmes. The SISFOH relies on data collected by government officials using a standardised questionnaire. The main outcome of SISFOH is the computation of a multidimensional welfare index (the SISFOH score) capturing the socio-economic conditions of households. This is compared with regional cutoffs to determine three poverty statuses: extreme poor, non-extreme poor and non-poor. This classification is valid for three years in urban areas and four years in rural areas.

[4] The largest collection of data for the SISFOH register took place in 2012. In the current study, we exploit a survey in which the sampling framework was based on that data collection. The variables collected for the register include the access to and quality of basic infrastructure (e.g., water, electricity and sewage), fuel type and quality, material quality of different parts of the dwelling, home overcrowding, education attainment, home assets and access to health insurance.

It is important to note that the households do not know their SISFOH score; they are only made aware of their classification in one of the three mentioned poverty groups. Further, the score is determined independently from the regional cutoff points, which are undisclosed to the public. The methodology to compute the score is also complex and very difficult to grasp, if a household wanted to manipulate their answers to become eligible for a social programme. Manipulation of eligibility is a serious threat to the identification of causal effects, but we provide arguments and statistical evidence in Section 6 that there is no manipulation problem that could invalidate our empirical design and results.

Apart from the roll-out censuses implemented to provide information to the SISFOH register, individuals can apply at municipality offices to obtain a poverty SISFOH classification. Once eligibility is confirmed, enrolment into *Pensión 65* can take about 25 days. As mentioned in Bernal et al. (2022), other methods for programme enrolment include i) information campaigns that are jointly organised by local governments and officers from the programme, and

ii) a search (carried-out by programme officials) for potential recipients who have not received their SISFOH classification or who do not yet have not their identity document (*Documento*

[3]The *Bono Gratitud* pilot programme ran between October 2010 and August 2011 and reached 21,783 participants distributed between 14 departments. The transfer was equal to 100 soles a month, and the eligibility

conditions were being aged 75 and above, and residing in a household classified as extreme poor.

[4]For more methodological details about the welfare index algorithm, see Valderrama and Pichihua (2011).

Nacional de Identidad), which is compulsory for eligibility checks.

3 Data

Our study exploits survey data specifically designed for the impact evaluation of *Pensión 65*. We match this (at the individual and/or household level) to three administrative data sources: i) mortality records for 2012-2019, ii) *Pensión 65* records and iii) SISFOH registers. The primary data source is the Survey of Health and Well-being of the Elderly, known as ESBAM (*Encuesta de Salud y Bienestar del Adulto Mayor*). The sample framework of the survey is intentionally designed to implement a Regression Discontinuity Design (RDD) to study the causal effects of the programme. The baseline survey was carried out between November and December 2012, and the follow-up survey was held between July and September 2015. ESBAM collects information covering several objective and subjective health measurements, demographics, income and expenditure—both for each elderly individual and the household. The information is collected via face-to-face interviews, while medical technicians collect data for anthropometric measurements, arterial pressure and blood samples from the elderly individuals.

The sample framework design takes into account 12 out of the 24 departments of Peru, because these regions had completed the collection of information for the SISFOH registers. These departments are Amazonas, Ancash, Cajamarca, Cusco, Huánuco, Junín, La Libertad, Loreto, Pasco, Piura, Puno and Lima (provinces). The other two conditions for being part of the sample framework are that i) households should be located within 0.30 standard deviations of the SISFOH score to the right or to the left of the threshold for extreme poverty, and ii) households should have at least one member aged between 65 and 80. The idea underlying this design is to try to observe households that are as similar as possible within the region around the eligibility threshold for *Pensión 65*. [5] In fact, Figure B–1 in the Appendix shows clearly that the ESBAM sample is very local when we compare it with the national distribution of the SISFOH score. That is, the sample is local in the sense that the SISFOH score for the ESBAM individuals is located just around the eligibility threshold.

The initial ESBAM sample size amounts to 4,238 individuals.[6] We match this data set to administrative records for the programme, SISFOH registers and mortality records using the National Identification Document number, which is included in the baseline of ESBAM. The *Pensión 65* records allow us to identify the recipients of the programme and when they re-

[5]More precisely, the sampling design consists of a two-stage random selection procedure: geographic clusters in the first stage and households with at least one older adult in the second stage. The primary sampling units (PSU) are defined as the census units in urban areas (blocks) and villages (*centro poblado*) in rural areas. The selection of PSU within each department and area takes place in the first stage according to a selection probability that is proportional to the total number of households, whilst the random sampling of households takes place in the second stage.

[6]The sample size is determined with the Minimum Detectable Effect (MDE) approach, in which the chosen sample allows us to detect an effect as long as it is above a certain threshold. The MDE in ESBAM is equal to 0.15 standard deviations, while the statistical power is set at 90% and the significance level is set at 5%.

ceive the transfer. The SISFOH register provides information about the eligibility score and the poverty group classification of the households. The mortality records are drawn from the National Population Register (*RENIEC*, from its Spanish name) and allow us to identify the survival or death of each individual between December 2012 and December 2019. The information includes the date of death, but not the cause. After dropping observations with inconsistent information or with missing data on key variables, the sample size is reduced to 3,885 individuals. The dropped observations include 137 individuals who were already recipients at the ESBAM baseline, 66 who declared in the survey that they were receiving contributory pensions, 59 who were classified as non-poor in the SISFOH registry, 23 with no SISFOH score information, three who were aged 81 and older, one who was deceased at baseline and 64 individuals who we could not identify in any records.

Table 1 shows the distribution of our sample according to the eligibility conditions and whether the individual survived or died between 2012 and 2019. From the 2,525 eligible individuals in 2019, 432 had died and had 2,093 survived, showing a raw mortality rate of 17%. From the 1,360 ineligible individuals, 245 had died, and 1,115 had survived, implying a mortality rate of 18%. The table also reports mortality differences across age groups and by gender. As expected, we find that women have a lower mortality rate than men (15% and 19%, respectively), and relatively younger individuals have a lower mortality rate than older individuals (the mortality rate is 11%, 18% and 31% for the age groups 65-70, 71-75 and 76-80, respectively).

Table 1: Distribution of observations in initial ESBAM sample

	Sex		Age in 2012			Overall
	Male	Female	65-70	71-75	76-80	
Overall	2,118	1,767	1,901	1,204	780	3,885
Survivor	1,705	1,503	1,686	984	538	3,208
Dead	413	264	215	220	242	677
Mortality rate	19%	15%	11%	18%	31%	17%
Eligible	1,406	1,119	1,206	803	516	2,525
Survivor	1,135	958	1,075	659	359	2,093
Dead	271	161	131	144	157	432
Mortality rate	19%	14%	11%	18%	30%	17%
Ineligible	712	648	695	401	264	1,360
Survivor	570	545	611	325	179	1,115
Dead	142	103	84	76	85	245
Mortality rate	20%	16%	12%	19%	32%	18%

Notes: The sample is composed of individuals observed in the baseline of the 2012 ESBAM survey. After dropping observations with inconsistent information or missing key information, the initial sample size is set to 3,885 individuals.

Table B–1 in the Appendix provides summary statistics of the initial sample for the main variables used in this paper. Table B–2 shows the summary statistics for the sample we exploit in the econometric results of our regression discontinuity analysis. This sample is based on the determination of optimal bandwidth according to Calonico et al., 2015 (see Section 5.1 for details). In this last table, which includes eligible and ineligible people who are even closer to the threshold, we observe that the mortality rate is 15.8% among eligible individuals and 17.7% among their ineligible counterparts.

An important feature of the ESBAM sample is that it is composed of very poor elderly individuals, in contrast to surveys used in other studies to study the mortality effects of (social) pensions that generally consider national surveys focused either on the total population or on the elderly population. The magnitude of this composition can be seen in Figure B–2 in the Appendix, reporting the ESBAM and national distribution of household income per capita for 2012. We note that about 60% (or 70%) of the ESBAM sample have income levels below the bottom 20% (or 25%) of the national income distribution. It is important to bear in mind this characteristic of our sample when we analyse and discuss our econometric results because of potential important reductions in mortality due to income effects among poor people.

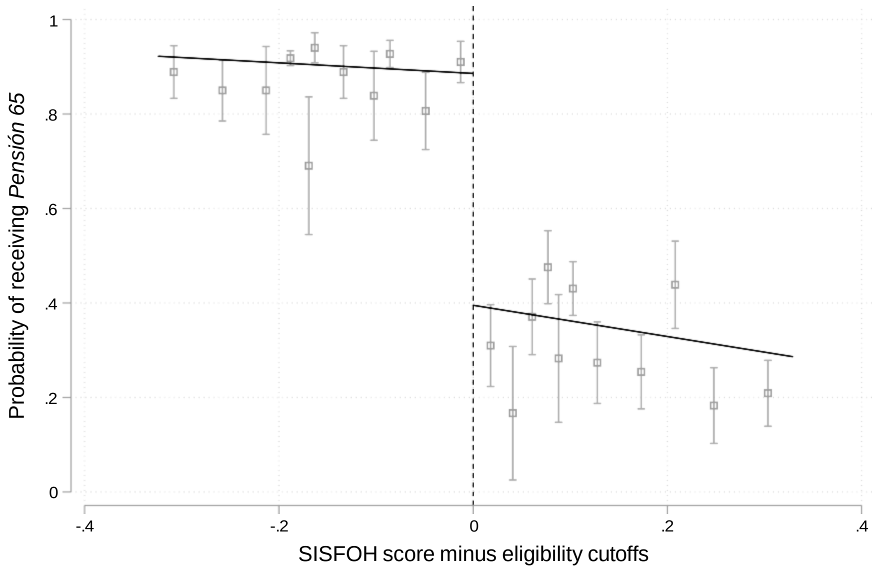
4 Empirical strategy

As explained before, households are given a score based on an official algorithm that takes into account their socioeconomic conditions and a set of weights for each socioeconomic variable. The comparison of the score with official regional cutoffs leads to the classification of households into extreme poor, non-extreme poor and non-poor. We argue that this classification provides a natural experiment in assigning eligibility to the programme. Thus, according to the centred score (the SISFOH score minus the cutoffs for extreme poverty), the individuals located to the left of the extreme poverty cutoff point (centred at zero) are eligible for the programme, whilst those located to the right are ineligible. The centred SISFOH score acts as the running variable, measuring the distance of an observation to the eligibility cutoff. These features of the programme facilitate the use of an RDD to analyse the potential impact of *Pensión 65* on the eligible population.

Figure 1 plots the probability of being a recipient of the programme at any time within the 2012–2019 period as a function of the running variable. The graph shows that the probabilities of being treated around the eligibility cutoff exist and are different on each side of the threshold, which are assumptions required in RDD for causal identification (Hahn et al., 2001). We observe that individuals becoming eligible for the programme by just crossing the cutoff point have a substantial increase (of approximately 50%) in the probability of becoming recipients. The probability limit of the eligible individuals to be treated is 90%, while the same probability for the ineligible individuals is 40%. Thus, being eligible indicates a high probability of receiving the benefits from the programme.

It is worth noting that the change in the probability of being treated differs depending on the period evaluated. As can be seen in Table B–3 and Figure B–3 in the Appendix, the strongest association between eligibility and being a recipient occurs after three years of exposure (the probability change was 85% in 2015).[7]

Figure 1: Probability of being a *Pensión 65* recipient



Notes: The graph plots the probability of receiving *Pensión 65* at any time in the period 2012-2019 as a function of the running variable (SISFOH score minus eligibility cutoffs). The support of the running variable has been partitioned into exclusive bins. The number of bins is selected optimally to minimise the integrated mean square error of the underlying regression function, and the location is based on quantile spaced method using spacings estimators as suggested in Calonico et al. (2015). The square points indicate the local mean of the outcome at the midpoint of each bin. The bars represent the 95% confidence intervals of the local means. The solid lines are linear regressions that fit separately on each side of the threshold. Observations to the left (right) of the vertical dashed line are eligible (ineligible) for the programme.

The potential effect of the programme is identified by the difference between the average value of the outcome to the left of the extreme poverty cutoff (eligible) and the average outcome to the right of the cutoff (ineligible). This is the Average Treatment Effect (ATE), which can be estimated in RDD using the following expression:

$$ATE = \lim_{z \to z_0^+} E(y_i | z_i = z) - \lim_{z \to z_0^-} E(y_i | z_i = z) \tag{1}$$

where y_i is the outcome, z_i is the running variable and z_0 is the cutoff. When treatment is not

[7] We also note that the proportion of treated individuals from the ineligible group of the baseline starts to increase after 2016, which coincides with a change in the SISFOH methodology (see Table B–3 in the Appendix). While there are 2,243 recipients accumulated up to 2015 (regardless of survival and eligibility conditions), there are 2,342 and 2,746 recipients accumulated up to 2016 and 2019, respectively. Thus, it is likely that the new SISFOH conditions of 2016 facilitated access to the programme for individuals who had previously been deemed ineligible but were very close to the eligibility threshold.

deterministically assigned, eligibility is not perfectly correlated with the treatment condition, and hence equation 1 is the intention-to-treat (ITT); that is, the effect on the individuals located just to the left of the threshold. ITT measures the impact of treatment eligibility, as determined by the threshold rule. One approach to estimate equation 1 is comparing means in a range of z on the left and right of the threshold. However, if the slope of $E[y_i|z_i]$ is non-zero on either side of the threshold, these averages will be biased estimates of the actual averages at the limit, as z_i tends to z_0. In practice, ITT estimates are typically formed by parametric fitting functions of $E[y_i|z_i, z_i \geq z_0]$ and $E[y_i|z_i, z_i \leq z_0]$ in the region around the threshold. Assuming linearity, the following econometric specification can be used to find the expected effects of the programme:

$$E[y_i|z_i] = \beta_0 + \beta_1 \cdot 1[z_i < z_0] + \beta_2 \cdot [z_i - z_0] + \beta_3 \cdot (z_i - z_0) \cdot 1[z_i < z_0] \tag{2}$$

where β_2 is the slope of the line to the right of the threshold, $\beta_2 + \beta_3$ is the slope of the line to the left of the threshold and β_1 is the difference at the cutoff (Imbens and Lemieux, 2008).

We use equation 2 to estimate the ITT of the programme on the mortality rate by means of linear regressions. In this case, the dependent variable takes the value of 1 if the individual has died and the value 0 if the individual has survived at a given period. In our main setup, we consider mortality observed in the whole 7-year period of analysis between 2012 and 2019. Therefore, $y_i = 1$ if the individual died anytime between 2012 and 2019 and $y_i = 0$ if the individual has survived at 2019. Auxiliary regressions will allow us to assess mortality at different periods. In addition, we include a vector of covariates in further regressions as a way to control for demographics and, importantly, for initial health conditions. We estimate the error terms clustering at the Primary Sampling Unit of the survey design.[8] Furthermore, in all regressions we apply a triangular weighting kernel in the distance from the RD cutoff (Calonico et al., 2014); that is, the observations closer to the eligibility threshold have a larger weight, whilst those further away from the threshold have a smaller weight.

Estimating the ITT effects for some relevant groups could be informative about how heterogeneous the effects of the program are on the mortality of distinctive groups. For this aim, we use equation 3, where $\tau_{i,s}$ is an indicator variable that identifies a person i who belongs to the sub-population s. In particular, we estimate effects for sub-populations grouped by sex, rural/urban areas, education (no schooling or some schooling) and age (65–70 or 71–80). The effects for the sub-populations of each group are quantified by $\beta_1 + \beta_5$ when $\tau_{i,s} = 1$, and β_1 when $\tau_{i,s} = 0$.

$$\begin{aligned} E[y_i|z_i] = {} & \beta_0 + \beta_1 \cdot 1[z_i < z_0] + \beta_2 \cdot [z_i - z_0] + \beta_3 \cdot (z_i - z_0) \cdot 1[z_i < z_0] \\ & + \tau_{i,s}(\beta_4 + \beta_5 \cdot 1[z_i < z_0] + \beta_6 \cdot [z_i - z_0] + \beta_7 \cdot [z_i - z_0] \cdot 1[z_i < z_0]) \end{aligned} \tag{3}$$

[8]We justify this clustering to deal with design uncertainty, as recommended by Abadie et al. (2020).

The data used to linearly estimate the ITT effects of *Pensión 65* can also be organised to estimate survival models. In this case, the data is organised so that we can observe whether the individual has survived or died at each month in the 2012–2019 period. According to Bor et al. (2014), the ITT estimator from the setting of discontinuous regressions can be easily extended to survival models. Continuity in the conditional expectation functions for each of the potential outcomes ($E[y_i(0)|z_i = z]$ and $E[y_i(1)|z_i = z]$) is sufficient for the identification of regression parameters across the class of generalised linear models, which relate the conditional expectation to a linear model via a continuous link function, such as the logarithm or logit. In this way, for applications in survival analysis, equation 2 can be adapted to parametric and semiparametric models that specify the hazard as a function of the assignment variable and time. In particular, the hazard regression models can be made linear with the log-hazard by replacing $E[y_i|z_i]$ in equation 2.

We use equation 4 to run survival models and estimate the ITT effect of the programme on the hazard ratio.[9] We use the logarithm of the risk of death ($h(t)$) as the dependent variable and assume a Gompertz-type parametric model, as is usually employed in the relevant empirical literature (see, for example, Chetty et al., 2016; Dodd et al., 2018; Olivera, 2019; Castellares et al., 2020 and Kulinskaya et al., 2020). We run sensitivity checks, including the use of alternative parametric functions such as Weibull and exponential.

$$log[h(t)] = log[h_0(t)] + \beta_0 + \beta_1 z_i + \beta_2 D + \beta_3 z_i D + \varepsilon_i \tag{4}$$

As mentioned before, we justify the use of the ITT on the large jump observed in the discontinuity around the eligibility threshold shown in Figure 1. In order to provide robustness for the validity of our identification, we perform various checks in Section 6. Thus, we assess the validity of the RDD assumptions, as well as the stability and sensitivity of our estimated effects. All these tests assure us that we are indeed identifying a causal effect of the programme on mortality.

5 Results

5.1 Linear ITT effects

The main results of the ITT effects of *Pensión 65* on the mortality rate are reported in Table 2. The dependent variable takes the value of 1 if the individual dies at any time within the 2012–2019 period and 0 if the individual survives. The first column utilises the full sample of the running variable around the eligibility threshold. In this case, we find that the mortality rate of the

[9]The proportional hazard model assumes that $h(t)$ is estimated by $h(t) = h_0(t) \cdot exp(\beta_0 + \beta_1 z_i + \beta_2 D + \beta_3 z_i D + \varepsilon_i)$, where $h_0(t)$ is a baseline hazard function that is assumed to be a Gompertz Distribution.

eligible individuals is 5.6 percentage points (pp) lower than that of ineligible individuals. The mortality rate of ineligible people is 18.2 pp, implying that the programme could potentially reduce the mortality rate of the eligible individuals by about 31% (5.6/18.2). However, smaller bandwidths—where individuals are more alike on both sides of the eligibility threshold—could help to reduce the potential bias of the estimations. Column 2 shows the results for a bandwidth of +/- 0.20, which includes approximately half of the sample. For this sample, the mortality rate of eligible individuals is reduced by 8.3 pp, while that of ineligible people is 19.5 pp.

Table 2: Effect of *Pensión 65* on mortality rate

	(1)	(2)	(3)
Intention-to-treat ($\hat{\beta}_1$)	-0.056	-0.083	-0.114
	(0.028)	(0.038)	(0.045)
	[0.047]	[0.028]	[0.011]
Constant ($\hat{\beta}_0$)	0.182	0.195	0.201
	(0.022)	(0.038)	(0.035)
	[0.001]	[0.028]	[0.001]
Bandwidth	+/- 0.330	+/- 0.2	+/- 0.145
Observations	3,885	2,104	1,577
Percentage Sample	Full sample	54%	41%

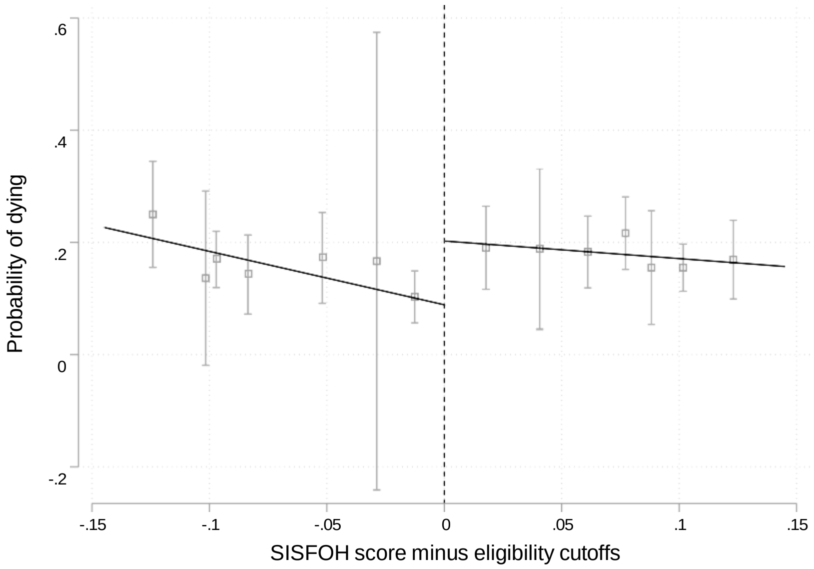
Notes: The table reports the ITT estimates for mortality observed in 7 years (Equation 2). The models use triangular kernel and local linear polynomial. The first model uses the full sample, which has a bandwidth of +/- 0.330. The second uses about half of the sample size, which has a bandwidth of +/- 0.2. The third uses the optimal bandwidth for point estimation as suggested by Calonico et al. (2015). The standard errors are clustered by the Primary Sampling Unit (PSU) of the sampling framing and are indicated in parentheses. P-values are reported in brackets.

In order to reduce the risk of obtaining biased estimators due to incorrect choice of bandwidth, in the third column of Table 2 we implement the data-driven procedure of Calonico et al. (2015) to obtain the optimal size of the bandwidth. In what is our preferred model, we observe that the mortality rate of eligible individuals could decline by 11.4 pp, implying a substantial reduction of 56.7% (0.114/0.201) with respect to the mortality rate of ineligible individuals.[10]

Figure 2 shows graphical evidence of the programme's ITT effect on the mortality rate. This figure employs the optimal bandwidth obtained in the last regression of Table 2 and clearly shows the reduction in the probability of dying when an individual crosses the eligibility threshold.

[10]The resulting optimal bandwidth is +/- 0.145, which we maintain for all further regressions. In any case, Figure D–4 in the Appendix plots the ITT effects for various bandwidths, including our optimal data-driven bandwidth. The estimates are always statistically significant and negative, although the magnitude of the effect tends to be smaller for wider bandwidths.

Figure 2: Intention-to-treat effects on mortality



Notes: The graph plots the probability of dying after seven years as a function of the running variable (SISFOH score minus eligibility cutoffs). The support of the running variable has been partitioned into exclusive bins. The number of bins is selected optimally to minimise the integrated mean square error of the underlying regression function, and the location is based on quantile spaced method using spacings estimators as suggested in Calonico et al. (2015). The square points indicate the local mean of the outcome at the midpoint of each bin. The bars represent the 95% confidence intervals of the local means. The solid lines are linear regressions that fit separately on each side of the threshold. Observations to the left (right) of the vertical dashed line are eligible (ineligible) for the programme.

It is a well-known fact that mortality has gradients with age and sex, and therefore controlling for these covariates in the regressions may reduce potential bias arising from the composition effects of our sample. Moreover, the ESBAM survey includes various measurements related to health status and mortality risk at the baseline that may control for initial health conditions and risk factors.[11] Therefore, we can reduce any potential estimation bias arising from initial differences between eligible and ineligible people on health status and risk factors. Table 3 reports the estimation results when we add these covariates into the regressions. Column 1 shows our original estimation without controls, and then gender and age are added in column 2. The magnitude of the ITT negative effect slightly reduces to -0.10 and is still statistically significant at 95% (*p-value* = 0.025). Column 3 adds all the health-related variables that were objectively measured in the survey by the interviewer and/or the medical technicians during the fieldwork. As before, the ITT effect is statistically significant (*p-value* = 0.063), but the magnitude of the estimator reduces to -0.083. Column 4 adds the health and nutrition variables reported by the individuals and shows an ITT effect of -0.096, which is statistically significant (*p-value* = 0.029). In the last column we add risk factors captured by the consumption of alcohol and tobacco and obtain an ITT effect equal to -0.098 (*p-value* = 0.026).

[11] See Tables A–1 and A–2 in the Appendix for the definitions of the covariates used in the analysis.

Thus, adding demographic covariates, initial health conditions and risk factors related to mortality does not change our results qualitatively. If anything, there is a reduction in the magnitude of the ITT effect of the programme on 7-year mortality from -0.11 to about -0.10.

Role of covariates

Table 3 reports the contribution to mortality of initial health conditions, nutrition and risk factors. Not surprisingly, males and older individuals exhibit a higher mortality risk. Individuals who showed high blood pressure (HBP) during the examination in the ESBAM fieldwork also have a higher mortality risk. This is in line with studies showing that HBP is one of the most important risk factors for cardiovascular disease, which has been reported as one of the main causes of mortality in old age (see Arima et al., 2011; Lev-Ari et al., 2021; Lee et al., 2022). Obesity also contributes to increasing cardiovascular risk and hence higher mortality risk. We capture obesity in ESBAM by weight and abdominal obesity. The latter is assessed by comparing waist circumference to cutoffs that are specific for Latin American populations (see ALAD, 2010; Pajuelo-Ramirez et al., 2019). Our results indicate that obesity contributes to a higher mortality rate.

Table 3: Effect of *Pensión 65* on mortality rate, including covariates

	(1)	(2)	(3)	(4)	(5)
ITT	-0.114**	-0.101**	-0.083*	-0.096**	-0.098**
	(0.045)	(0.045)	(0.045)	(0.044)	(0.044)
Male		0.043**	0.067**	0.072**	0.077**
		(0.019)	(0.028)	(0.029)	(0.030)
Age		0.017***	0.013***	0.013***	0.013***
		(0.002)	(0.002)	(0.002)	(0.003)
High blood pressure			0.053**	0.043*	0.043*
			(0.023)	(0.023)	(0.023)
Anaemia			0.033	0.038	0.038
			(0.024)	(0.024)	(0.024)
Weight			0.005**	0.006***	0.006***
			(0.002)	(0.002)	(0.002)
Abdominal obesity			0.045	0.049*	0.049*
			(0.030)	(0.030)	(0.030)
Arm span			-0.000	-0.001	-0.001
			(0.001)	(0.001)	(0.001)
Mid-upper arm circ. (MUAC)			-0.015**	-0.012**	-0.012**
			(0.006)	(0.006)	(0.006)
Calf circumference (CC)			-0.016***	-0.012**	-0.013**
			(0.006)	(0.006)	(0.006)
Cognitive functioning			-0.016***	-0.012**	-0.012**
			(0.006)	(0.006)	(0.006)
Chronic diseases				0.008	0.007
				(0.009)	(0.009)
Health today				-0.009	-0.010
				(0.022)	(0.022)
Nutrition score (MNA)				-0.015***	-0.015***
				(0.005)	(0.005)
Alcohol					-0.002
					(0.025)
Tobacco					-0.017
					(0.028)
Constant	0.201***	-1.043***	-0.046	0.018	0.017
	(0.035)	(0.174)	(0.317)	(0.314)	(0.315)
Observations	1,577	1,577	1,513	1,483	1,481

Notes: The table reports the ITT estimates for mortality observed over 7 years (equation 2) including covariates related to the mortality risk. The models use triangular kernel, local linear polynomial and the optimal bandwidth for point estimation as suggested by Calonico et al. (2015) (obtained in Table 2). The standard errors are clustered by the Primary Sampling Unit (PSU) of the sampling framing and are indicated in parenthesis. $*p < 0.10$, $**p < 0.05$, and $***p < 0.01$ indicate statistical significance levels.

Mid-upper arm circumference (MUAC) and calf circumference (CC) are well-known indicators of muscle loss, capturing nutritional status and ultimately affecting the mortality risk of older individuals. It has been shown that individuals with low muscle mass (i.e., thinness) have a higher risk of mortality (Wijnhoven et al., 2010; Schaap et al., 2018; Weng et al., 2018). As indicated in Bernal et al. (2022), low values of MUAC or CC are strongly associated with mortality, with a predictive power even greater than that of the Body Mass Index (BMI). Our results appear to confirm these associations between mortality and values of MUAC and CC. We observe that the coefficients for these markers are negative and statistically significant in all the models in Table 3; that is, individuals with signs of thinness are more likely to die. The magnitude of the effect of one additional centimetre in CC or MUAC is similar in magnitude to the effect of being one year younger.

Cognitive functioning is captured by a reduced version of the Mini-Mental State Examination (MMSE) (Folstein et al., 1975), which was operationalised during the survey fieldwork. The study by Leist et al. (2020) explains this score in greater detail and assesses its relationship with nutrition by exploiting the baseline round of ESBAM (see definition in Table A–1). We find that a higher level of cognitive functioning is associated with lower mortality.

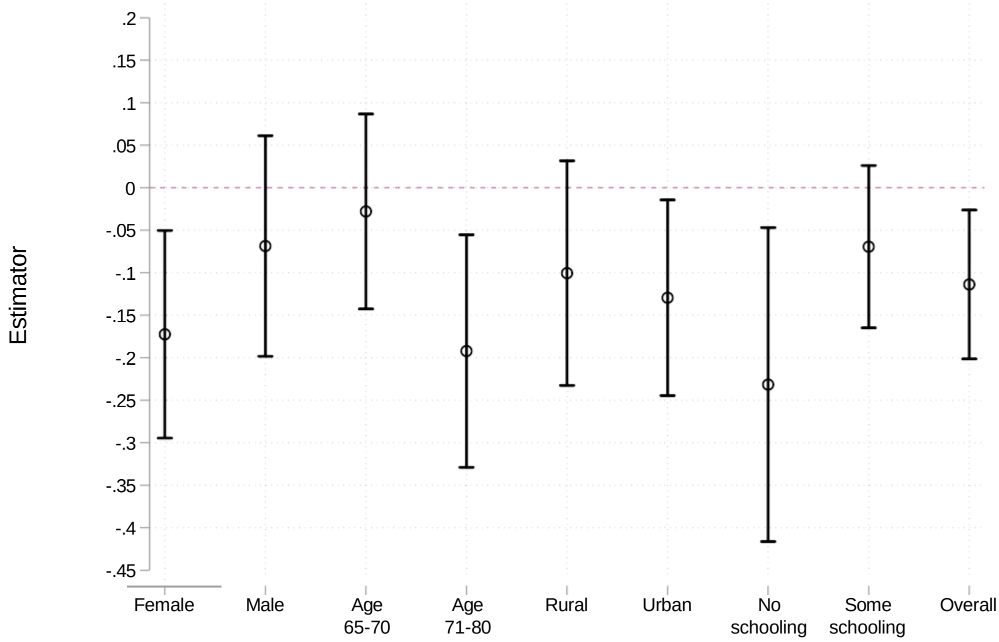
The Mini Nutritional Assessment (MNA, the empirical definition of which is explained in detail in Table A–2) is a score capturing dietary quality and is useful to rapidly assess malnutrition risks through a few questions posed to the elderly individuals (Guigoz, 2006; Harris and Haboubi, 2005; Vellas et al., 1999). The study by Bernal et al. (2022)—who make use of the follow-up survey of ESBAM—finds evidence that MNA may be one of the key mechanisms through which *Pensión 65* could affect nutrition-related health outcomes among eligible individuals. With regard to the relationship with mortality, we find a strong statistical link to mortality (β_2 = -0.015; *p-value* = 0.002 in the last model of Table 3). Thus, increasing the quality of diet and decreasing the risk of malnutrition is associated with a reduction in mortality.

Heterogeneous effects

In order to assess whether the programme may have differential mortality effects for certain groups of individuals, we estimate models based on equation 3. We report the estimated ITT coefficients across four distinctive groups (gender, age, area and education) in Figure 3. While the overall effect of the programme in reducing mortality among eligible individuals is statistically significant, we do not find evidence of any specific effects on groups of males, younger old adults (aged 65–70), persons residing in rural areas and individuals having some education.[12] The ITT effects are statistically significant for individuals who are female, aged 71–80, who live in urban areas and who do not have any years of schooling. It is well known that being older and having lower human capital (e.g., captured by education) is associated with higher mortality rates. Therefore, our results regarding old and uneducated individuals may indicate that the programme could substantially reduce the mortality rate for these populations, which are already facing a high level of mortality risk. Thus, the relative survival gains triggered by the programme could be more salient for these groups.

[12]Individuals in the ESBAM sample tend to have very low educational attainment due to poverty conditions experienced in their lifetime. For example, 27% of individuals have no years of schooling, while 52% have incomplete primary education and only 14% have completed primary education.

Figure 3: Heterogeneous effects on mortality rate



Notes: The graph plots the estimated ITT coefficients from equation 3 for four distinctive demographic groups (by sex, age, area and education) and the overall effect. The vertical lines indicate 95% confidence intervals.

We also assess whether the effects of *Pensión 65* are different for individuals living in households that receive transfers from the other main social programme in Peru (*Juntos*) compared with individuals who live in households that do not receive these transfers. We do not find statistically significant results in this regard.[13] Furthermore, we evaluate whether having more than one older adult at home (and hence more than one potential recipient) may lead to different effects of the programme, but again we do not find significant results.[14]

5.2 ITT effects with survival models

The use of survival models is an alternative to the linear regressions used in the previous section to estimate the ITT effect. As already explained, we use the log of the hazard ratio of mortality as the dependent variable to obtain our ITT estimates in a comparable setting to the linear models (see equation 4). The results are reported in Table 4 and are based on a Gompertz type parametric model.[15]

[13] *Juntos* is a conditional cash transfer programme that provides benefits to households where there are children and/or pregnant women on the condition that these members fulfil certain required health and education commitments. To be eligible for this programme, households must be classified as poor by SISFOH (that is, as extreme or non-extreme poor). Given that our RDD compares extreme and non-extreme poor individuals who are very close to the eligibility cutoff, then any household of our sample could be potentially eligible for *Juntos*.

[14] The effect is 11.1% and 11% for households with one and two eligible individuals, respectively (the results are not reported).

[15] The results do not change qualitatively if we use other parametric functions, such as Exponential or Weibull, or even if a Cox regression is estimated. We report the ITT estimates of alternative functions in Table C–1 in the

The last column of Table 4 shows the ITT effect of the programme on the log of the mortality hazard rate when we use the selected optimal bandwidth. We observe that eligible individuals have a 57% lower risk of dying than ineligible individuals (hazard ratio = $exp(-0.846)$ = 43%), which is the same value as the percentage variation in the mortality rate when using the linear ITT models.

Table 4: Effect of *Pensión 65* on log of mortality hazard rate

	(1)	(2)	(3)
Intention-to-treat ($\hat{\beta}_1$)	-0.389	-0.585	-0.846
	(0.192)	(0.255)	(0.324)
	[0.040]	[0.022]	[0.009]
Constant ($\hat{\beta}_0$)	-3.909	-3.770	-3.768
	(0.160)	(0.215)	(0.243)
	[0.001]	[0.001]	[0.001]
Bandwidth	+/- 0.330	+/- 0.2	+/- 0.145
Observations	3,885	2,104	1,577
Percentage Sample	Full sample	54%	41%

Notes: The table reports the ITT estimates for the log of mortality hazard rate observed during 7 years (equation 4). The estimator corresponds to a Gompertz-type model. The models use triangular kernel, local linear polynomial and the optimal bandwidth for point estimation as suggested by Calonico et al. (2015) (obtained in the last model of Table 2). The standard errors are indicated in parenthesis. P-values are reported in brackets.

Figure C–1 in the Appendix plots the ITT effect on the log of mortality hazard ratio as a function of the running variable. As shown before in Figure 2 with the linear estimations, we also observe a clear reduction in the mortality risk of individuals when they pass the eligibility threshold. Furthermore, the survival ITT estimates show the same behaviour regarding the assessment of the effect on alternative bandwidths across heterogeneous groups of individuals and covariates (see Figures D–5, C–2 and Table C–2 in the Appendix).

5.3 Potential mechanisms

Among the potential mechanisms behind the effect of the transfer on mortality, we note that Bernal et al. (2022) use the follow-up of the ESBAM survey (fielded between July and September 2015) to estimate the effects of *Pensión 65* on nutrition-related health outcomes. They find that the programme has impacts on reducing anaemia and depression symptoms, and increasing nutrition quality, food expenditure, cognitive functioning, healthcare utilisation and self-reported health, as well as improving mortality risk markers, such as the mid-upper arm circumference and calf circumference. As already documented, some of these factors have well-known effects on mortality, and therefore we could consider them as leading mechanisms

Appendix.

for the effect of the pension transfer on reducing mortality (also see Table 3). That is, the transfer may allow individuals to increase their food expenditure and nutrition quality, and visit health facilities more frequently, which can reduce anaemia incidence and mortality risks.

We also accessed the follow-up survey of 2015, so that we are able to run RD regressions to find the ITT effects of the programme on several outcomes that are potentially mechanisms affecting the mortality rate. From the 3,885 observations of our baseline, we found 3,514 individuals who were surveyed in the follow-up. This number is larger than the 3,351 subjects used in Bernal et al. (2022), because we were able to manually identify respondents whose SISFOH score was missing.

Table F–1 in the Appendix shows the ITT effects of the programme. The first set of results in the table use the full sample of the follow-up survey and produce similar results to those obtained by Bernal et al. (2022). Because the design of the sampling framework involves a very local sample, the authors argue that one could use the full sample without needing to reduce the already small bandwidths. The second set of results show what the ITT effects of the programme would be if we use the same bandwidth and kernel weighting utilised in our analysis of 7-year mortality (bandwidth equal to 0.1448). In this case, the programme may have significant impacts on increasing cognitive functioning, reporting chronic diseases, self-reported health and healthcare utilisation, while reducing obesity and food expenditure per capita at the threshold.[16]

The third set of results show the ITT effects when we use the non-parametric approach suggested by Calonico et al. (2015) for each outcome (rdrobust with kernel weights and polynomial of degree one, and MSE-optimal bandwidths) that is closer to our main analysis of mortality. For this approach, we observe that the programme reduces the incidences of hypertension and obesity, improves MUAC (i.e., reduces the mortality risk) and self-reported health and healthcare utilisation, but that it reduces food expenditure per capita at the threshold ($p-value$=0.082) even when the effect is positive when we employ the full sample. The survey does not allow us to identify the consumption of each family member and therefore we should interpret the result for food expenditure per capita with caution. Furthermore, we detect a statistically significant increase in the number of household members, which could explain the negative impact on food expenditure per capita. The programme does not show impacts on total and household food expenditure under the non-parametric approach.

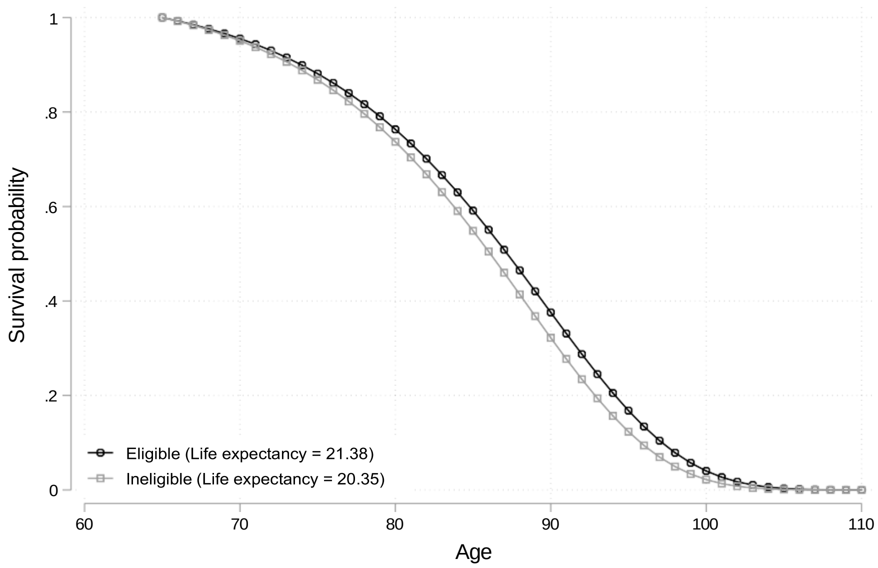
5.4 Policy impact

An important policy outcome of our analysis is estimating how much longer a person eligible for the programme could live. Is the *Pensión 65* programme able to extend the lifespan of its recipients? If so, then for how long? The structure of our survival data from 2012 to 2019 allows us to

[16]The positive effect of the programme on chronic diseases can be interpreted as the effect of having more income to attend healthcare facilities, and receive diagnoses of illnesses and be given information to treat them.

use actuarial methods to estimate life tables for eligible and ineligible individuals. We organise the data by year of observation and age, and identify the number of persons dying at each age between 2012 and 2019. We obtain the average mortality rates between age x and x + 1 using all the available cohorts providing this information, and then we compute the raw number of survivors by age.[17] We use a Gompertz type function to estimate survival curves at age 65 for both eligible and ineligible individuals and report the results in Figure 4. The estimated curves show that eligible individuals tend to live longer than ineligible individuals, resulting in a difference of 1.03 years in life expectancy.

Figure 4: Survival curves for ESBAM sample by eligibility condition



Notes: The figure shows the estimated survival functions of eligible and ineligible individuals. The estimation employs the full ESBAM sample of deceased and surviving individuals between 2012 and 2019 and assumes a Gompertz-type mortality function.

The estimations indicate that ineligible individuals have a life expectancy at age 65 equal to 20.35 years, whilst this is 21.38 for eligible individuals. To put these figures into context, the current official life tables for the main contributory pension system in Peru (the Private Pension System, SPP) indicate that the average life expectancy of both sexes at age 65 is 23.43 years. Our estimations indicate that the programme could extend life expectancy (measured at age 65) by about 1 year; that is, the life expectancy of eligible individuals may increase by 5.1% (=1.03/20.35).

In the cost-benefit analysis literature focusing on the impact of regulations on life expectancy (e.g. Viscusi, 1994; Robinson et al., 2019), a policy is considered cost effective if its monetary costs are lower than the gains in terms of the value of statistical life (VSL). The VSL

[17]For example, the mortality rate between age 70 and 71 is the average of the mortality rates of the 1947 cohort observed in 2013, the 1948 cohort observed in 2014, the 1949 cohort observed in 2015, and so on. This procedure implies the assumption that we treat cohorts between 1932-1947 as just one cohort. We use the full sample in order to have enough observations to estimate survival functions by age and eligibility condition.

can thus be understood as the willingness to pay for reducing the risk of mortality. As explained in Robinson et al. (2019), a policy causing a decrease in mortality over a given time period will reduce the number of deaths and increase life expectancy, and VSL could accordingly capture the total monetary value of the individual risk reductions as the value per expected life saved. The estimation of VSL utilising specific data is more widespread among high-income countries, but there are some studies that estimate and/or extrapolate VSL values for other selected countries. Table E–1 in the Appendix reports these values for Peru in 2012. Depending on the approach, the values go from 0.36 to 3.33 million US dollars, with an average of 0.98 million.

The cost of the *Pensión 65* programme for an eligible individual is estimated as the discounted (interest rate equal to 3%) sum of all the pension transfers the individual could receive during the expected life length starting at age 65, which amounts to 8,753 US dollars in 2012. That is, the cost for enabling one more expected year of life is 8,753 dollars. In line with Miglino et al. (2023), we multiply this amount by the life expectancy estimated for eligible individuals (21.38 years) and compare it with the estimates of VSL reported in Table E–1 in the Appendix.[18] The cost of the programme is 187,143 US dollars, which is lower than any of the VSL estimates for Peru. Indeed, the cost of the programme is only 19% or 30% of the average and median values of VSL, respectively.

A complementary way for reporting the policy impact of the programme—and for comparison with other studies—is to estimate the mortality-income elasticity, which is the percentage change in mortality due to a 1% change (increase) in income. Given that our analysis is based on individuals at the baseline, we assume that eligible individuals will receive the pension transfer and ineligible individuals will not receive it. We compute augmented individual incomes by adding the pension transfer (125 soles) to the household income per capita of the eligible individuals, and find that the income of eligible individuals could increase by 46.5% on average. For consistency, we also estimate the average effect of the programme on mortality, obtaining a variation equal to 22.6%. Thus, the elasticity is equal to -0.486 (= 22.6% / 46.5%) with 95% confidence intervals between -0.064 and -0.907.[19]

Our elasticity estimate is larger than the values found in other papers studying the effects of social pensions on mortality in middle-income countries with less developed social security systems. For instance, Miglino et al. (2023) find an elasticity of -0.386 based on 4-year mortality for people aged 65 and older participating in Chile's social pension programme, Barham and Rowberry (2013) find an elasticity of about -0.18 based on 1-year mortality for people aged 65 and older who are recipients of Mexico's social programme, *Progresa*, Huang and Zhang (2021) find an elasticity of -0.38 based on 1-year mortality for recipients aged 60 and older from the Chinese NRPS programme and Jensen and Richter (2004) find an elasticity of -0.244 based on

[18] However, there is a difference in the method used to estimate life expectancy. Miglino et al. (2023) assume that their treatment and control groups follow the same mortality profile in the Chilean population after their observation period of 4 years, while we estimate life expectancy specific to each group.

[19] Alternatively, if we use household expenditure per capita instead of household income per capita, the elasticity would be -0.546, with 95% confidence intervals between -0.078 and -1.014.

2-year mortality for male pensioners aged 60 who suffered pension arrears in Russia. It should be noted that we consider a longer period than other studies to compute the mortality rate (we estimate mortality after 7 years).

This could be one of the reasons why we obtain a larger elasticity. Furthermore, it is worthwhile to mention that the population analysed in our study is very poor and has experienced multiple deprivations across their lifetime, with little access to healthcare, education and quality nutrition. All of this contributes to a higher mortality risk at the start of the programme. Thus, the effect of the income transfer could be very important (and more elastic) in preventing death for the very poor.

6 Validation, falsification and robustness

In this section, we show evidence for our identification assumptions and robustness. First, we prove that the running variable is unlikely to have been manipulated. Second, we assess the validity of the design by performing a falsification exercise. Third, we show how sensitive the results are to the exclusion of observations very close to the cutoff. Lastly, we further illustrate the robustness of the results by changing the specification of the models and time of exposure to the programme.

6.1 Manipulation of the running variable

As Lee and Lemieux (2010) point out, if individuals cannot manipulate the assignment variable, then a treatment variation near the threshold is randomised as though in a randomised experiment. Thus, showing evidence that households have not manipulated the running variable is essential for the credibility of the estimate derived from the RD strategy. We concur with the arguments given by Bernal et al. (2022) as to why the eligibility process is unlikely to be susceptible to manipulation: (i) Household answers used in the SISFOH were collected before the implementation of *Pensión 65*, so there was no incentive to manipulate responses to participate in a non-existent programme. (ii) The algorithm to compute the SISFOH index is too complex to be understood by the individuals, and the regional eligibility thresholds are unknown to the public. (iii) Most of the variables included in the computation of the SISFOH index are obtained in person by government officials during the fieldwork, so that they cannot be easily manipulated by the individuals. Thus, manipulation would be unlikely.

We nevertheless test whether households could have manipulated the running variable, first using the approach suggested by McCrary (2008). This indicates that in the absence of manipulation, the density of the running variable should be continuous around the threshold. To formally test whether the density of the running variable is continuous at the threshold, we use the local polynomial density estimator and test statistic as described in Cattaneo et al. (2018). Figure D–1 in the appendix plots the estimated empirical density. This graphical representation of the test clearly shows that the running variable is continuous at the threshold. Therefore, the test's null hypothesis is that the running variable's density is continuous at the threshold; we fail to reject the null hypothesis at conventional levels (*p-value* = 0.132).

A second manipulation test is whether the predetermined characteristics of people change discontinuously at the threshold. As Cattaneo et al. (2020) point out, one of the most critical RD falsification tests involves examining whether treated units are similar to control units in terms of observable characteristics near the cutoff. This test follows from the idea that if people cannot precisely manipulate the running variable, there should be no systematic differences between individuals with similar values for this variable. We focus on 15 covariates previously used in the analysis, all measured at the baseline. To test whether the predetermined covariates are continuous at the threshold, we estimate equation 2 using each of the predetermined covariates as the outcome. The estimation results are plotted in Figure D–2 in the Appendix. All the variables are statistically not different from zero (at 95% confidence level), except for alcohol use. These results indicate that the predetermined covariates are continuous at the threshold. In addition, we do not observe any apparent discontinuity at the cutoff when we plot each covariate as a function of the running variable in Figure D–3 in the Appendix.

In general, these empirical results are consistent with the idea that the institutional setup of *Pensión 65* makes it difficult for people to get around the thresholds that classify households as extremely poor. Consequently, we conclude that manipulation of the running variable is unlikely in this setting.

6.2 Placebo cutoffs

We assess the validity of the RDD for estimating the impact of the programme at placebo thresholds. To carry out this test, we choose the following thresholds located equidistantly around the actual eligibility cutoff: -0.06, -0.04, -0.02, 0.02, 0.04 and 0.06. Next, we estimate the impact of the programme at placebo thresholds and report the results in Table D–1 in the Appendix. We find no evidence of programme treatment effects at any of the placebo thresholds. In all cases, the placebo estimates are statistically indistinguishable from zero at the usual levels of significance. We conclude that the mortality probability and hazard function only change discontinuously at the centred zero threshold.

6.3 Sensitivity to observations near the cutoff

Another falsification procedure seeks to investigate how sensitive the results are to the response of units that are located very close to the cutoff. The idea is that the empirical effects should not be drastically determined by few observations that are very close to the cutoff. Cattaneo et al. (2020) propose checking the sensitivity of the results to the exclusion of these few observations (known as the "donut hole approach"). The authors point out that this strategy is also helpful to assess the sensitivity of the results to the unavoidable extrapolation applied in local polynomial estimation; the reason being that the few observations nearest to the cutoff are likely to be of considerable influence when fitting the estimation. We choose the following bandwidths located equidistantly around the actual eligibility threshold: 0.002, 0.004, 0.006, 0.008 and 0.01. We then estimate the impact, excluding the observations that are in these intervals, and report the results in Table D–2 in the Appendix. In general, we observe that the exclusion of these observations does not alter the conclusions of the analysis, either in the linear model or in the survival model.

6.4 Robustness analysis

We analyse the sensitivity of our results to different sizes of bandwidths and different periods to evaluate mortality and different model specifications. Figures D–4 and D–5 in the Appendix show the ITT effects, considering alternative bandwidths both for linear and survival models. We observe that the estimates are statistically significant and negative, yet the magnitude of the effect is smaller for wider bandwidths. Figure D–6 in the Appendix shows the estimated ITT effects on mortality for different time windows. There are no statistically significant effects for one or two years of observed mortality, but the effects start to be significant after the third year. In fact, there are no significant differences for the effect on mortality on the eligible population after the third year of observation. Lastly, Figure D–7 in the Appendix plots the ITT effects for different polynomial orders. Interestingly, the negative effect of the programme on mortality remains in all these specifications.

7 Conclusions

This paper details a study into the effect of Peru's social pension programme, *Pensión 65*, on the mortality rate of elderly poor people. As the programme provides pensions to individuals aged 65 and above who do not have any other pension benefits and live in households classified as extreme poor by the official targeting welfare index, we are able to exploit a discontinuity generated by this index. This discontinuity arises when eligible and ineligible individuals have an index just below or above the official eligibility cutoff point. Therefore, we estimate intention-to-treat effects in a regression discontinuity setting.

Some important features of our sample are that we use a survey fielded at the beginning of the programme rollout among individuals who had not been programme recipients; in other words, we use baseline data. This survey was intentionally designed to apply a regression discontinuity design and estimate the causal effects of the programme in a follow-up survey. The sample framework was designed to include only people located very close to the eligibility threshold, both the eligible and ineligible. We matched each individual in our sample to administrative records for the programme and mortality records from the national population register for the 2012-2019 period.

Analysing mortality over 7 years, we find that the programme can reduce the mortality rate of eligible individuals by about 11.4 percentage points. Furthermore, we compute that *Pensión 65* could increase the life expectancy of eligible individuals by one year. The estimated monetary cost associated with the improvement in life expectancy is much lower than the value of a statistical life in Peru (the cost being 19-33% of VSL), implying that the policy is cost effective. The estimated mortality–income elasticity is somewhat higher than the values reported in other papers studying the mortality effects of social pensions. However, it should be noted that we have a larger period of observed mortality and the focus of our analysis is on very poor elderly people who have faced various deprivations during their lifetime, including limited access to healthcare, nutrition and education. All these features lead to a high mortality risk, so that the effect of the pension could be very important (and more elastic) in preventing death for the very poor.

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Online Appendix

A Definition of variables

Table A–1: Definition of variables

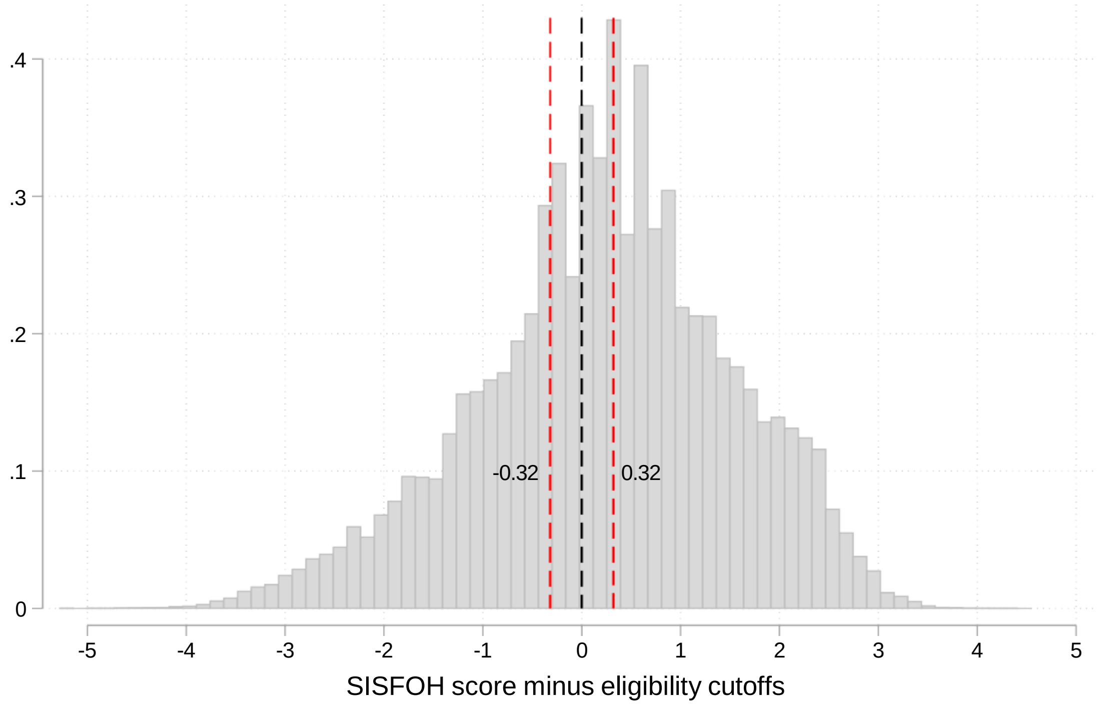
Variable	Definition
High blood pressure	It takes value 1 if the systolic blood pressure is greater than or equal to 140 (mm Hg) or if diastolic blood pressure is greater than or equal to 90 (mm Hg), and 0 otherwise.
Anaemia	It takes value 1 if the individual has anaemia, and 0 otherwise. The anaemia condition is determined according to haemoglobin levels analysed from blood samplings taken during the interview.
Weight	Body weight in kilograms.
Abdominal obesity	It takes value 1 if the waist measure is larger than the cutoffs that indicate obesity according to the norms set up by the Latin American Diabetes Association (see ALAD 2010 and Pajuelo-Ramirez et al. 2019), and 0 otherwise. These cutoffs are 94 cm and 88 cm for men and women, respectively.
Arm span	Arm span in centimetres.
Mid-upper arm circumference (MUAC)	Upper middle arm circumference in centimetres.
Calf circumference (CC)	Calf circumference in centimetres.
Cognitive functioning	It is a score (0-13) computed from the points assigned to the correct answers to four questions. *Orientation*: day of the week, day of the month, month, and year. *Immediate memory*: recall of three words read by the interviewer. *Delayed memory*: recall of the exact words again later in the interview. *Command*: three actions that the respondent must complete in order: "I will give you a piece of paper. Take this in your right hand, fold it in half with both hands and place it on your legs".
Chronic diseases	It is the total number of chronic medically diagnosed diseases reported by the individual from a list of 13 diseases.
Health today	It takes value 1 if the individual rates her health as good or very good from a 1-4 Likert scale, and 0 otherwise.
Health compared to last year	It takes value 1 if the individual rates her health as the same, better or much better with respect to last year from a 1-5 Likert scale, and 0 if she rates her health as worse or much worse.
Health compared to others	It takes value 1 if the individual rates her health as good or very good with respect to other people of similar age from a 1-4 Likert scale, and 0 otherwise.
Subjective health index	It is an index computed with the three subjective health questions mentioned before. First, we standardised the original variables containing their Likert-scale values (mean and standard deviation equal to 0 and 1) and sum them up. Second, we re-scale this value to obtain an index ranging between 0 and 1. Thus, larger values imply better perceived health.

Table A–2: Definition of variables

Variable	Definition
Mini Nutritional Assessment (MNA) score	It is a score measuring the quality of diet and the risks of under-nutrition and malnutrition among old individuals. The scores originally ranged from 0 to 30, but the available information in ESBAM allows us to compute a score ranging between 0 and 19. The information to compute the MNA includes variables indicating whether the individual i) eats three or more meals per day; ii) eats dairy products at least once a day; iii) eats fruits and vegetables at least twice a day; iv) drinks less than three glasses of water per day; v) eats eggs, beans or legumes at least once a week; vi) eats meat, fish or poultry at least three times a week.
Alcohol	It takes value 1 if the individual drank alcohol at least once during the three months previous to the interview, and 0 otherwise. It is measured in the baseline ESBAM survey, but not on the follow-up survey.
Tobacco	It takes value 1 if the individual smoked during the month previous to the interview (or before), and 0 otherwise. It is measured in the baseline ESBAM survey, but not on the follow-up survey.
Depression symptoms	It is the number of depression symptoms (score 0-9) measured with the geriatric depression scale from Sheikh and Yesavage (1986). This was measured only in the follow-up survey.
Juntos	It takes value 1 if the individual declared the household is the recipient of the conditional transfer program *Juntos*, and 0 otherwise.
Attended health centre	It takes value 1 if the individual who had any disease or symptom in the last month went to a health centre to treat them, and 0 otherwise. The value is set to missing for people who had no any disease in the last month.
Individual health expenditure	Expenditure (Soles per month) used by the individual in health services.
Individual medicine expenditure	Expenditure (Soles per month) used by the individual to buy medicines.
Working hours	Total number of hours worked in the previous week, including main and secondary occupations.
Working	It takes value 1 if the individual worked the previous week, and 0 otherwise.
Household expenditure	Total household expenditure (Soles per month).
Household food expenditure	Household expenditure on food (Soles per month).
Number of household members	It is the number of members residing permanently in the household.

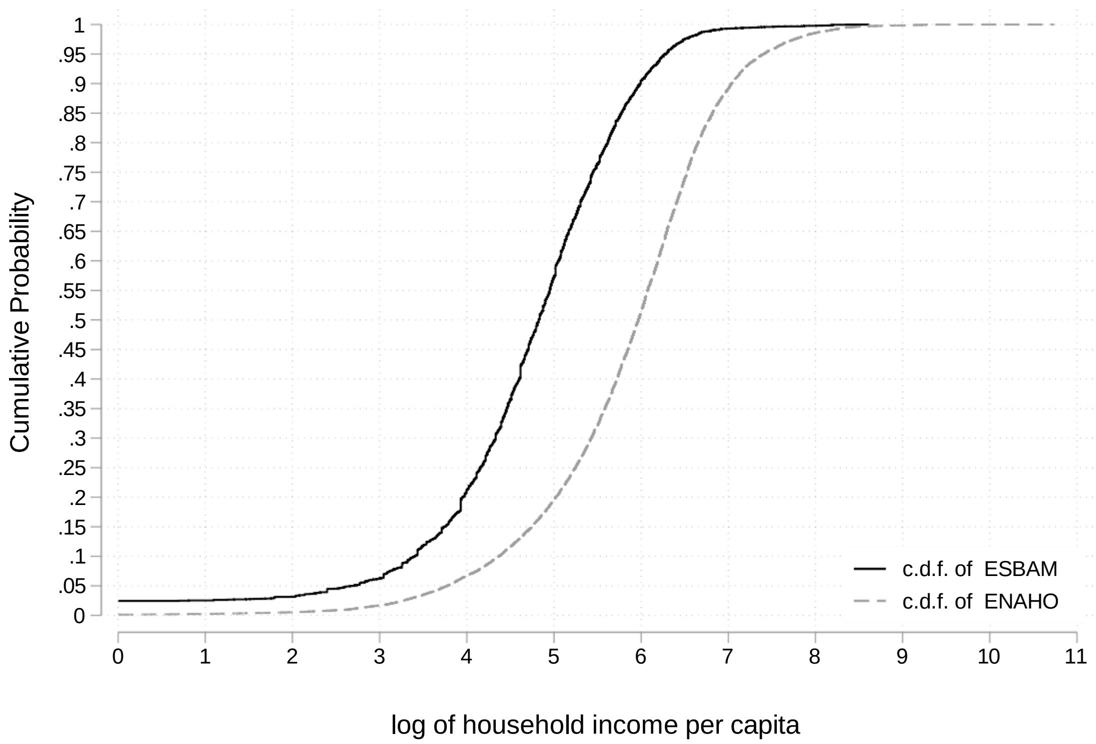
B Descriptive tables and figures

Figure B–1: National distribution of the centred SISFOH score



Notes: This figure plots the national distribution of the running variable, that is the SISFOH score minus eligibility cutoffs (histogram bars). The vertical red lines indicate the maximum and minimum values (bandwidth) found for the running variable in the ESBAM sample. The sampling framework correspond to observations located within this bandwidth. The data come from the SISFOH census of 2012/2013.

Figure B–2: Cumulative distribution of household income per capita in Peru and ESBAM



Notes: The figure plots the cumulative distribution of monetary gross household income per capita in Peru and the ESBAM Sample. The national income distribution is computed by exploiting the National Household Survey (ENAHO) collected in 2012. Income is transformed as log(1+income) for visualisation purposes.

Table B–1: Distribution of observations in sample

	Overall			**Eligible**			**Ineligible**		
	Mean	**SD**	**N**	**Mean**	**SD**	**N**	**Mean**	**SD**	**N**
Key variable									
Dead (0/1)	0.174	0.379	3,885	0.171	0.377	2,525	0.180	0.384	1,360
Running variable	-0.066	0.161	3,885	-0.171	0.069	2,525	0.129	0.082	1,360
Treated (0/1)	0.707	0.455	3,885	0.903	0.296	2,525	0.343	0.475	1,360
Covariates									
Male (0/1)	0.545	0.498	3,885	0.557	0.497	2,525	0.524	0.500	1,360
Age	71.646	4.396	3,885	71.723	4.365	2,525	71.503	4.453	1,360
High blood pressure (0/1)	0.338	0.473	3,835	0.347	0.476	2,500	0.320	0.467	1,335
Anaemia (0/1)	0.315	0.465	3,818	0.319	0.466	2,488	0.307	0.461	1,330
Weight (Kg.)	55.560	10.518	3,826	55.004	10.345	2,495	56.603	10.762	1,331
Abdominal obesity (0/1)	0.341	0.474	3,885	0.313	0.464	2,525	0.391	0.488	1,360
Arm span (cm.)	155.932	10.787	3,838	155.801	10.871	2,501	156.179	10.628	1,337
Mid-upper arm circum. (cm.)	26.220	3.242	3,838	26.085	3.149	2,500	26.471	3.398	1,338
Calf circum. (cm.)	31.764	3.053	3,832	31.680	2.991	2,497	31.920	3.162	1,335
Cognitive functioning (0-13)	10.740	2.035	3,817	10.767	2.044	2,480	10.692	2.019	1,337
Chronic diseases (0-13)	1.040	1.322	3,885	1.028	1.315	2,525	1.062	1.334	1,360
Good health (0/1)	0.570	0.495	3,866	0.564	0.496	2,512	0.582	0.493	1,354
MNA score (0-19)	11.809	2.712	3,760	11.722	2.652	2,451	11.973	2.814	1,309
Alcohol (0/1)	0.195	0.396	3,881	0.183	0.387	2,522	0.217	0.412	1,359
Tobacco (0/1)	0.200	0.400	3,869	0.207	0.405	2,515	0.186	0.389	1,354
Juntos (0/1)	0.088	0.284	3,885	0.080	0.271	2,525	0.104	0.305	1,360

Notes: The sample is composed of individuals observed in the baseline of the 2012 ESBAM survey. After dropping observations with inconsistent information or missing key information, the sample size is set to 3,885 individuals.

Table B–2: Distribution of observations in optimal selected sample

	Overall			**Eligible**			**Ineligible**		
	Mean	**SD**	**N**	**Mean**	**SD**	**N**	**Mean**	**SD**	**N**
Key variable									
Dead (0/1)	0.169	0.375	1,577	0.158	0.365	682	0.177	0.382	896
Running variable	0.012	0.082	1,577	-0.074	0.036	682	0.077	0.032	896
Treated (0/1)	0.602	0.490	1,577	0.894	0.308	682	0.379	0.486	896
Covariates									
Male (0/1)	0.545	0.498	1,577	0.557	0.497	682	0.536	0.499	896
Age	71.458	4.354	1,577	71.509	4.270	682	71.418	4.418	896
High blood pressure (0/1)	0.341	0.474	1,559	0.403	0.491	677	0.293	0.455	882
Anaemia (0/1)	0.302	0.459	1,548	0.283	0.451	669	0.316	0.465	879
Weight (Kg.)	56.082	10.532	1,555	56.894	10.714	673	55.462	10.354	882
Abdominal obesity (0/1)	0.355	0.479	1,577	0.383	0.486	682	0.334	0.472	896
Arm span (cm.)	156.453	10.407	1,560	156.789	10.670	675	156.198	10.200	885
Mid-upper arm circum. (cm.)	26.393	3.255	1,560	26.921	3.153	675	25.990	3.276	885
Calf circum. (cm.)	31.886	3.087	1,556	32.235	3.103	673	31.619	3.050	883
Cognitive functioning (0-13)	10.748	2.041	1,554	10.991	1.944	673	10.562	2.094	881
Chronic diseases (0-13)	0.991	1.296	1,577	1.098	1.374	682	0.910	1.228	896
Good health (0/1)	0.576	0.494	1,574	0.589	0.492	681	0.567	0.496	893
MNA score (0-19)	11.903	2.757	1,522	12.161	2.544	655	11.708	2.893	867
Alcohol (0/1)	0.195	0.396	1,576	0.181	0.385	681	0.206	0.404	895
Tobacco (0/1)	0.196	0.397	1,574	0.185	0.389	681	0.204	0.403	893
Juntos (0/1)	0.117	0.322	1,577	0.123	0.329	682	0.113	0.316	896

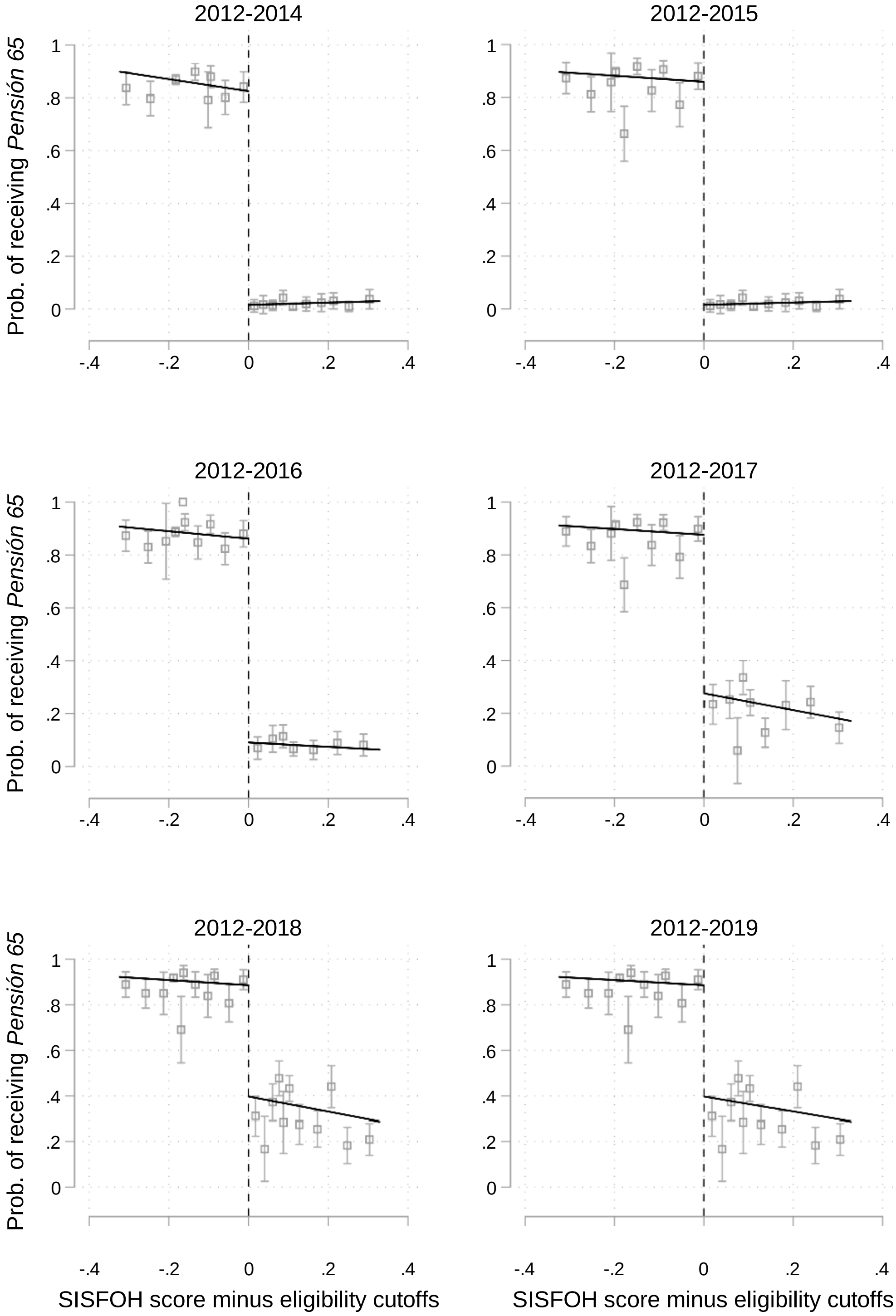
Notes: The sample is composed of individuals observed in the baseline of the 2012 ESBAM survey within the optimal bandwidth of +/-0.145 around the eligibility threshold, resulting in a sample size of 1,578 individuals. The optimal bandwidth is obtained from the point estimation model as suggested by Calonico et al. (2015)

Table B–3: Cumulative number of *Pensión 65* recipients

Year	Survived eligibles	Survived ineligibles	Num. of recipients	RD Estim.	S.E.	95% C.I.	
2013	2,475	1,338	1,963	0.689	0.029	0.632	0.745
2014	2,427	1,307	2,191	0.822	0.023	0.777	0.866
2015	2,370	1,272	2,243	0.852	0.020	0.812	0.891
2016	2,316	1,237	2,342	0.787	0.025	0.738	0.836
2017	2,242	1,194	2,567	0.602	0.033	0.537	0.667
2018	2,172	1,149	2,674	0.525	0.033	0.461	0.589
2019	2,093	1,115	2,746	0.472	0.034	0.405	0.539

Notes: The first and second columns indicate the number of individuals who have survived until December of each year by the eligibility condition measured at the baseline (i.e. according to the SISFOH rules of 2012). The third column shows the accumulated number of individuals each year who have received the transfer from the programme, regardless of their survival or disease condition. The RD estimator is computed as the change in the intercept of two estimated linear regressions that fit separately on each side of the eligibility cutoff.

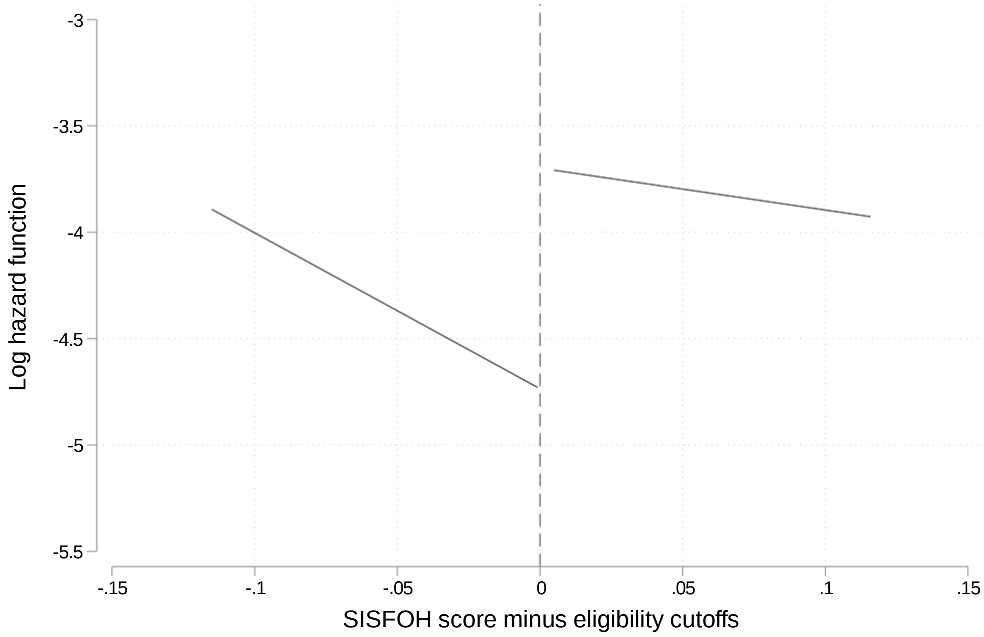
Figure B–3: Probability of being a *Pensión 65* recipient at different evaluation periods



Notes: The graphs plot the probability of receiving *Pensión 65* anytime in the indicated period as a function of the running variable (SISFOH score minus eligibility cutoffs). The support of the running variable has been partitioned into exclusive bins. The number of bins is selected optimally to minimise the integrated mean square error of the underlying regression function, and the location is based on quantile spaced method using spacings estimators as suggested in Calonico et al. (2015). The square points indicate the local mean of the outcome at the mid-point of each bin. The bars represent the 95% confidence intervals of the local means. The solid lines are linear regressions that fit separately on each side of the threshold. Observations to the left (right) of the vertical dashed line are eligible (ineligible) to the programme.

C Tables and figures of survival models

Figure C–1: Intention-to-treat in survival model



Notes: The graph plots the log of the hazard ratio of mortality observed over 7 years as a function of the running variable (SISFOH score minus eligibility cutoffs). The parametric model follows a Gompertz distribution. The lines are linear regressions that fit separately on each threshold side. Observations to the left (right) of the vertical dashed line are eligible (ineligible) to the programme.

Table C–1: Effect of *Pensión 65* on log of mortality hazard rate under alternative functions

Model	ITT Estimator	95% C.I.	
Cox	-0.853	-1.620	-0.086
Exponential	-0.838	-1.470	-0.206
Weibull	-0.847	-1.483	-0.210

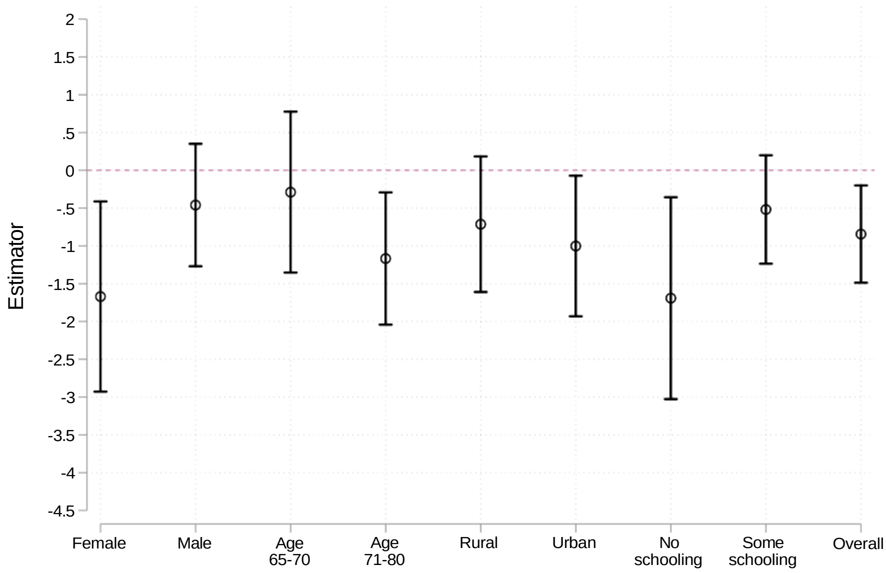
Notes: The table reports the ITT estimates for the log of mortality hazard rate observed over 7 years (equation 4). The estimators correspond to a non-parametric version (Cox model) and two parametric models (Exponential and Weibull). The models use triangular kernel, local linear polynomial and the optimal bandwidth for point estimation as suggested by Calonico et al. (2015) (obtained in the Table 2).

Table C–2: Effect of *Pensión 65* on log of mortality hazard rate including covariates

	(1)	(2)	(3)	(4)	(5)
ITT	-0.846***	-0.782**	-0.648*	-0.771**	-0.779**
	(0.324)	(0.334)	(0.340)	(0.347)	(0.347)
Male		0.333**	0.524***	0.540***	0.570***
		(0.136)	(0.196)	(0.202)	(0.208)
Age		0.112***	0.090***	0.087***	0.089***
		(0.015)	(0.016)	(0.016)	(0.016)
High blood pressure			0.369**	0.329**	0.329**
			(0.161)	(0.164)	(0.164)
Anaemia			0.230	0.277*	0.285*
			(0.154)	(0.155)	(0.156)
Weight			0.036**	0.045***	0.044***
			(0.015)	(0.015)	(0.015)
Abdominal obesity			0.328	0.369*	0.380*
			(0.216)	(0.223)	(0.223)
Arm span			-0.001	-0.007	-0.007
			(0.010)	(0.011)	(0.011)
Mid-upper arm circ. (MUAC)			-0.128***	-0.113**	-0.113**
			(0.044)	(0.044)	(0.044)
Calf circumference (CC)			-0.108***	-0.090**	-0.091**
			(0.035)	(0.036)	(0.036)
Cognitive functioning			-0.111***	-0.084**	-0.084**
			(0.034)	(0.035)	(0.035)
Chronic diseases				0.046	0.045
				(0.055)	(0.055)
Health today				-0.089	-0.094
				(0.164)	(0.165)
Nutrition score (MNA)				-0.100***	-0.100***
				(0.036)	(0.036)
Alcohol					0.073
					(0.197)
Tobacco					-0.144
					(0.188)
Constant	-3.768***	-12.084***	-5.046**	-4.481**	-4.585**
	(0.243)	(1.174)	(2.122)	(2.209)	(2.205)
Observations	1,577	1,577	1,513	1,483	1,481

Notes: The table reports the ITT estimates for the log of mortality hazard rate observed over 7 years (equation 4), including covariates related to the mortality risk. The estimator corresponds to a Gompertz-type model. The models use triangular kernel, local linear polynomial and the optimal bandwidth for point estimation as suggested by Calonico et al. (2015) (obtained in Table 2). The standard errors are indicated in parenthesis. $*p < 0.10$, $**p < 0.05$, and $***p < 0.01$ indicate statistically significance levels.

Figure C–2: Heterogeneous effects on the log of mortality hazard rate



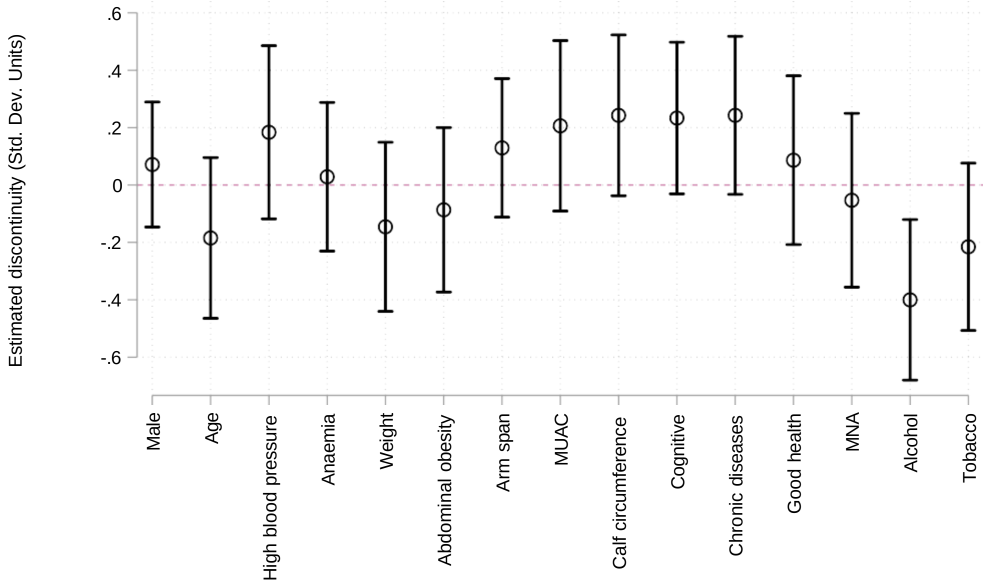
Notes: The graph plots the estimated ITT coefficients from equation 4 for four distinctive demographic groups (by sex, age, area, and education) and the overall effect. The vertical lines indicate 95% confidence intervals.

D Sensitivity and robustness checks

Figure D–1: Histogram and manipulation test based on density discontinuity

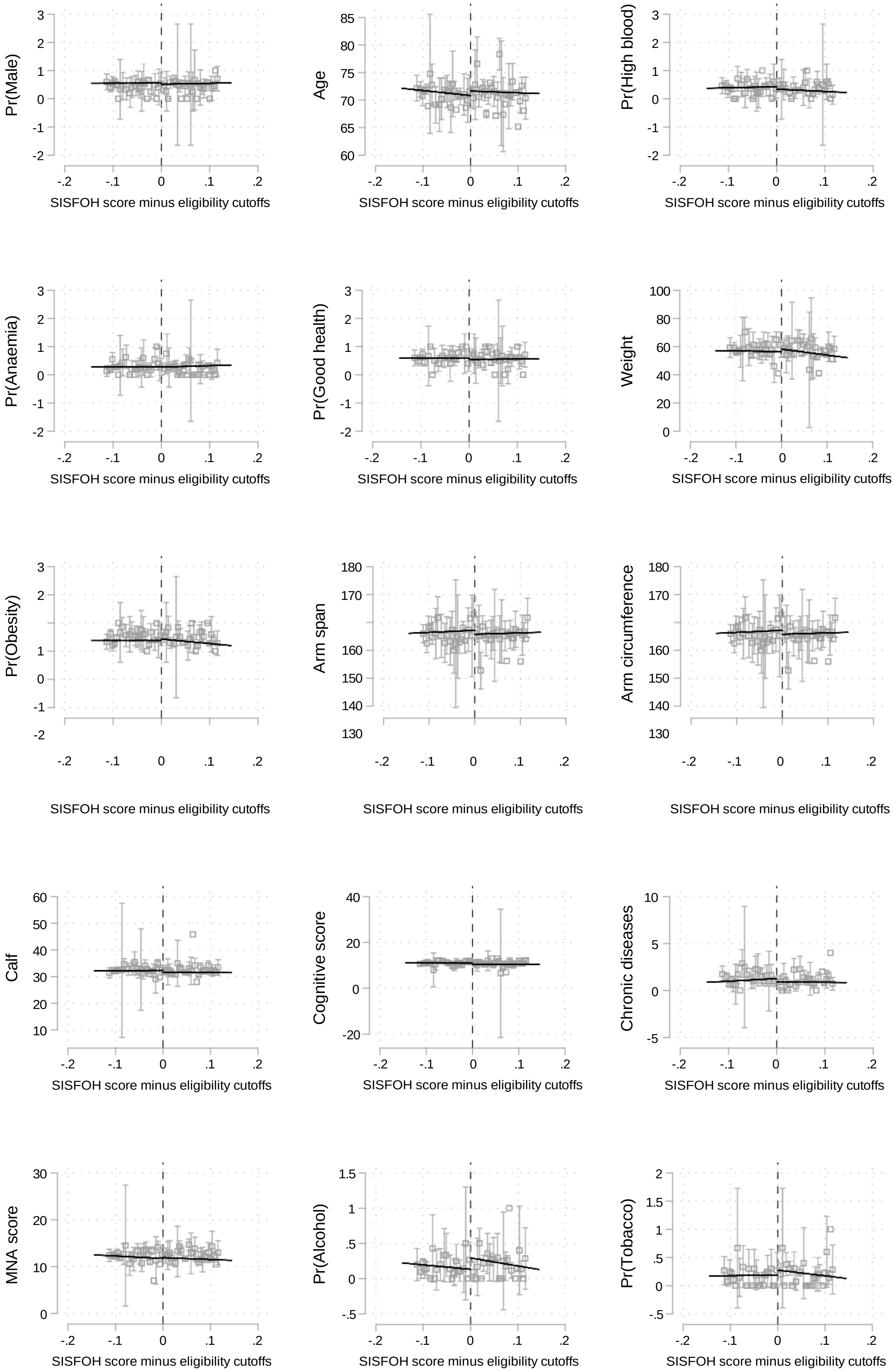
Notes: Panels A and B plot the histogram and empirical density of the running variable (SISFOH's index minus thresholds). Panel (b) corresponds to the test proposed by Cattaneo et al. (2018), using a bandwidth size of 0.16 points of the running variable on the left side of the cutoff and a bandwidth size of 0.10 on the right side of the cutoff. Also, a local cubic approximation is used in density estimators and bias-corrected density estimators. No significant discontinuity is found (pvalue=0.1323 under the null hypothesis that density is continuous at the threshold).

Figure D–2: Balance of covariates



Notes: This figure plots the ITT estimates of equation 2 using the listed covariates as dependent variables instead of mortality. Variables are standardised to facilitate comparison. All the estimated models use the triangular kernel, local linear polynomial, and the optimal bandwidth for point estimation as suggested by Calonico et al. (2015) (obtained in Table 2). The vertical lines indicate 95% confidence intervals.

Figure D–3: Continuity in observables



Notes: The graph plots the listed covariates as a function of the running variable (SISFOH score minus eligibility cutoffs). The support of the running variable has been partitioned into exclusive bins. The number of bins is selected optimally to minimise the integrated mean square error of the underlying regression function, and the location is based on quantile spaced method using spacings estimators as suggested in Calonico et al. (2015). The square points indicate the local mean of the outcome at the mid-point of each bin. The bars represent the 95% confidence intervals of the local means. The solid lines are linear regressions that fit separately on each side of the threshold. Observations to the left (right) of the vertical dashed line are eligible (ineligible) to the programme.

Table D–1: ITT effects under alternative cutoffs

Alternative cutoffs (x100)	Optimal bandwidth	OLS model		Survival model	
		ITT	P-value	ITT	P-value
-6	0.209	0.029	0.515	0.212	0.459
-4	0.145	-0.010	0.922	-0.027	0.969
-2	0.116	-0.069	0.115	-0.542	0.108
0	0.145	-0.114	0.011	-0.846	0.009
2	0.344	-0.033	0.255	-0.225	0.243
4	0.213	-0.027	0.544	-0.180	0.522
6	0.238	-0.038	0.403	-0.259	0.374

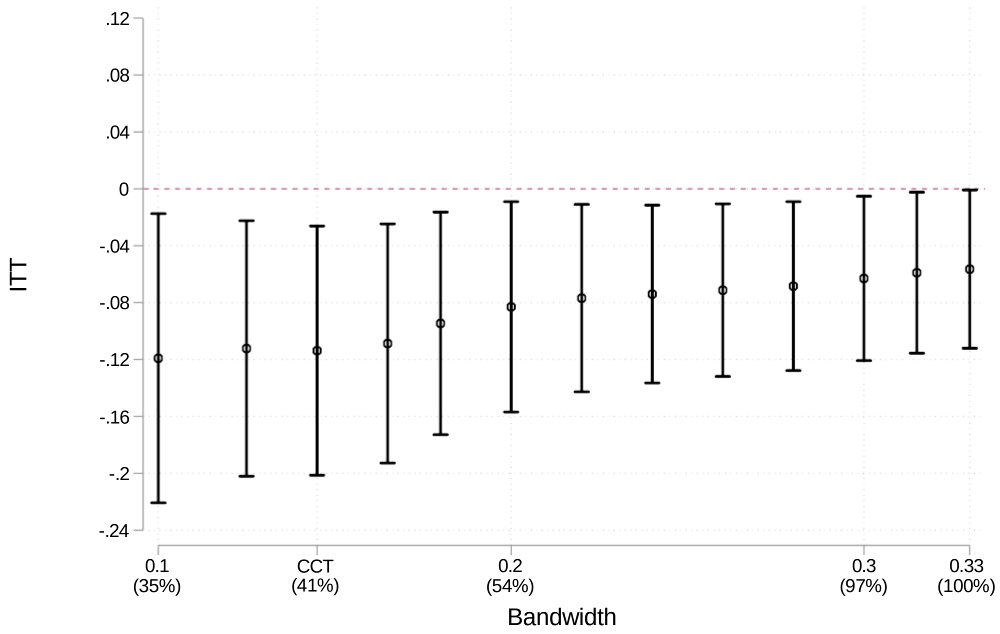
Notes: The table reports the ITT effects estimated for equations 2 and 4 in alternative cutoffs. The models use triangular kernel and local linear polynomial, and use the optimal bandwidth for point estimation as suggested by Calonico et al. (2015) obtained in linear regression. The standard errors are clustered by the Primary Sampling Unit (PSU) of the sampling framing.

Table D–2: Sensitivity to observations near the cutoff (donut hole approach)

Donut-hole Radius (x1000)	Excluded Obs. Left	Excluded Obs. Right	OLS Model ITT	OLS Model p-value	Survival Model ITT	Survival Model p-value
0	0	0	-0.114	0.011	-0.846	0.009
2	7	0	-0.118	0.009	-0.875	0.008
4	11	0	-0.114	0.046	-0.839	0.011
6	16	18	-0.103	0.033	-0.761	0.027
8	16	20	-0.108	0.027	-0.790	0.022
10	17	21	-0.110	0.026	-0.796	0.022

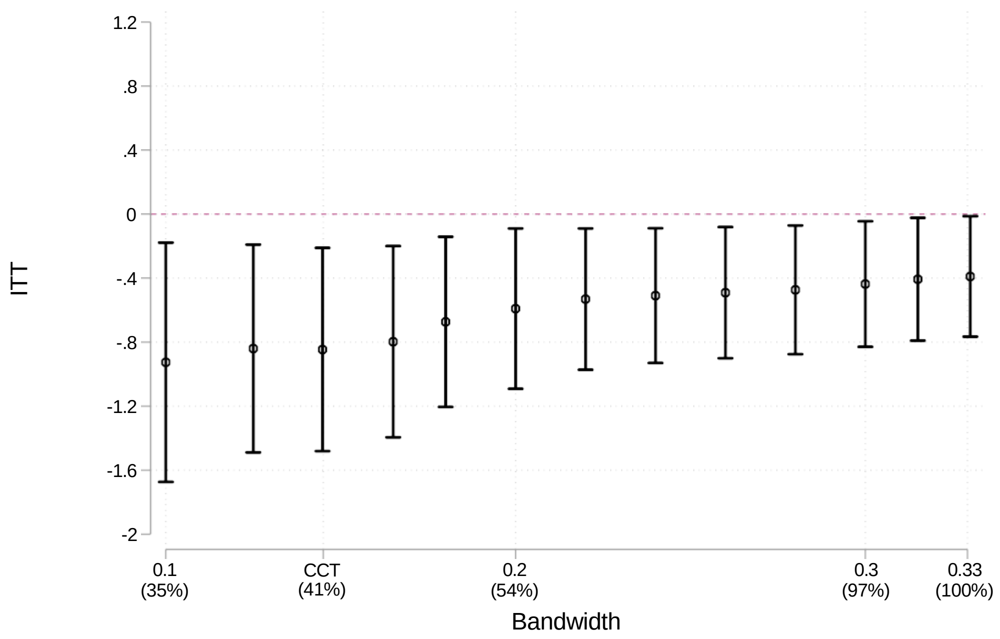
Notes: The table reports the ITT effects estimated for equations 2 and 4 excluding observations around cutoff. All the estimated models use triangular kernel, and the optimal bandwidth for point estimation as suggested by Calonico et al. (2015) (obtained in the Table 2). The standard errors are clustered by the Primary Sampling Unit (PSU) of the sampling framing.

Figure D–4: ITT effects by alternative bandwidths



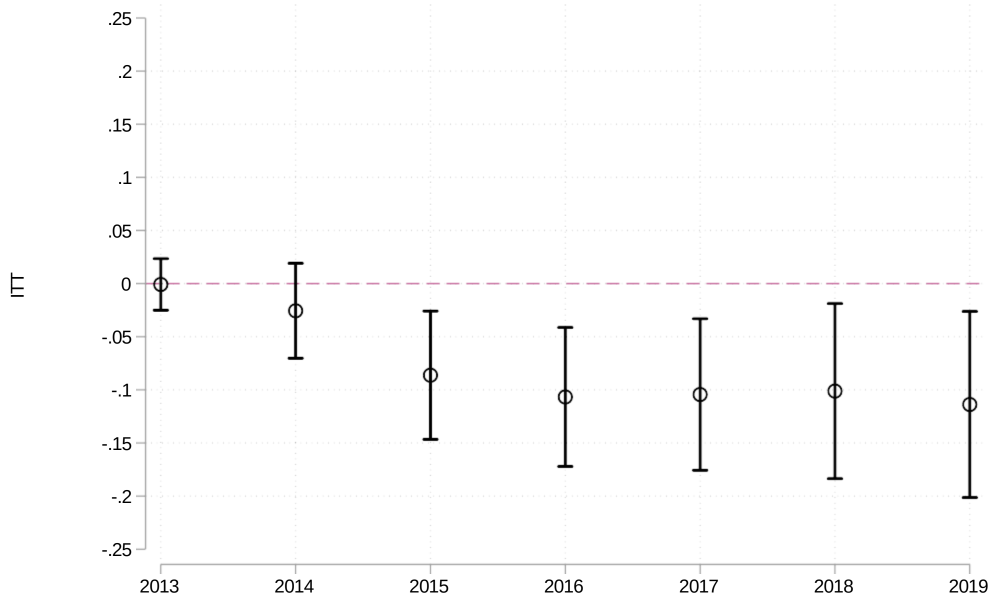
Notes: This figure plots the ITT effects estimated for equation 2 for alternative bandwidths. All the estimated models use triangular kernel and local linear polynomial. The horizontal axis shows the percentage of the sample employed for each estimated model. CCT corresponds to the optimally estimated bandwidth proposed by Calonico et al. (2015). The vertical lines indicate 95% confidence intervals.

Figure D–5: ITT effects on the log of mortality hazard ratio by alternative bandwidths



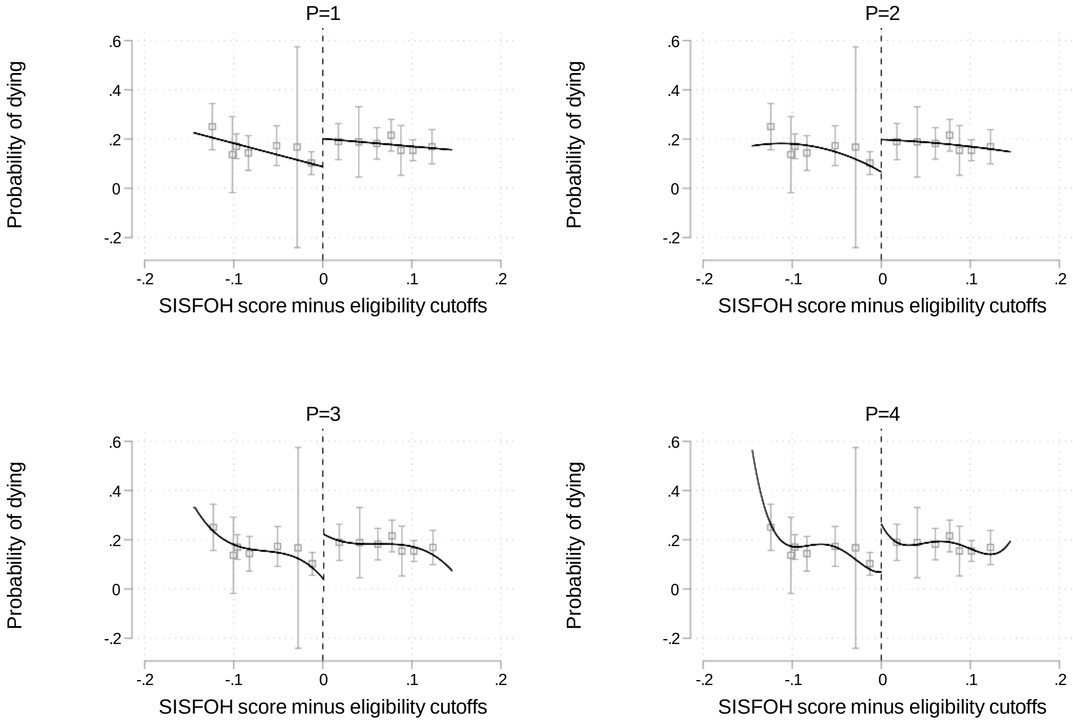
Notes: This figure plots the ITT effects estimated for equation 4 for alternative bandwidths. All the estimated models use triangular kernel and local linear polynomial. The horizontal axis shows the percentage of the sample employed for each estimated model. CCT corresponds to the optimally estimated bandwidth proposed by Calonico et al. (2015). The vertical lines indicate 95% confidence intervals.

Figure D–6: ITT effects by period of observed mortality



Notes: This figure plots the ITT effects estimated for equation 2 for alternative periods of observed mortality. The horizontal axis indicates the last year (December) of observed mortality, starting in December 2012. All the estimated models use the triangular kernel, local linear polynomial, and the optimal bandwidth for point estimation as suggested by Calonico et al. (2015) (obtained in Table 2). The vertical lines indicate 95% confidence intervals.

Figure D–7: ITT estimator assuming different order of polynomials



Notes: This figure plots the ITT effects estimated for equation 2 for different order of polynomials. The support of the running variable has been partitioned into exclusive bins. The number of bins is selected optimally to minimise the integrated mean square error of the underlying regression function, and the location is based on quantile spaced method using spacings estimators as suggested in Calonico et al. (2015). The square points indicate the local mean of the outcome at the mid-point of each bin. The bars represent the 95% confidence intervals of the local means. The solid lines are linear regressions that fit separately on each side of the threshold. Observations to the left (right) of the vertical dashed line are eligible (ineligible) to the programme.

E Value of Statistical Life (VSL)

Table E–1: Value of Statistical Life (VSL) estimations for Peru (2012)

Study	Features	VSL (USD)
Robinson et al. (2019)	base=160; $\varepsilon = 1.5$	427,711
Robinson et al. (2019)	base=100, $\varepsilon = 1.0$	606,786
Robinson et al. (2019)	base=160, $\varepsilon = 1.0$	970,858
Viscusi and Masterman (2017)	$\varepsilon = 1.0$	1,044,306
Sweis (2022)	$\gamma = 0.1$	3,348,777
Sweis (2022)	$\gamma = 1.0$	362,030
Sweis (2022)	$\gamma = 0.5$	633,552
Mardones and Riquelme (2018)	predicted from other studies	451,746

Notes: This table shows the Value of Statistical Life (VSL) estimated for Peru in different studies. All cases have been adapted to show the VSL in 2012 United States dollars. Robinson et al. (2019) extrapolate VSL estimates of USD using different base values and income elasticity (ε). The base value multiplies the Gross National Income (GNI) per capita, while the ε summarises the rate at which VSL changes with income. Viscusi and Masterman (2017) uses unitary income elasticity and their US estimate of VSL to compute VSL in 189 countries. Sweis (2022) uses a consumption-health maximisation framework to measure the VSL in selected countries in order to measure the total value of loss from deaths caused by COVID-19. She presents estimates of VSL by different values of γ, which is the degree of homogeneity of the utility function (a smaller gamma implies more benefits to invest in health and survive longer), yet the author prefers $\gamma = 0.5$ to measure the value of COVID-19 deaths. Mardones and Riquelme (2018) use VSL estimates from different studies to estimate the relationship between Gross Domestic Product (GDP) per capita and VSL, and then predict the VSL for selected Latin American countries.

F Mechanisms

Table F–1: ITT effects of *Pensión 65* on various outcomes (2015 follow-up sample)

	All sample		Bandwidth 0.1448		Non-parametric	
Outcomes	Effect	N	Effect	N	Effect	N
High blood pressure	0.091	3,494	-0.175	1,414	-0.284*	1,235
Anaemia	-0.246***	3,454	0.000	1,397	0.228	469
Weight	0.127	3,478	-0.122	1,407	-0.294	644
Abdominal obesity	0.118	3,512	-0.244*	1,424	-0.498*	473
Arm span	0.014	3,481	-0.062	1,409	0.265	469
Mid-upper arm circ. (MUAC)	0.322***	3,496	0.086	1,415	0.250*	1,828
Calf circumference (CC)	0.260***	3,492	-0.117	1,415	-0.093	689
Depression symptoms	-0.237***	3,511	-0.151	1,424	0.239	476
Cognitive functioning	0.333***	3,449	0.380***	1,403	-0.058	443
Chronic diseases	0.356***	3,512	0.562***	1,424	-0.052	449
Nutrition score (MNA)	0.307***	3,354	-0.015	1,355	-0.148	621
Health today	0.131	3,506	0.226*	1,422	-0.008	481
Health compared to last year	0.292***	3,503	0.327**	1,422	0.267*	1,247
Health compared to other people	0.197**	3,455	0.084	1,401	0.022	1,220
Subjective health index	0.246***	3,454	0.217	1,400	0.100	649
Attended health centre	0.347***	2,474	0.718***	1,005	0.570**	476
Indiv. health expenditure	0.106	3,512	0.173	1,424	0.157	1,856
Indiv. medicine expenditure	0.120**	3,512	0.127	1,424	0.098	3,037
Working hours	-0.298***	3,512	-0.108	1,424	-0.102	1,322
Working	-0.311***	3,512	-0.094	1,424	-0.068	1,243
Household expenditure	0.544***	3,512	0.025	1,424	-0.071	1,322
Household food expenditure	0.486***	3,512	-0.109	1,424	-0.203	743
Expenditure per capita	0.332***	3,494	-0.233	1,416	-0.495	634
Food expenditure per capita	0.382***	3,494	-0.328**	1,416	-0.418*	654
Number of household members	0.276***	3,512	0.461***	1,424	0.396***	3,507

Notes: The table reports the ITT effects of *Pensión 65* on various outcomes measured during the follow-up survey fielded between July and September 2015. All the outcomes have been standardised to show mean equal to zero and standard deviation equal to one. From the 3,885 observations of our baseline, we found 3,514 individuals surveyed in the follow-up. The first column reports the ITT effects on all the 2015 sample, the third column reports the ITT effects when we use the bandwidth considered in our main analysis of mortality on the baseline sample (bandwidth equal to 0.1448) and kernel weights, and the fifth column shows the ITT effects when we use the non-parametric approach suggested by Calonico et al. (2015) for each outcome (rdrobust with kernel weights and polynomial of degree one, and MSE-optimal bandwidths). The standard errors are clustered by the Primary Sampling Unit (PSU) of the sampling framing. $*p < 0.10$, $**p < 0.05$, and $***p < 0.01$ indicate statistically significance levels based on those standard errors.