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**Escuela de Posgrado**

# Public and Social Pensions: Investigating Redistribution and Mortality Outcomes

Tesis para optar por el grado académico de Doctor en Economía que presenta:

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*Para Viviana, Joaquín y Alejandro*

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# Abstract

This doctoral research explores two critical dimensions of pension systems in developing countries, focusing on Peru. The first dimension analyses the role of income-mortality differentials and pension eligibility conditions on the level of regressivity and progressivity of Peru's public pension system, using administrative records from 1999 to 2018 to do so. We consider the joint effect of (i) insufficient contributions, by which the poorest contribute to the pension system but ultimately do not qualify for pensions because of insufficient contributions, and (ii) differing mortality by socioeconomic status in contributing to regressivity of the system. We find that the impact of insufficient contributions is more important than the impact of higher mortality in making the system regressive.

The second dimension assesses the effects of Peru's social pension programme, Pension 65, on mortality. The programme provides pensions to people aged 65 and older who are extremely poor and do not have other pensions. The analysis relies on survey data obtained at the baseline and matched to mortality records of 2012-2016. We exploit the discontinuity around the welfare index used by the programme to determine eligibility and estimate intention-to-treat effects. We find that after four years, the programme could reduce mortality among eligible people by about 10.7 percentage points, implying about one year more in life expectancy.

# Resumen

Esta investigación doctoral explora dos dimensiones críticas de los sistemas de pensiones en los países en desarrollo, centrándose en Perú. La primera dimensión analiza el papel de los diferenciales de ingreso-mortalidad y las condiciones de elegibilidad de las pensiones en el nivel de regresividad y progresividad del sistema público de pensiones de Perú, se utiliza para ello registros administrativos de 1999 a 2018. Se considera el efecto conjunto de (i) la insuficiencia de aportes, por la cual los más pobres contribuyen al sistema de pensiones pero finalmente no califican para pensiones debido a aportes insuficientes, y (ii) la mortalidad diferencial por estatus socioeconómico en la contribución a la regresividad del sistema. Se constata que el impacto de la insuficiencia de cotizaciones es más importante que el impacto de una mayor mortalidad a la hora de hacer regresivo el sistema.

La segunda dimensión evalúa los efectos del programa de pensiones sociales de Perú, Pensión 65, sobre la mortalidad. El programa proporciona pensiones a las personas mayores de 65 años que son extremadamente pobres y no tienen otras pensiones. El análisis se basa en datos de encuestas obtenidos en la línea de base y emparejados con los registros de mortalidad de 2012-2016. Se explota la discontinuidad en torno al índice de bienestar utilizado por el programa para determinar la elegibilidad y se estima los efectos por intención de tratar. Se encontra que después de cuatro años el programa podría reducir la mortalidad entre las personas elegibles en alrededor de 10,7 puntos porcentuales, lo que implica alrededor de un año más en la esperanza de vida.

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# Introduction

This doctoral thesis examines public and social pension systems, focusing on Peru and analysing their impact on the distribution of pension wealth and mortality among the elderly. Through two primary studies, the research addresses two critical dimensions of pension systems: the regressivity of pay-as-you-go (PAYG) systems and the effects of social pensions on mortality among the extremely poor elderly. Both studies provide relevant empirical evidence for public policy formulation, highlighting the challenges and opportunities for improving the effectiveness and equity of pension systems in developing countries.

The first study, titled "Regressivity in Public Pension Systems: The Case of Peru", aims to assess the progressivity or regressivity of the PAYG pension system in Peru. This analysis is justified by the need to understand how pension access rules, such as minimum contribution requirements and differences in life expectancy based on socioeconomic status, impact the distribution of pension wealth among retirees. Specifically, it aims to determine whether the Peruvian pension system, akin to other systems in Latin America, tends to favour higher-income individuals at the expense of the poor, potentially exacerbating social inequalities. The findings of this section have been published as "Regressivity in Public Pension Systems: The Case of Peru", in The Journal of the Economics of Ageing, Volume 29, 2024, 100532, ISSN 2212-828X, https://doi.org/10.1016/j.jeoa.2024.100532 (available at ScienceDirect).

The second study, "The effects of social pensions on mortality among the extremely poor elderly", focuses on evaluating the causal impact of the social pension programme "Pension 65" on mortality among the extremely poor elderly in Peru. This study is justified by the growing importance of social pension programmes in developing countries, where informal labour markets and the lack of access to contributory social security systems are prevalent. The objective is to determine whether the monetary transfers from these programmes significantly reduce mortality among beneficiaries, which could have important implications for social policy and public health.

In the first study, a multifaceted methodology is employed to analyse the regressivity of the Peruvian pension system. Administrative records from the public pension system are used, which include detailed information on affiliates, their contributions, and their employment histories. These data were matched with information from the civil registry to investigate the date of death, information which is crucial for estimating life expectancy and the probability that individuals will continue to receive a pension. The data is analysed by an approach based on Von Gaudecker and Scholz (2007a) work to determine individuals' socioeconomic levels, estimating socioeconomic status (SES) based on accumulated income points during the pre-retirement period. Besides, a Heckman model is applied to correct potential selection biases, which estimates the probability of an individual qualifying for a pension, considering both years of contribution and other socioeconomic factors.

Additionally, survival models estimate the probability of an individual living long enough to receive a pension, capturing differences in mortality across socioeconomic groups. These models are fundamental for defining indicators of pension wealth, which incorporate pension amounts and individuals' life expectancy. Finally, simulations are conducted to estimate the distributive effects of three key scenarios: (i) an increase in the life expectancy of lower-income individuals, (ii) the provision of proportional pensions to those who do not meet the minimum contribution threshold, and (iii) both scenarios combined. These simulations allow for a comparison of how these policies might affect the distribution of pension wealth, mainly whether they could reduce system regressivity.

In the second study, a regression discontinuity design (RDD) is applied to estimate the causal effect of the "Pension 65" programme on elderly mortality. For this purpose, a specialised survey explicitly designed for this study is used, combined with administrative records from the programme and mortality statistics. The survey provides detailed information on beneficiaries and non-beneficiaries of the programme, while administrative records allow for the verification of eligibility and mortality status. The analysis focuses on individuals near the eligibility threshold for the programme, enabling a comparison between those who receive the pension and those who do not, assuming that treatment assignment is quasi-random around the threshold.

The first study's results revealed that the Peruvian pension system exhibits regressive characteristics, primarily due to insufficient contributions among lower-income individuals and heterogeneity in life expectancy to a lesser extent. On average, individuals in the lowest income quartile contribute 15 fewer years than those in the highest quartile, representing a significant gap in the accumulation of pension rights. Additionally, it is found that lower-income individuals have a life expectancy of 5 years shorter than higher-income individuals, reducing the period during which they can receive a pension. However, when quantifying these effects, it is observed that insufficient contributions account for approximately 70% of system regressivity, while differences in life expectancy contribute to the remaining 30%. This suggests that, although both factors are essential, the lack of contributions is the primary driver of regressivity.

Furthermore, a recent policy allowing access to proportional minimum pensions with fewer years of contribution is evaluated. The conclusion is that although this measure mitigates some distributive issues, it cannot make the system fully progressive. Simulations show that while this policy reduces the gap in the accumulation of pension rights, it does not fully address differences in life expectancy, limiting its impact on reducing regressivity.

The second study found that the “Pension 65” programme significantly reduces the four-year mortality rate among eligible individuals by 10.7%, equivalent to a 92.2% reduction compared to ineligible individuals at the eligibility threshold. This effect is robust to various validation and falsification tests, and it is estimated that the programme could increase beneficiaries’ life expectancy by approximately one year. Additionally, a mortality-income elasticity of -0.95 is identified, suggesting that the impact of monetary transfers on reducing mortality is particularly significant among the extremely poor elderly.

This thesis is structured into four chapters that comprehensively address key aspects of public and social pension systems in the Peruvian context. Chapter 1 serves as the general introduction to the document, presenting the context, objectives, and justification of the research and a description of the thesis structure. Chapter 2 is titled “Regressivity in Public Pension Systems: The Case of Peru”. Chapter 3 is titled “The effects of social pensions on mortality among the extremely poor elderly”. Finally, the last chapter presents the general conclusions of the thesis. This chapter synthesises the main findings of the previous chapters, discusses their implications for public policy, and proposes recommendations for improving the equity and effectiveness of pension systems in Peru and other developing countries.

# Chapter 1

# Regressivity in public pension systems: the case of Peru

**ABSTRACT.** We study the role of income-mortality differentials and pension eligibility conditions on the level of regressivity and progressivity of Peru's public pension system, using administrative records from 1999 to 2018. We consider the joint effect of insufficient contributions, by which the poorest contribute to the pension system but ultimately do not qualify for pensions because of insufficient contributions, and differing mortality by socioeconomic status in contributing to regressivity of the system. We find that insufficient contributions are more important than higher mortality's impact in making the system regressive.

## 1.1 Introduction

By establishing minimum and maximum pensions, pay-as-you-go (PAYG) systems acquire a progressive character, as those with lower incomes would receive, in relative terms, higher pensions. In particular, when a minimum pension is established, those with lower incomes benefit from higher salary replacement rates (RR). This progressive effect is reinforced by implementing a maximum pension limit, resulting in those with higher incomes seeing a lower RR (Altamirano et al. (2019)).

Such limits on pensions are a common practice in PAYG systems, as are requirements for a minimum number of contributions to qualify for a pension. Pension systems in Latin America require around 22 years of contributions to obtain a minimum pension, while Peru, the focus of this

[1]This chapter has been published in The Journal of the Economics of Ageing, Volume 29, 2024, 100532, ISSN 2212-828X (https://www.sciencedirect.com/science/article/abs/pii/S2212828X2400032X).

work, requires 20 years (see Table A–1 in the Appendix). The requirement of a minimum number of contributions could render the pension system regressive because those with lower incomes tend to accumulate fewer contributions throughout their working lives than those with higher incomes (Montenegro Trujillo et al. (2013); Altamirano et al. (2019)). Such regressivity has been documented for Colombia, Uruguay, Brazil, Ecuador, and Argentina, as well as for Latin America and the Caribbean in general (Lasso et al. (2004), Méndez et al. (2009), Azuero Zúñiga (2020), Montenegro Trujillo et al. (2013), Cisoe et al. (2019), Álvarez et al. (2020), Altamirano et al. (2018), and Alonso et al. (2014)).

In addition to contribution requirements, varying life expectancies by socioeconomic status (SES) may also lead to regressivity in pension systems. Evidence from developed countries suggests people with a lower SES have a shorter life expectancy than people with a higher SES (e.g., Deaton (2002), Gerdtham and Johannesson (2004), Von Gaudecker and Scholz (2007a), Smith (2007), Smith and Goldman (2007), Dowd et al. (2011), Belloni et al. (2013)). Hence, even if qualifying for a pension, low-income retirees could receive a pension for a shorter period than high-income retirees. Therefore, a higher RR for low-income retirees does not guarantee a progressive income distribution in the public pension system. The correlation between life expectancy and SES means that the uniform application of pension rules to all individuals may result in a penalty for low-income individuals and a bonus for high-income ones, introducing another regressive component to the system. Whitehouse and Zaidi (2008) has documented significant socioeconomic differences in mortality among men in the United States, Germany, and the United Kingdom and how these differences reduce progressivity in the pension system. Cristia (2009) corroborates these findings for the United States, warning that differential mortality could undermine the progressivity built into social security benefit formulas.

This study assesses how early mortality of low-income individuals and contribution requirements affect the level of progressivity (or regressivity) in the Peruvian PAYG pension system. Our underlying hypothesis is that low-income individuals have higher mortality and contribute less than high-income individuals. To assess whether this is true, as well as the effects of this on the system, we analyze the administrative records of the Peruvian PAYG system from July 1999 to August 2018, including information on all affiliated individuals who survived to at least age 65.

Following closely the strategy employed by Von Gaudecker and Scholz (2007a) for the German pension system, we estimate SES levels as a function of accumulated earning points during the pre-retirement period in order to capture individuals' SES in the years before and close to retirement. The distribution of earning points shows a concentration at very low levels, implying that only one-fourth of enrolled individuals could receive a pension. We can compare SES and the distribution of expected pension wealth to assess how much the pension system punishes or favours income redistribution among its affiliates. Because the concept of expected pension wealth uses the mortality profiles of different individuals (e.g. rich and poor, men and women), we also estimate the differential effects of the income-mortality gradient on the levels and distribution of pension wealth.

We find that the poorest individuals contribute less and live less. On average, those in the lowest income quartile contribute 15 fewer years and live five fewer years than those in the highest quartile (i.e., at age 65, those in the lowest quartile have a life expectancy of five fewer years than those in the highest quartile). Consequently, for the poorest, contributions to a pension system for which they will not qualify and shorter life expectancy contribute to pension system regressivity, with the contributions causing more of the system regressivity.

We also assess the possible effects of a pension policy implemented in late 2021 to allow those with 10 or 15 years of contributions to qualify for lower, "proportional" minimum pensions. While this new policy mitigates the distributional problems of the public pension system, it is insufficient to make the system fully progressive.

Our work makes three significant contributions to the literature: (i) it provides evidence on the regressivity caused by the insufficiency of contributions in PAYG systems, (ii) it documents the effects of early mortality among low-income people in a developing country and its consequent regressive impact on pensions, and (iii) it shows the joint effect of insufficient contributions and early mortality, making a novel contribution to the specialized literature. Our study of the distributional effects of minimum periods of contributions and possible solutions, such as reduced minimum pensions, will also be of interest to other countries with pension systems having similar requirements.

The rest of the paper is organized as follows. Section 1.2 describes the pension system in Peru. Section 1.3 describes the data we use in the analysis. Section 1.4 details the empirical strategy. Section 1.5 presents and discusses the empirical results. Section 1.6 presents our conclusions and policy implications.

## 1.2 The Peruvian Pay-As-You-Go pension system

The Peruvian pension system comprises two primary schemes[1], offering distinct choices to individuals. Firstly, the Private Pension System (SPP by its acronym in Spanish), launched in June 1993, is a defined contribution (DC) system using individual retirement accounts. Pension fund

[1]Table A–3 include principal regulations governing the Peruvian pension system.

managers, known as AFP (Administradoras de Fondos de Pensiones), receive contributions and invest these personalized savings in regulated and supervised investments. Secondly, the Public Pension System, known as the National Pension System (SNP by its acronym in Spanish), functions as a defined benefit (DB) system. The SNP operates as a PAYG system, with contributions from individuals and supplementary government transfers ensuring the disbursement of pension benefits.

When individuals first enter the workforce, they must choose one of these schemes. If they do not do so within ten days, they are enrolled in the SPP. Individuals can switch from the SNP to the SPP anytime, but the reverse is prohibited. A key influence on the preference for one system over the other is how pension benefits are calculated and provided. Unlike the SNP, the SPP does not have a guaranteed minimum pension except for a specific group of affiliates (born before 1945) who previously switched between systems. This means that the pension savings accrued during retirement in the SPP are not supplemented with government transfers. The SNP determines benefits based on specific pension regulations, including minimum and maximum pension amounts. Until October 2021, 20 years of contributions were necessary to get a pension at the legal retirement age in the SNP. Any contribution period under these 240 months would not qualify for pension entitlement. Contributions are not refunded for individuals who do not meet this minimum contribution requirement.

Since November 2021, workers who made at least 10 years of contributions can request 'proportional' retirement pensions. For those who contributed at least 20 years, the SNP offers a minimum pension of 500 Soles per month (54% of the minimum wage) and a maximum pension of 893 Soles per month (96% of the minimum wage). Those who contributed at least 10 but fewer than 15 years can receive pensions of 250 Soles per month, while those who contributed at least 15 but fewer than 20 years can receive 350 Soles per month.

In both systems, the retirement age is 65, and contributions are based on labour earnings that meet or exceed the minimum wage (930 Soles). While there are variations in contribution rates and fees between the two schemes, they both operate on the premise of 12 payments per year. This implies that the income base for pension contributions does not include the two additional salary bonuses specified in labour legislation. The SNP has a total contribution rate of 13%; the SPP contribution rate is 10%, but it increases to 11.9%-13% when managing fees and insurance premium fees are added.

Formal sector employees must contribute to a pension system, while self-employed and other workers may contribute voluntarily. The substantial size of Peru's informal labour market leads to lower coverage through infrequent contributions to the pension system. As a consequence of this, there is high labour participation of the elderly population in poverty; according to Table A–2, it is estimated that in 2023, 74% of people in extreme poverty between 65 and 70 years of age actively participate in the labour market), also, 51% of the labour force was registered in the SPP and 29% in the SNP. Still, consistent contributors were limited to 19% of the labour force in the SPP and 9% in the SNP[2].

A crucial distinction between the two pension schemes lies in their financial sustainability. While SPP pensions are inherently self-sufficient and do not rely on government support, their implementation in 1993 and the subsequent transition were not without costs. The primary public expenditures associated with the SPP are "Recognition Bonds" (Bonos de Reconocimiento), constituting a pledged public transfer to individuals who shifted from the public pension system to the private one. These bonds were granted around the pension system transition, and a portion of the contributions made to the public system were acknowledged.

Conversely, the SNP relies on the contributions of current affiliates to fund present pensions. The government channels resources to help finance these payments. Additionally, the SNP operates with a reserve fund known as the "Fondo Consolidado de Reserva" (FCR), which contributes resources to cover pension expenditures. In 2023, 76% of the pension payroll was financed through contributions, 11% through the FCR, and the remaining 13% through treasury transfers (See Table A–4).

Since some payroll financing is derived from taxes, all individuals contribute to this funding, including those not affiliated with any system, likely belonging to the informal sector and those affiliated with the SNP who will not receive a pension due to insufficient contributions. This represents a regressive element contrasting with the progressive effect of higher-income individuals contributing through taxes. Therefore, supplementary government transfers, along with the sources of tax revenues funding these transfers, play a crucial role in determining the overall regressivity or progressivity of the system. In this sense, this study can be considered a partial analysis of the regressivity problem in the SNP.

## 1.3 Data

To assess the SNP's progressivity, we use three types of administrative records: contribution records from the country's tax collection agency (SUNAT), pension claims from the Pension Normalisation Office (ONP), and mortality information from the National Registry of Identification and Civil Status (RENIEC).

[2]Table A–4 and Figure A–1 show the main statistics of the Peruvian pension system and the evolution of affiliates and contributors in the SNP and SPP from 2000 to 2023.

The SUNAT data are longitudinal, with monthly information on contributions, labour income, sex, and date of birth from July 1999 to August 2018. The ONP data include the number of contributions made during the working life for members who applied for a pension. The history of pensions paid and observed during the study period is also known. Information on contributions has been digitized from July 1999 onwards; previous periods are only known once the member applies for qualification, and the ONP constructs the history of prior contributions.

The information always comes from computer systems that guarantee quality. The individual records are matched between the different sources using the national identity document (DNI). The ONP has access to SUNAT information and, through an institutional agreement, periodically crosses the information of its affiliates with RENIEC. Additionally, the ONP periodically excludes members who move to the SPP. In this way, the date of death is always included in the data, and affiliation data are always up to date.

Our sample considers members born between 1939 and 1952 who survived to age 65. We estimate SES for these individuals by examining contributions during the five years before retirement. Our sample consists of 276,885 people. Table 1.1 presents descriptive statistics of our sample. We find that the average contribution density is 44% and that 7% of the members died during the time horizon analyzed. By SES, contribution density is 0.3% for the bottom quartile and 94.1% for the top quartile. Mortality is more significant in the lower quartiles than the higher ones. Among our sample, only 43% applied for a pension; or those applying, 89% met the requirement of contributing at least 20 years.

## 1.4 Empirical strategy

We must undertake four tasks to analyze the distributional effect of insufficient contributions and the early mortality of the poorest on pension wealth. These are (i) establishing a criterion for measuring SES, (ii) estimating the contributions of individuals who have not applied for a pension, (iii) determining survival probabilities, and (iv) defining the variables that gauge the wealth of individuals.

The following analysis considers an important caveat: while low income can indeed lead to higher mortality rates, it is also possible that poor health, which itself can increase mortality, may result in lower income and reduced contributions. Thus, as indicated by Lee and Sanchez-Romero (2019), there may be a problem of reverse causality.

Table 1.1: Descriptives

| | N | Average density | Percentage of deaths | Earning points Average | P25 | Median | P75 |
|---|---|---|---|---|---|---|---|
| ***Total*** | 276,885 | 44.2% | 7.3% | 26.0 | 0.2 | 12.1 | 37.9 |
| ***Sex*** | | | | | | | |
| Male | 187,548 | 41.7% | 8.1% | 26.4 | 0.2 | 10.3 | 38.3 |
| Female | 89,337 | 49.4% | 5.6% | 25.2 | 0.2 | 17.1 | 37.4 |
| ***SES*** | | | | | | | |
| Q1 | 69,085 | 0.3% | 8.2% | 0.001 | 0 | 0 | 0 |
| Q2 | 69,237 | 10.9% | 9.6% | 4.0 | 1.1 | 2.9 | 6.4 |
| Q3 | 69,285 | 71.4% | 6.5% | 27.1 | 20.0 | 28.7 | 34.4 |
| Q4 | 69,278 | 94.1% | 4.9% | 72.9 | 44.8 | 54.9 | 84.9 |
| ***Aplication*** | | | | | | | |
| Not | 158,305 | 29.0% | 7.9% | 17.4 | 0 | 2.4 | 24.3 |
| Yes | 118,580 | 64.5% | 6.5% | 37.5 | 9.0 | 33.4 | 48.5 |
| Accepted | 105,147 | 65.5% | 6.5% | 37.9 | 10 | 33.9 | 48.7 |
| Denied | 13,433 | 56.4% | 6.7% | 34.4 | 4.2 | 27.5 | 46.9 |
| ***Cohort*** | | | | | | | |
| 1939 | 7,954 | 45.7% | 22.5% | 26.4 | 4.3 | 18.2 | 31.7 |
| 1940 | 8,557 | 47.6% | 19.6% | 27.6 | 2.7 | 16.7 | 34.9 |
| 1941 | 8,535 | 45.3% | 18.5% | 26.7 | 0.9 | 13.9 | 34.5 |
| 1942 | 11,005 | 41.9% | 16.2% | 24.7 | 0.4 | 10.0 | 34.1 |
| 1943 | 12,396 | 42.0% | 13.9% | 24,7 | 0 | 9.9 | 35.1 |
| 1944 | 14,889 | 40.7% | 12.3% | 24.0 | 0 | 8.4 | 35.0 |
| 1945 | 17,299 | 42.0% | 10.2% | 24.8 | 0 | 9.4 | 37.1 |
| 1946 | 20,093 | 43.4% | 8.6% | 25.7 | 0.2 | 11.2 | 38.2 |
| 1947 | 23,107 | 43.6% | 6.9% | 25.8 | 0.2 | 11.4 | 38.2 |
| 1948 | 24,933 | 44.3% | 5.5% | 26.2 | 0.2 | 12.3 | 39.5 |
| 1949 | 27,500 | 45.0% | 4.7% | 25.7 | 0 | 12.2 | 38.6 |
| 1950 | 30,924 | 44.9% | 3.2% | 26.6 | 0 | 12.2 | 39.1 |
| 1951 | 32,529 | 45.6% | 2.0% | 27.0 | 0 | 13.1 | 39.3 |
| 1952 | 37,164 | 44.9% | 1.1% | 26.7 | 0 | 12.6 | 38.6 |

*Notes:* The table is based on administrative data from the SNP. Density is defined as the total number of months that the member contributed between 1999 and 2018 in relation to the total number of months available.

### 1.4.1 Socio-Economic Status (SES)

There is no standardized method for estimating SES (Braveman et al. (2005); Christiansen et al. (2018)). Researchers employ various strategies to determine SES depending on their conceptual model, study design, and available data. For instance, previous research has estimated through (i) the summation of all income received by families adjusted for inflation, as Dowd et al. (2011) did in the United States; (ii) the summation of pensions, as Belloni et al. (2013) did for Italy; and (iii) the "earning points" strategy, where wealth is calculated as the sum of relative income concerning average income, as illustrated by Von Gaudecker and Scholz (2007a) in the context of Germany.

We follow closely the "earning points" (EP) strategy to estimate SES as a function of accumulated EP during the pre-retirement period. EP is a measure of the relative monthly labour income position. In any given month "t", for each cohort, the earnings points for contribution periods (EP) of an individual "i" are calculated as:

$$EP_{it} = \frac{earning_{it}}{average \quad earnings_t}$$

Thus, the wage is less than average if $EP_{it}$ is less than 1. The accumulated sum of the earning points, $AEP_i$, is calculated between 60 and 64 years old. We define the indicator so that a member who has not contributed in that period would obtain a score of 0. In contrast, those who always contributed and whose salaries were always equal to the average would receive a score of 60. By estimating AEPs this way, we can compare wealth across individuals as we calculate individual wealth at the same stage of life for each individual. $AEP_i$ is used to calculate the quartiles used to approximate the NSE.

Table 1.1 shows the bottom quartile of our sample accumulated no more than 0.2 AEPs. Our sample's median number of AEPs was 12.1, while the average was 26. Figure A–2 shows the asymmetric distribution of AEPs among our sample. We derive quartiles from the number of AEPs for each individual. Figure A–3 shows evidence that people with lower contributions between 60 and 64 also have the lowest relative salary. On the other hand, Tables A–6, A–7, A–8, and A–9 show that people classified as having the lowest SES are those with the lowest income and contributions even before age 60.

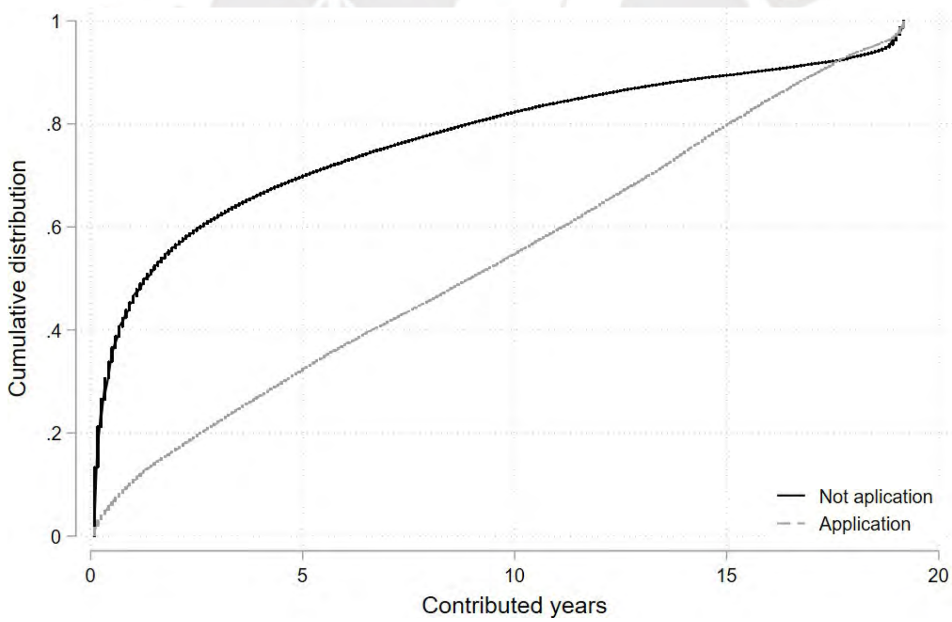
A limitation of using the quartile distribution is that it does not change when a society becomes more or less unequal, so the effect of changes in distribution on mortality cannot be analyzed (Lee and Sanchez-Romero (2019)). Unfortunately, as proposed in this document, no information is available to construct the SES using a criterion that considers an absolute indicator like education rather than a relative one.

### 1.4.2 Contribution prediction

Not all people who reach retirement age initiate an application, and they may never do so due to their small number of contributions. As noted earlier, we find only 43% of individuals in our sample completed an application for a pension. Put another way, individuals may decline to apply and later receive a pension for the same reason why an application is denied: insufficient contributions.

We only know contributions for individuals who have not applied for a pension since the digitization of contribution records in July 1999. Figure 1.1 shows the difference in contributions between those who applied and those who did not apply since then. Among those who did not apply, 60% contributed fewer than 2.5 years, while among those who did apply, only 20% contributed a few years. Similarly, contribution density is 23% for those who did not apply but 47 per cent for those who did.

Figure 1.1: Distribution of contributions between 1999 and 2018




*Notes:* The figure plots the cumulative distribution of contributions between 1999 and 2018.

We performed a Heckman two-stage regression to estimate the contributions unobserved before July 1999. The dependent variable is the total contributions credited by the ONP, and the primary independent variable is the amount of contributions observed since July 1999. The selection equation measures the probability that members submit a request to access a pension; we used contributions between 60 and 64 years of age as an exclusion variable. Table A–10 in the appendix presents our equation results, which we use to estimate the accumulated contributions of those who at age 65 did not apply for a pension with the ONP are estimated[3].

Regression models 1 and 2 of Table A–10 have as explanatory variables the observed contributions, an indicator variable for sex, and a variable indicating whether the individual died after age 65. Model 3 includes fixed effects of the cohort and their interactions with observed contributions. The latter is the model chosen for the predictions because it considers the heterogeneity between cohorts; the period observed between 1999 and 2018 for each cohort represents different moments in the life cycle of people and can condition their rate of contributions to the system.

Our results indicate some evidence of selection bias in the sample. Figure A–4 shows the differences in estimated contributions between our OLS estimate and the Heckman estimate, and Figure A–5 shows the distribution of estimated contributions for those who did not apply as well as for those who did apply.

Table 1.2 shows the average predicted values for both unobserved and observed contributions. The results are statistically equivalent for those who applied: both ONP and the Heckman estimates suggest about 26 years of contributions. From the Heckman model on those who did not apply and who lack records before 1999, we estimate 7.7 years of contributions each by age 65. It is found that the mean number of years of contributions is 10.0 for those in the bottom SES quartile and 24.8 for those in the top quartile (see Table A–11). We further estimate that 65% of the sample will not reach the 20 years of contributions needed to qualify for a pension.

Table 1.2: Contributions observed and estimated by the Heckman model

| **Application** | **Accreditaded by ONP** | **Heckman's model** |
|---|---|---|
| Not applied | | 7.7 |
| | | (0.011) |
| Applied | 26.0 | 25.7 |
| | (0.026) | (0.014) |
| Total | 26.0 | 15.5 |
| | (0.026) | (0.019) |

*Notes:* The table is based on administrative data from the SNP. SE in parenthesis.

[3]Values imputed with $E(y_{1i}|x_{1i}, y_{2i} = 0) = x_{1i}\beta_1 - \sigma_2 \frac{f(-x2_i\beta_2/\sigma_2)}{F((-x_{2i}\beta_2/\sigma_2))}$, where $x_{1i}$ are explanatory of the regression, and $x_{2i}$ the determinants of the selection equation.

### 1.4.3 Survival analysis

Receipt of pensions depends on surviving to and past the age of eligibility. In the data we analyze, 93% of individuals remain alive through the study period (Table 1.1)). This makes it imperative to estimate the duration of their survival to calculate how much they will ultimately receive from the pension program. We estimate survival probabilities by quartiles with a proportional hazard model that assumes a parametric Gompertz-type survival[4]. Under this logic, the hazard ratio to person $i$ is specified as:

$$h(t_i) = exp(\gamma t)\lambda. \tag{1.1}$$

$$\lambda = exp(x_i\beta). \tag{1.2}$$

where the baseline is:

$$h_0(t) = exp(\gamma t)exp(\beta_0). \tag{1.3}$$

and $\beta_0$ is an intercept term within $x_i\beta$.

We measure survival from the attainment of 65 years to death or censoring at the end of the observation period. The regression controls for SES quartiles by sex are shown in Table A–12. The results are as expected: the risk of mortality increases with age, the risk is higher in men than in women, and the risk is higher at lower socioeconomic levels. The logarithm of the hazard ratio for males and females is shown below:

Males

$$Log(h_{t_i}) = 0.105 * t + 0.730 * NSE_1 + 0.550 * NSE_2 + 0.202 * NSE_3 - 5.184 * NSE_4$$

[4]It should be noted that the results are qualitatively the same if other distribution functions are considered. Subsection 1.5.2 gives an account of this. Also, according to Chetty et al. (2016), Figure A–6 shows the empirical mortality and the Gompertz prediction. Table A–13, on the other hand, compares the life expectancy using the Gompertz prediction and the results for all Peruvian populations. According to Figure A–6, the fit is reasonable, especially for men in the first quartile. Table A–13 is consistent with the hypothesis of the lower survival of the poorest because the data for all Peruvian populations also include the poorest people.

Females

$$Log(h_{t_i}) = 0.088 * t + 0.463 * NSE_1 + 0.459 * NSE_2 + 0.189 * NSE_3 - 5.325 * NSE_4$$

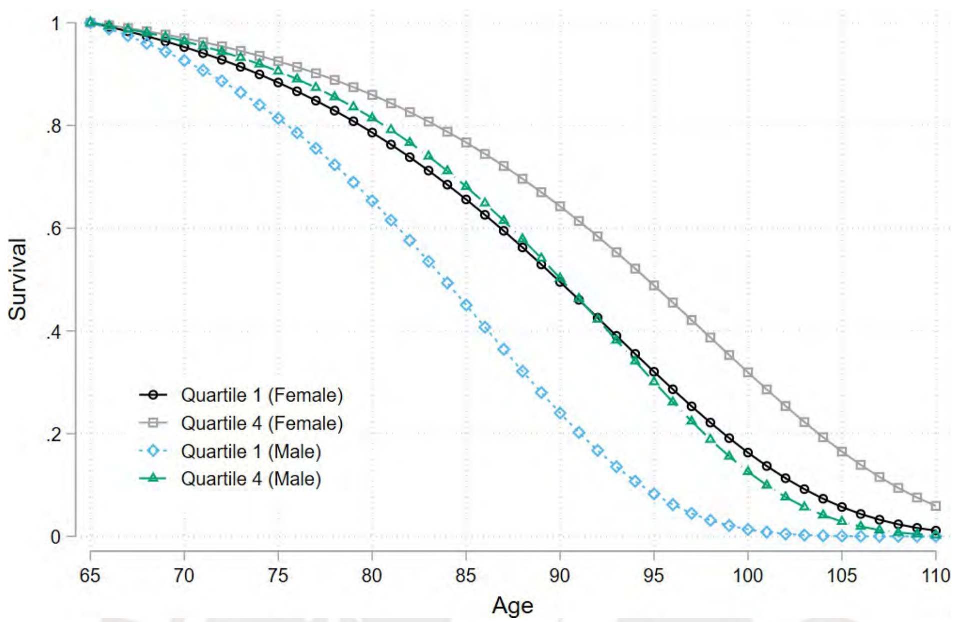
where $NSE_i$ is a dichotomous variable that is activated according to the socioeconomic level "*i*".

We estimate mortality tables using the survival functions as input for each socioeconomic level, differentiating by sex. The latter is possible because the population under study is all 65 or older, so the jump from survival to age at death or censorship is direct. Assuming a parametric function such as Gompertz also allows us to extrapolate survival to unobserved ages in the sample. Thus, considering a maximum survival age of 110 years, one can construct the actuarial operator "*number of survivors at age x*", $l_x$, as $l_x = 100,000 \cdot S(x)$. The estimated values of $l_x$ make it possible to calculate the annuity price (AP) need to estimate pension wealth.[5]

As Figure 1.2 shows, survival is higher for women than men and higher for those in the top SES quartile than the bottom one. Residual life expectancy measured at age 65 is estimated at 24.1 years for women in the bottom quartile and 18.4 years for men there, while women in the top quartile have a residual life expectancy of 28.4 years and men have one of 24.1 years (see Figures A–7 and A–8 in the Appendix).

[5]The annuity price is the amount of capital required to finance one unit of pension for life, taking into account a discount interest rate and mortality tables. The $l_x$ are the key elements of the mortality tables. The factor 100,000 is just the conventional assumption of an initial population at age zero.

Figure 1.2: Survival functions by SES quartiles




*Notes:* The figure shows the survival functions after assuming a Gompertz-type function in the survival model.

### 1.4.4 Pension wealth

We examine three outcomes of pension wealth. The first outcome is *Pension Wealth* ($PW$), which is the sum of all pension benefits and those expected to be received. The calculation of this variable follows the methodology employed by Olivera (2019). Instead of using life expectancy as the time horizon for receiving the pension, we use the price annuity (PA) specific to each individual. The income flows are brought to present value to ensure comparability across generations and maintain neutrality to inflation when the individual turns 65.

The age $x$ at which individual $i$ receives his first pension could be higher than 65 depending on the time it takes to process; in the first pension, the first payment includes interest and accruals; this value is called *Initial* and corresponds to the first summand of equation 1.4. The pensions paid are observed up to the age $y$, at the end of the study period, or when the person dies, the amount paid is the second summand. After that age, if the person survives, pensions are paid as long as the person is still alive. Hence, this summand considers the survival probabilities; this component is the third summand. The maximum age to which the pension would be paid (actuarial infinity) is denoted by $\omega$ (110). The pension payment is estimated beyond age and considers life tables estimated with the survival models differentiating quartile, $q$, and *sex*.

$$PW_{i,x,y,q,sex} = \frac{Initial}{(1+r)^{x-65}} + \frac{P \cdot FF(y,x)}{(1+r)^{x-65}} + \frac{P \cdot PA(y,q,sex)}{(1+r)^{y-65}} \tag{1.4}$$

$$PA_{y,q,sex} = \sum_{t=1}^{\omega-y} \frac{1}{(1+r)^t} \cdot \frac{l_{y+t}^{q,sex}}{l_y^{q,sex}} \tag{1.5}$$

$$FF_{y,x} = \sum_{t=1}^{y-x} \frac{1}{(1+r)^t}. \tag{1.6}$$

in this formula, $r$ represents the assumed interest rate (2%), $l_{y+t}^{q,sex}/l_y^{q,sex}$ is the probability of surviving during $t$ periods for a person of age belonging to quartile $q$ and of a given sex, and $P$ is the amount of the annual pension (null in the case of the deceased observed in the study period and of those who lack sufficient contributions for a pension).

Our second outcome of interest is *Net Pensionable Wealth* (*NPW*), defined as the difference between *Pension Wealth* and contributions ($A$) made. We can estimate the contributions accumulated by a person $i$ at age 65, assuming a constant contribution density during the working life, by:

$$A_i = w \cdot \tau \cdot d_i \cdot \frac{(1+r)^{46} - 1}{r}. \tag{1.7}$$

where $w$ is the annual salary; $\tau$ is the contribution rate; $d_i = C_i/46$; and $C_i$ is the time in years contributed by members in their working life (accredited by the ONP in the case of those who applied or estimated with the Heckman model for those who did not). We assume that people's working life begins at 20, consistent with the most frequent value observed for the start of the first contribution in the SNP.

Therefore, NPW is defined as:

$$NPW_{i,x,y,q,sex} = PW_{i,x,y,q,sex} - A_i. \tag{1.8}$$

Both PW and NPW are expressed in relative terms concerning the average annual wage observed, in a logic similar to the usual definition of replacement rate.

Finally, our third outcome is the *Relative Pension Wealth* (*RPW*), which we define as:

$$RPW_{i,x,y,q,sex} = \frac{PW_{i,x,y,q,sex}}{A_i}. \tag{1.9}$$

We propose to study the effect of heterogeneity in life expectancy and exclusion of pensions on PW, NPW, and RPW. To do this, we first estimate a baseline scenario in which all actual individual characteristics and binding pension rules are used. We then estimate three alternative counterfactual scenarios in which we manipulate some of the individuals' characteristics and pension rules. Comparing the baseline with the counterfactual allows us to assess the "effects" of these manipulated characteristics and regulations on the degree of regressivity or progressivity in the pension system. The counterfactual scenarios are:

1. *Greater survival*: the individuals of lower SES are assigned higher survival, which we consider by assuming that survival is the same for everyone and corresponds to the highest quartile.

2. *Non-exclusion*: everyone receives a pension, meaning that the individuals with contributions below the threshold receive a hypothetical pension proportional to the contributions made and whose maximum value corresponds to the minimum legal pension.

3. *Combined effect*: the joint effect of (1) and (2).

## 1.5 Results

### 1.5.1 Main effects

Table 1.3 illustrates the regressive effects of the SNP. In the baseline scenario, *Pension Wealth* for those in the first quartile is 3.1 times the annual salary and 13 times the annual salary for those in the fourth quartile. Similarly, those in the first quartile see a loss in *Net Pension Wealth* that is equivalent to 0.6 times their annual salary, while those in the fourth quartile see net pension wealth 7 times their yearly salary. The results of the *Relative Pension Wealth* indicate that, on average, the system may be regarded as almost actuarially fair (pensions are 1.1 times the contributions), but there is significant heterogeneity across quartiles. For example, on average, those belonging to the first quartile receive half of what they have contributed, while those in the last quartile receive twice as much.

Thus, the actuarially fair result is achieved with an inequitable distribution, where the poorest finance the pensions of the less poor. In monetary terms, this regressive result implies that those belonging to the first quartile finance the contributions of those belonging to the upper quartiles. In particular, 33% of the subsidized pensions in the upper quartiles are implicitly funded by the contributions of the lower quartiles (see Table A–14 in the appendix).

The poorest's lower survival and insufficient contributions affect the progressive nature of the distribution of pension wealth. We can conclude this after assuming maximum survival and no exclusion and their effect on the gradient of *Pension Wealth*, *Net Wealth*, and *Relative Pension Wealth* concerning SES. The results show that the gradients of all outcome variables improve after the simulations. Notably, in the case of the RPW, the distribution becomes progressive. We can explain this result because the poorest are also the lowest contributors. The average effects are shown in Table 1.3 and Figure 1.3, and the entire distribution of changes is shown in Figure A–9 in the Appendix.

The level of regressivity for those in the first quartile is reduced once we assume non-exclusion and maximum survival. The PW in quartile 1 goes from 3.1 times the annual income to 9.7 times under this combined effect. NPW for the first quartile goes from a net loss, or -0.6 times annual salary, to 6 times under the combined impact of the simulation. Finally, RPW for the first quartile increases from 0.5 times annual salary to 2.6 times under the combined effect. In all cases, proportional pensions have a more significant effect than higher survival on pension wealth (See Table 1.3). We find no significant differential effects when performing the analysis by sex or birth cohort (See Tables A–15, A–16, A–17, A–18, A–19 in the Appendix).

It is worth noting that net pension wealth is lower than pension wealth because this indicator considers the size of contributions. In distributive terms, this is especially important when the pension is zero because while pension wealth accumulates all zeros in this scenario, net wealth has a negative balance equal to the amount contributed during the working life.

As noted above, the non-exclusion counterfactual has a more critical impact than survival on pension wealth and constitutes the primary source of regressivity. One implication of this finding is the need for public policy to seek a less regressive design, although this can be costly. Moving from a positive gradient to one with a zero slope using proportional pensions requires a government transfer that is equivalent to an amount superior to the contributions of its members because the RPW goes from 1.1 (an actuarial equilibrium) to a value of 2.4. This scenario could be less onerous if the SNP did not compete with the SPP for higher-income members.

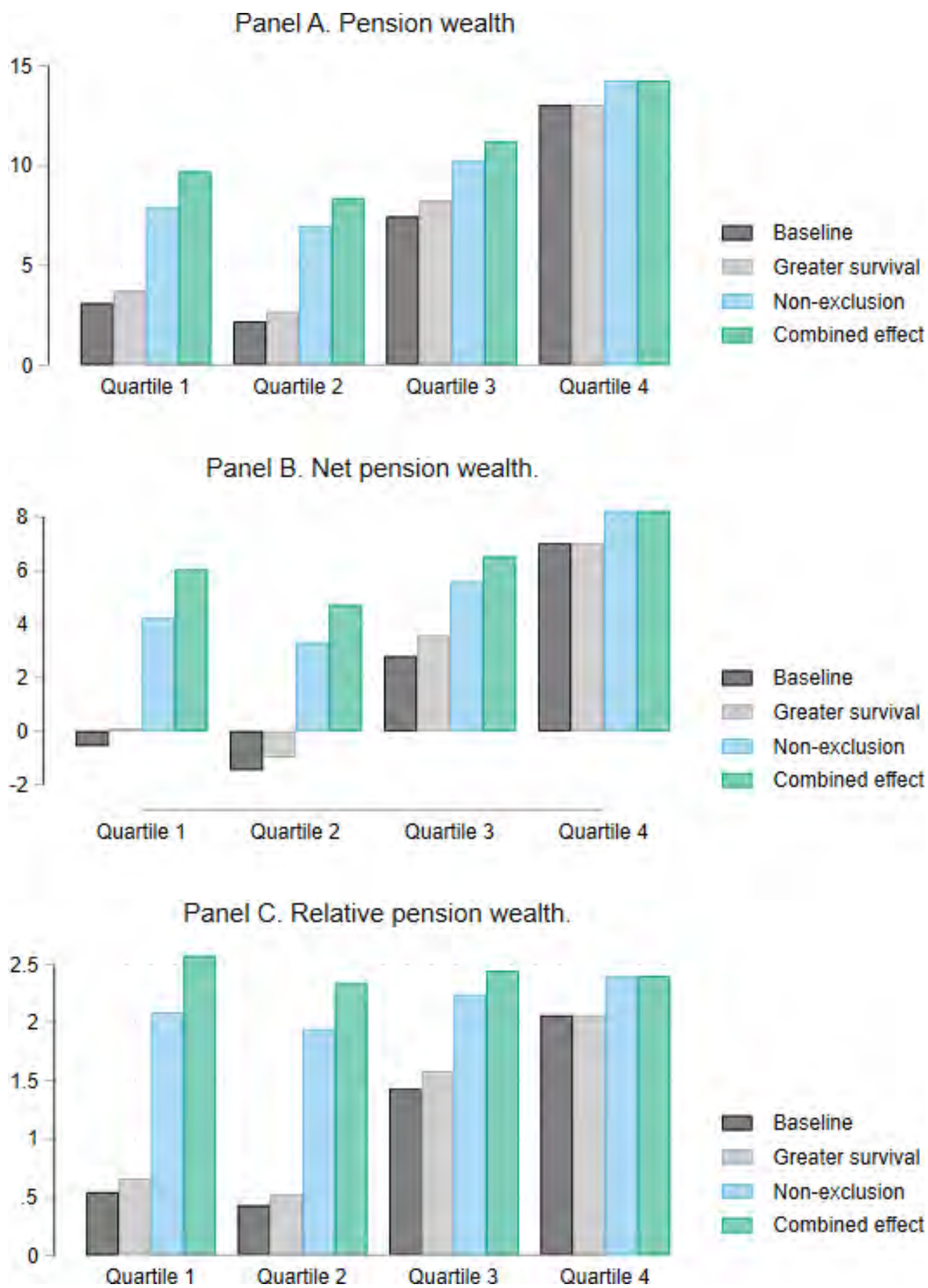
The longevity gaps affect the actuarial fairness and progressivity of public pension systems not only in Peru; other studies illustrate the impact of longevity gaps on actuarial fairness and the progressivity of public pension systems across different countries. For example, Jijiie et al. (2022) examines various European nations, highlighting the regressive nature of Defined Benefit and Notional Defined Contribution schemes due to socioeconomic mortality differences. Bravo and Holzmann (2021) focus on European and OECD countries, demonstrating how disparities in life expectancy can lead to significant implicit subsidies across generations. Lee and Sánchez-Romero (2019) investigates the United States, revealing that increasing longevity gaps undermine the intended progressivity of the Social Security system. Alvarez et al. (2021) analyze Chile, showing that socioeconomic disparities in longevity expose lower-income men to higher pension costs and more significant longevity risks. These studies underscore the necessity of adjusting pension parameters to account for socioeconomic mortality differences to enhance equity and progressivity

Table 1.3: Average effect on pension wealth by quartiles

| | **Pension wealth (PW)** | | | |
|---|---|---|---|---|
| **Quartile** | **Baseline** | **Greater survival$^{(1)}$** | **Non-exclusion$^{(2)}$** | **Combined effect$^{(3)}$** |
| 1 | 3.1 | 3.7 | 7.9 | 9.7 |
| | (0.03) | (0.03) | (0.02) | (0.02) |
| 2 | 2.2 | 2.7 | 7.0 | 8.4 |
| | (0.02) | (0.02) | (0.01) | (0.01) |
| 3 | 7.5 | 8.2 | 10.2 | 11.2 |
| | (0.02) | (0.02) | (0.01) | (0.01) |
| 4 | 13.0 | 13.0 | 14.3 | 14.3 |
| | (0.03) | (0.03) | (0.02) | (0.02) |
| Total | 6.3 | 6.7 | 9.5 | 10.5 |
| | (0.01) | (0.02) | (0.01) | (0.01) |
| | **Net pension wealth (NPW)** | | | |
| **Quartile** | **Baseline** | **Greater survival$^{(1)}$** | **Non-exclusion$^{(2)}$** | **Combined effect$^{(3)}$** |
| 1 | -0.6 | 0.1 | 4.2 | 6.0 |
| | (0.02) | (0.03) | (0.02) | (0.02) |
| 2 | -1.5 | -1.0 | 3.3 | 4.7 |
| | (0.02) | (0.02) | (0.01) | (0.01) |
| 3 | 2.8 | 3.6 | 5.6 | 6.5 |
| | (0.02) | (0.02) | (0.01) | (0.01) |
| 4 | 7.0 | 7.0 | 8.2 | 8.2 |
| | (0.02) | (0.02) | (0.02) | (0.02) |
| Total | 2.0 | 2.4 | 5.3 | 6.4 |
| | (0.01) | (0.01) | (0.01) | (0.01) |
| | **Relative pension wealth (RPW)** | | | |
| **Quartile** | **Baseline** | **Greater survival$^{(1)}$** | **Non-exclusion$^{(2)}$** | **Combined effect$^{(3)}$** |
| 1 | 0.5 | 0.7 | 2.1 | 2.6 |
| | (0.004) | (0.005) | (0.002) | (0.002) |
| 2 | 0.4 | 0.5 | 1.9 | 2.3 |
| | (0.003) | (0.004) | (0.013) | (0.015) |
| 3 | 1.4 | 1.6 | 2.2 | 2.4 |
| | (0.004) | (0.005) | (0.006) | (0.006) |
| 4 | 2.1 | 2.1 | 2.4 | 2.4 |
| | (0.004) | (0.004) | (0.006) | (0.006) |
| Total | 1.1 | 1.2 | 2.2 | 2.4 |
| | (0.002) | (0.003) | (0.004) | (0.004) |

*Notes:* The table is based on administrative data from the SNP. Standard errors are reported in parenthesis. (1) the individuals of lower SES are assigned higher survival, which we consider by assuming that survival is the same for everyone and corresponds to the highest quartile; (2) everyone receives a pension, meaning that the individuals with contributions below the threshold receive a hypothetical pension proportional to the contributions made and whose maximum value corresponds to the minimum legal pension; (3) the joint effect of (1) and (2).

Figure 1.3: Average effect on pension wealth by quartiles




*Notes:* The figure plots the survival functions by SES quartiles. *Greater survival:* the individuals of lower SES are assigned higher survival, which we consider by assuming that survival is the same for everyone and corresponds to the highest quartile; *Non-exclusion:* everyone receives a pension, meaning that the individuals with contributions below the threshold receive a hypothetical pension proportional to the contributions made and whose maximum value corresponds to the minimum legal pension; *Combined effect:* the joint effect of (1) and (2).

### 1.5.2 Robustness analysis

Here, we note the implications for pension wealth based on two assumptions used in the estimation: the rate of return and the survival function. In addition to the rate of return of $r = 2\%$, we consider the rates of $r = 1\%$, $r = 3\%$, and $r = 4\%$. In the case of survival, we explore the implications of assuming Exponential and Weibull-type distribution functions rather than Gompertz.

Figures A–10, A–11, and A–12, in the appendix show the results of simulations that use alternative return rates, while Figures A–13, A–14 and A–15 report the results of simulations that assume alternative survival functions. In all cases, the simulations show that the general conclusions do not change: early mortality of the poorest and exclusion for not reaching the minimum threshold are regressive elements in a system that claims to be progressive. Nor does it change the conclusion that the most important effect is caused by the exclusion criteria. Although the effects of mortality and exclusion on pension wealth outcomes may differ in magnitude with respect to our first results, our alternative simulations still show a positive correlation between SES and these outcomes.

## 1.6 Conclusions

This study aimed to test the hypothesis that a public pension system, which is intended to be progressive, can actually be regressive due to both the system's regulations and socio-economic inequalities in mortality. The Peruvian public pension system is examined to investigate the impact of shorter lifespans among the poorest individuals and the minimum contribution requirement for accessing pensions on pension wealth. This analysis aims to determine the level of progressivity or regressivity of the system.

To test this hypothesis, we used administrative records with monthly information from July 1999 to August 2018, from which it was possible to obtain data on the contributions made, remuneration, date of death in applicable cases, and whether the member started a pension application, had the minimum number of years of contributions needed to qualify for a pension, and the amount of the pension received.

We accessed unique administrative data of affiliates and pensioners and found that the poorest tend to contribute less and have a lower life expectancy than others in the pension system. Through simulations and the use of alternative counterfactuals, we found that not providing pensions to members who may contribute but do not qualify for them has a more significant regressive impact than the effect of early mortality. An internal regulation that strictly denies a pension to individuals who have not contributed for at least 20 years can cause more harm than the well-known gradient between mortality and SES. These results remain unchanged with demographic structure and are robust to different discount rates and survival functions.

Our work is consistent with previous findings on the regressivity caused by insufficient contributions in PAYG systems in some countries in the region (Lasso et al. (2004), Méndez et al. (2009), Azuero Zúñiga (2020), Montenegro Trujillo et al. (2013), Cisoe et al. (2019), Álvarez et al. (2020), Altamirano et al. (2018) and Alonso et al. (2014)), and also with the evidence provided for developed countries on the early mortality of the poorest and its regressive effects. The novelty of this research has been to show the joint effects of insufficient contributions and early mortality, and its finding is that the impact of insufficient contributions is more significant than that of early mortality.

The analysis reveals several policy recommendations aimed at addressing socioeconomic disparities within pension systems. For individuals facing exclusion due to insufficient contributions—since people with lower socioeconomic status (SES) tend to contribute less and thus risk not reaching the minimum contribution threshold—alternatives should be considered to compensate this subset of members. Recent policies have established alternative minimum contribution thresholds to grant new "proportional minimum pensions". For instance, if an individual's contributions span 10 to 15 years, the minimum pension is set at half the standard value, while those with contributions spanning 15 to 20 years would receive a minimum pension at 75% of the ordinary value.

To address the longevity gap between different SES groups, benefit formulas should be redesigned to reflect varying life expectancies based on SES, as recommended by Lee and Sánchez-Romero (2019), Bravo and Holzmann (2021), and Bailey and Li (2023). This could involve modifying the retirement age according to SES. Additionally, in the context of increasing life expectancy, the legal retirement age should be debated to incentivize individuals to delay their retirement.

Regarding contributions, all contributed years, and the total amount contributed should be considered when calculating pension benefits. Furthermore, past contributions should be indexed so that they do not disproportionately favor contributions made toward the end of working life (Lee and Sánchez-Romero (2019)).

Effective policy design also requires constructing life tables based on SES. Variables such as educational level, income, and type of occupation should be explored as indicators of SES to create more accurate and equitable policies (Ayuso et al. (2016)).

Finally, a comprehensive solution should consider integrating the National Pension System (SNP) and the Private Pension System (SPP). This integration aims to restore the solidarity principle, where higher-income individuals contribute more to finance lower pensions. Institutional rules should incorporate mechanisms like a universal pension and ensure that the contribution rate is directly related to income. Such measures would help compensate for the earlier mortality experienced by lower-income individuals.

A limitation of the empirical analysis in this paper is that it was not possible to estimate socio-economic status using the entire wealth history over the life cycle of individuals due to data limitations. We also do not know the socio-economic status of the household to which the member belongs. Instead, we used the history of individual contributions in the last five years before the legal retirement age to estimate SES. While imperfect, this can be considered an adequate method because it is applied at the same stage of life for all individuals. Another challenge to our empirical analysis is that the sample is truncated due to the lack of information on people who died before July 1999. This may mean our results show low-bound effects of those in the poorest quartile: should such individuals, on average, die earlier and not observed in the sample, then the regressive effects we find would be greater than estimated.

# Chapter 2

# The effects of social pensions on mortality among the extremely poor elderly

**ABSTRACT.** We study the effects of Peru's social pension programme *Pension 65* on mortality. The programme provides pensions to people aged 65 and older who are extremely poor and do not have other pensions. The analysis relies on survey data obtained at the baseline and matched to mortality records of 2012-2016. We exploit the discontinuity around the welfare index used by the programme to determine eligibility and estimate intention-to-treat effects. We find that after four years, the programme could reduce mortality among eligible people by about 10.7 percentage points, implying about one year more in life expectancy.

## 2.1 Introduction

Social security participation is low in developing countries, primarily due to 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 establishing 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)).

A substantial body of literature studies the effects of social pensions in low- and middle-income countries. However, 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 essential for public intervention, let alone a genuinely objective health outcome at advanced ages.[1]

This paper studies the causal effects of Peru's non-contributory pension programme, *Pension 65*, on elderly mortality. The programme provides a monthly pension of 125 soles, equivalent to approximately 32 US dollars, or 13% of the official minimum wage in 2021. Although this amount may seem low, it could be significant 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 2012-2016.

While empirical evidence suggests that social pensions may have a negative impact on mortality rates, the results vary depending on the specific programme characteristics, the economic development of the country in question, and the profile of the target population, among other factors. In developed economies, for example, Balan-Cohen (2008) finds that the Old Age Assistance (OAA) programme in the US is associated with a sizeable decrease in male mortality over age 64 after 1940. By contrast, Stoian and Fishback (2010) find that this programme had no significant impact on American urban mortality rates before 1940. For Canada, Emery and Matheson (2012) find no effect of a means-tested social pension programme on mortality for people aged 65-69, but they find that the universal social pension programme for people aged 70 and above (Old Age Security, OAS) reduced mortality by 4.2%.[2] Moreover, Fitzpatrick and Moore (2018) find for Social Security in the US, an increase by 2% in male mortality associated with retirement from the labour force and lifestyle changes.

About 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) pro-

[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 (2007b); 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)).

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

gramme 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, *Pension Basica*, Miglino et al. (2022) 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 of 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 *Pension 65* programme gives a lifetime pension to people aged 65 and above who do not have any other pension and reside in a household classified as extremely 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: extremely 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 (extremely poor) and just ineligible (non-extreme poor) individuals, located on each side of very close to the eligibility threshold. We provide evidence rejecting 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 eligibility threshold. We estimate the programme's intention-to-treat (ITT) effect and find that the 4-year mortality rate of eligible individuals is reduced by 10.7 percentage points, implying a substantial reduction of 92.2% concerning the mortality rate of ineligible individuals at the eligibility threshold.

This result is robust to various checks, including adding 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 assessing 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 significant policy result for an income transfer programme. The cost-benefit analysis reveals that the cost of increasing life expectancy is well below (about 19-30%) the estimates of the value of a statistical life. Thus, the programme is cost-effective.

Furthermore, we compute a mortality-income elasticity of -0.95, which is higher than the value found in other studies. We argue that this could be because we analyse very poor elderly people who have experienced multiple deprivations during their lifetimes, including inadequate access to healthcare, nutrition, and education. These factors lead to a higher mortality risk at the programme's start. Thus, the effect of the income transfer could be significant (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. (2024) – who use the follow-up of our survey in 2015 – find that Pension 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 impact on mortality of the transfer.

The remainder of this paper is organised as follows. Section 2.2 describes the NCP programme, while Section 2.3 presents the data and the empirical strategy. Section 2.4 discusses the validity of the RDD. Section 2.5 analyses and discusses the results and the policy impacts. Section 2.6 presents and discusses evidence for validation, falsification and robustness checks. Lastly, Section 2.7 concludes.

## 2.2 Non-contributory pensions in Peru

*Pension 65* is a government programme that provides social pensions to individuals aged 65 and above who do not have any other pension and reside in a household classified as extremely poor by the national targeting system SISFOH. The scheme is part of the wave of new non-contributory pension (NCP) programmes launched in Latin America in recent years. *Pension 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. However, it can incur some out-of-pocket expenditures. In principle, all individuals classified as poor by SISFOH are eligible for SIS – that is, both the extremely poor and the non-extreme poor – but it is likely to involve relatively lower participation by non-extreme poor people in SIS.

The pension amount has not changed since the programme's implementation at the end of 2011. While the transfer was equivalent to 47 US dollars in 2012, representing 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 GDP. These percentages have not changed substantially since 2015, when 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. In 2012, the roll-out included 14 departments where a previous small-scale and short-lived pilot NCP programme had previously been in place.[3]

As mentioned, SISFOH (*Sistema de Focalización de Hogares* in Spanish) is the national targeting system in Peru. It maintains a national register of the socio-economic conditions of households 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 primary 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: extremely poor, non-extreme poor and non-poor. This classification is valid for three years in urban and four years in rural areas.[4] The most extensive data collection for the SISFOH register occurred in 2012. In the current study, we exploit a survey based on the sampling framework of 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 used to compute the score is also complex and very difficult to grasp if a household wants to manipulate its 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 Sections 2.4 and 2.6 that no manipulation problem 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 *Pension 65* can take about 25 days. As mentioned in Bernal et al. (2024), other methods for programme enrolment include i) information campaigns that local governments and officers jointly organise 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 Nacional de Identidad*), which is

[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 extremely poor.

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

compulsory for eligibility checks.

## 2.3 Data and empirical strategy

### 2.3.1 Data

Our study exploits survey data specifically designed for the impact evaluation of *Pension 65*. We match this (at the individual and/or household level) to three administrative data sources: i) mortality records for 2012-2016, ii) *Pension 65* records and iii) SISFOH records. 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 conducted 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 expenditures 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 considers 12 out of the 24 departments of Peru because these regions had completed collecting 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 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 *Pension 65*.[5] Figure B–1 in the Appendix clearly shows 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 because 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

[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

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 *Pension 65* records allow us to identify the programme recipients and when they receive 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 2016. The information includes the date of death but not the cause. After dropping observations with inconsistent information or 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 2.1 shows the distribution of our sample according to the eligibility conditions and whether the individual survived or died between 2012 and 2016. Of the 2,525 eligible individuals in 2012, 209 had died, and 2,316 had survived, showing a raw mortality rate of 8%. Of the 1,360 ineligible individuals, 123 had died, and 1,237 had survived, implying a raw mortality rate of 9%. 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 (7% and 10%, respectively), and relatively younger individuals have a lower mortality rate than older individuals (the mortality rate is 5%, 8% and 20% for the age groups 65-70, 71-75 and 76-80, respectively).

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%.

Table 2.1: 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 | 1,904 | 1,649 | 1,801 | 1,106 | 646 | 3,553 |
| Dead | 214 | 118 | 100 | 98 | 134 | 332 |
| Mortality rate | 10% | 7% | 5% | 8% | 17% | 9% |
| *Eligible* | 1,406 | 1,119 | 1,206 | 803 | 516 | 2,525 |
| Survivor | 1,274 | 1,042 | 1,144 | 737 | 435 | 2,316 |
| Dead | 132 | 77 | 62 | 66 | 81 | 209 |
| Mortality rate | 9% | 7% | 5% | 8% | 16% | 8% |
| *Ineligible* | 712 | 648 | 695 | 401 | 264 | 1,360 |
| Survivor | 630 | 607 | 657 | 369 | 211 | 1,237 |
| Dead | 82 | 41 | 38 | 32 | 53 | 123 |
| Mortality rate | 12% | 6% | 5% | 8% | 20% | 9% |

*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–3 in the Appendix provides summary statistics of the initial sample for the main variables used in this paper. Table B–4 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 2.5.1 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 7.8% among eligible individuals and 10% among their ineligible counterparts.

An essential 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 either focused 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 essential reductions in mortality due to income effects among poor people.

### 2.3.2 Empirical strategy

As explained before, households are given a score based on an official algorithm that considers 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 extremely poor, non-extreme poor and non-poor. We argue that this classification provides a natural experiment 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 situated 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 programme features facilitate the use of an RDD to analyse the potential impact of *Pension 65* on the eligible population.

The programme's potential effect 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:

$$ATE = \lim_{z \to z_0^+} E(y_i|z_i = z) - \lim_{z \to z_0^-} E(y_i|z_i = z) \tag{2.1}$$

where $y_i$ is the outcome, $z_i$ is the running variable and $z_0$ is the cutoff. When treatment is not deterministically assigned, eligibility is not perfectly correlated with the treatment condition, and hence equation 2.1 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 2.1 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:

$$E[y_i|z_i] = \beta_0 + \beta_1 \cdot 1[z_i < z_0] + \beta_2 \cdot [z_i - z_0] + \beta_3 \cdot (z_i - z_0) \cdot 1[z_i < z_0] \tag{2.2}$$

where $\beta_2$ 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 $\beta_1$ is the difference at the cutoff (Imbens and Lemieux (2008)).

We use equation 2.2 to estimate the ITT of the programme on the mortality rate using linear regressions. In this case, the dependent variable takes the value of 1 if the individual has died and 0 if the individual has survived at a given period. In our main setup, we consider mortality observed in the whole 4-year analysis period between 2012 and 2016. Therefore, $y_i = 1$ if the individual died anytime in 2012–2016 and $y_i = 0$ if the individual survived in 2016. Auxiliary regressions will allow us to assess mortality at different periods. In addition, we include a vector of covariates in further regressions to control for demographics and, importantly, initial health conditions. We estimate the error terms clustering at the Primary Sampling Unit of the survey design.[7] 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 2.3, 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 $\beta_1$ when $\tau_{i,s} = 0$.

$$
\begin{aligned}
E[y_i|z_i] = \beta_0 + \beta_1 \cdot 1[z_i < z_0] + \beta_2 \cdot [z_i - z_0] + \beta_3 \cdot (z_i - z_0) \cdot 1[z_i < z_0] \\
+ \tau_{i,s}(\beta_4 + \beta_5 \cdot 1[z_i < z_0] + \beta_6 \cdot [z_i - z_0] + \beta_7 \cdot [z_i - z_0] \cdot 1[z_i < z_0])
\end{aligned}
\tag{2.3}
$$

The data used to linearly estimate the ITT effects of *Pension 65* can also be organised to estimate survival models. In this case, the data is organised to observe whether the individual has survived or died each month in the 2012–2016 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 to survival analysis, equation 2.2 can be adapted to parametric and semiparametric models that specify the

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

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 2.2.

We use equation 2.4 to run survival models and estimate the ITT effect of the programme on the hazard ratio.[8] We use the logarithm of the risk of death ($h(age)$) 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 alternative parametric functions such as Weibull and exponential.

$$log[h(age)] = log[h_0(age)] + \beta_0 + \beta_1 z_i + \beta_2 D + \beta_3 z_i D + \varepsilon_i \tag{2.4}$$

As mentioned before, we justify using the ITT on the large jump observed in the discontinuity around the eligibility threshold shown in Figure 2.1. We discuss the validity of our RDD in the next Section 2.4 and perform various robustness checks in Section 2.6 to assess 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.

## 2.4 RD validity

### 2.4.1 First stage

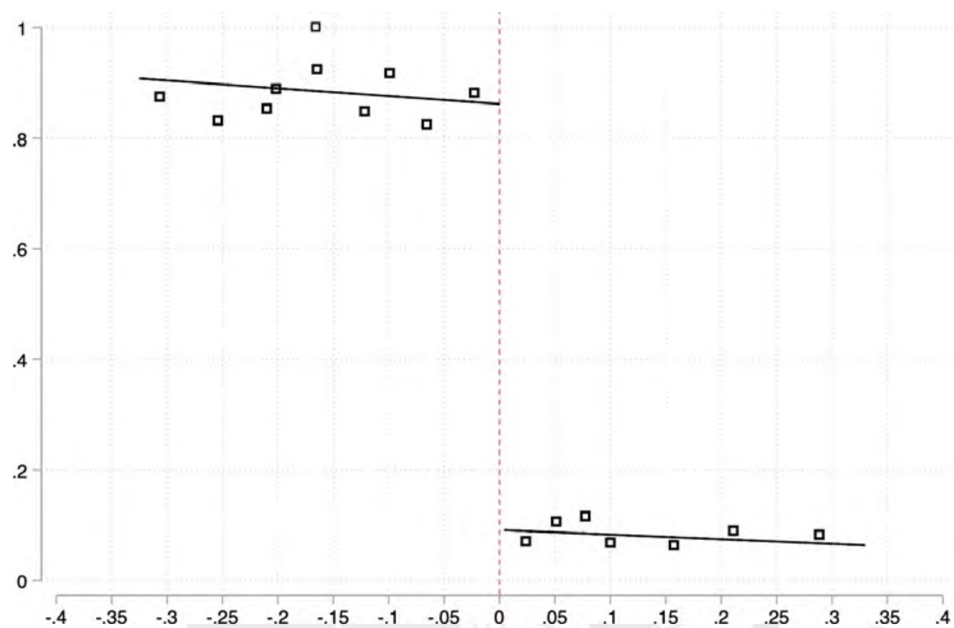
Figure 2.1 plots the probability of being a programme recipient at any time within the 2012–2016 period as a function of the running variable. The graph shows that the probabilities of being treated around the eligibility cutoff exist and differ on each side of the threshold, which are assumptions required 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 76%) in the probability of becoming recipients. The probability limit of the eligible individuals to be treated is 85%, while the same probability for the ineligible individuals is 9%. 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

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

period evaluated. As can be seen in Table B–5 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 also 85% in 2015).[9]

Figure 2.1: Probability of being a *Pension 65* recipient




*Notes:* The graph plots the probability of receiving Pension 65 at any time in the period 2012-2016 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 the 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 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.

### 2.4.2 Continuity of the running variable and predetermined covariates

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

[9]A major change in the SISFOH conditions at the end of 2016 facilitated access to the programme for individuals who had previously been deemed ineligible but were very close to the eligibility threshold. We note that the proportion of treated individuals from the ineligible baseline group increased markedly after 2016. Our analysed period 2012-2016 is unaffected by this programme condition change.

for the credibility of the estimate derived from the RD strategy. We concur with the arguments given by Bernal et al. (2024) as to why the eligibility process of *Pension 65* is unlikely to be susceptible to manipulation: (i) Household answers used in the SISFOH were collected before the implementation of *Pension 65*, so there was no incentive to manipulate responses to participate in a non-existent programme. (ii) The algorithm used to compute the SISFOH index is too complex for individuals to understand, 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 the individuals cannot easily manipulate them. Thus, manipulation would be unlikely.

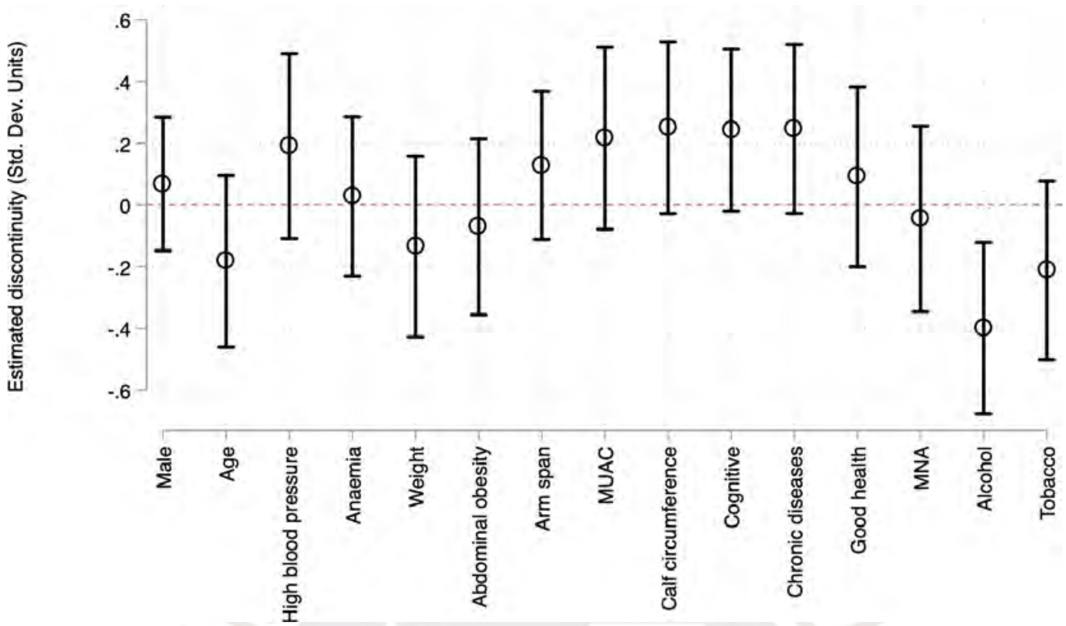
We nevertheless test whether households could have manipulated the running variable, first using the approach suggested by McCrary (2008). This indicates that in the absence of manipulation, the density of the running variable should be continuous around the threshold. To formally test whether the density 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 B–6 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) points 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, all measured at the baseline (and detailed in the next section). To test whether the predetermined covariates are continuous at the threshold, we estimate equation 2.2 using each covariate as the outcome. The estimation results are plotted in Figure 2.2. 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 B–7 in the Appendix[10].

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

[10] In section 2.6 we show additional evidence in support of the above conclusion.

Figure 2.2: Balance of covariates




*Notes:* This figure plots the ITT estimates of equation 2.2 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 2.2). The vertical lines indicate 95% confidence intervals.

## 2.5 Results

### 2.5.1 Linear ITT effects

The main results of the ITT effects of *Pension 65* on the mortality rate are reported in Table 2.2. The dependent variable takes the value of 1 if the individual dies at any time within the period 2012–2016 and 0 if the individual survives. The first column utilises the full sample of running variables around the eligibility threshold. In this case, we find that the mortality rate of the eligible individuals is 6.0 percentage points (pp) lower than that of ineligible individuals. The mortality rate of ineligible people is 11.5 pp, implying that the programme could reduce the mortality rate of the eligible individuals by about 52% (6.0/11.5). However, smaller bandwidths — where individuals are more alike on both sides of the eligibility threshold — could help reduce the estimations' potential bias. 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 11.3 pp.

Table 2.2: Effect of *Pension 65* on mortality rate

| | (1) | (2) | (3) |
|---|---|---|---|
| Intention-to-treat ($\hat{\beta}_1$) | -0.060 | -0.083 | -0.107 |
| | (0.020) | (0.028) | (0.033) |
| | [0.003] | [0.003] | [0.001] |
| Constant ($\hat{\beta}_0$) | 0.115 | 0.113 | 0.116 |
| | (0.017) | (0.025) | (0.028) |
| | [0.000] | [0.000] | [0.000] |
| Bandwidth | +/- 0.330 | +/- 0.2 | +/- 0.150 |
| Observations | 3,885 | 2,104 | 1,598 |
| Percentage Sample | Full sample | 54% | 41% |

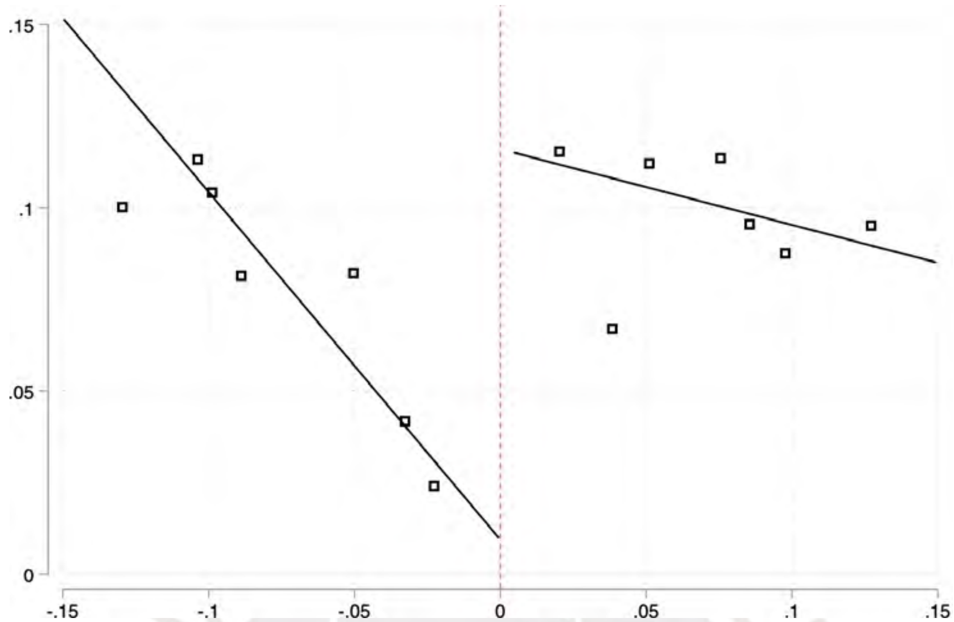
*Notes:* The table reports the ITT estimates for mortality observed in 4 years (Equation 2.2). The models use triangular kernel and local linear polynomial. The first model uses the full sample, which has a bandwidth of +/- 0.330. The second uses about half of the sample size, which has a bandwidth of +/- 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.

To reduce the risk of obtaining biased estimators due to incorrect choice of bandwidth, in the third column of Table 2.2 we implement the data-driven procedure of Calonico et al. (2015) to obtain the optimal bandwidth size. In what is our preferred model, we observe that the mortality rate of eligible individuals could decline by 10.7 pp, implying a substantial reduction of 92.2% (0.107/0.116) concerning the mortality rate of ineligible individuals.[11]

Figure 2.3 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 2.2 and clearly shows the reduced probability of dying when an individual crosses the eligibility threshold.

[11] The resulting optimal bandwidth is +/- 0.150, which we maintain for all further regressions. In any case, Figure B–8 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 2.3: Intention-to-treat effects on mortality




*Notes:* The graph plots the probability of dying after four years as a function of the running variable (SISFOH score minus eligibility cutoffs). The model uses a triangular kernel and local linear polynomial. 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 the 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 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; 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 of health status and mortality risk at the baseline that may control for initial health conditions and risk factors.[12] Therefore, we can reduce any potential estimation bias arising from initial differences between eligible and ineligible people on health status and risk factors. Table 2.3 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 -0.099 and is still statistically significant at 95% (*p-value* = 0.033). Column 3 adds all the health-related variables objectively measured in the survey by the interviewer and/or the medical technicians during the fieldwork. As before, the ITT effect is statistically significant

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

(*p-value* = 0.032), but the magnitude of the estimator reduces to -0.077. Column 4 adds the health and nutrition variables reported by the individuals and shows an ITT effect of -0.094, which is statistically significant (*p-value* = 0.031). In the last column, we add risk factors captured by the consumption of alcohol and tobacco and obtain an ITT effect equal to -0.088 (*p-value* = 0.031).

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 4-year mortality from -0.107 to about -0.088.

**Role of covariates**

Table 2.3 reports the contribution to mortality of initial health conditions, nutrition and risk factors. Detailed definitions of these variables can be found in Tables B–1 and B–2 in the Appendix. 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 2.3: Effect of *Pension 65* on mortality rate, including covariates

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| ITT | -0.107*** | -0.099*** | -0.077** | -0.094*** | -0.088*** |
| | (0.033) | (0.033) | (0.032) | (0.031) | (0.031) |
| Male | | 0.027* | 0.051** | 0.059*** | 0.053*** |
| | | (0.015) | (0.020) | (0.020) | (0.020) |
| Age | | 0.010*** | 0.007*** | 0.007*** | 0.007*** |
| | | (0.002) | (0.002) | (0.002) | (0.002) |
| High blood pressure | | | 0.041** | 0.034* | 0.035* |
| | | | (0.018) | (0.018) | (0.019) |
| Anaemia | | | 0.035** | 0.038** | 0.038** |
| | | | (0.018) | (0.017) | (0.017) |
| Weight | | | 0.003** | 0.003** | 0.003** |
| | | | (0.002) | (0.002) | (0.002) |
| Abdominal obesity | | | 0.024 | 0.026 | 0.028 |
| | | | (0.020) | (0.020) | (0.020) |
| Arm span | | | -0.000 | -0.001 | -0.001 |
| | | | (0.001) | (0.001) | (0.001) |
| Mid-upper arm circ. (MUAC) | | | -0.012*** | -0.011** | -0.010** |
| | | | (0.004) | (0.004) | (0.004) |
| Calf circumference (CC) | | | -0.009** | -0.008* | -0.007* |
| | | | (0.004) | (0.004) | (0.004) |
| Cognitive functioning | | | -0.016*** | -0.013*** | -0.012*** |
| | | | (0.004) | (0.004) | (0.004) |
| Chronic diseases | | | | 0.007 | 0.007 |
| | | | | (0.006) | (0.006) |
| Health today | | | | -0.024 | -0.025 |
| | | | | (0.017) | (0.017) |
| Nutrition score (MNA) | | | | -0.006* | -0.006* |
| | | | | (0.004) | (0.004) |
| Alcohol | | | | | 0.038* |
| | | | | | (0.022) |
| Tobacco | | | | | 0.003 |
| | | | | | (0.021) |
| Constant | 0.116*** | -0.645*** | 0.179 | 0.252 | 0.226 |
| | (0.028) | (0.133) | (0.233) | (0.230) | (0.225) |
| Observations | 1,598 | 1,598 | 1,533 | 1,503 | 1,501 |

*Notes:* The table reports the ITT estimates for mortality observed over 4 years (equation 2.2) 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 2.2). 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. (2024), low values of MUAC or CC are strongly associated with mortality, with a predictive power even more significant than that of the Body Mass Index (BMI). Our results 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 2.3; 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 to the impact 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 B–1). We find that a higher level of cognitive functioning is associated with lower mortality.

The Mini Nutritional Assessment (MNA) is a score capturing dietary quality and is helpful in rapidly assessing malnutrition risks through a few questions posed to elderly individuals (Guigoz (2006); Harris and Haboubi (2005); Vellas et al. (1999)). The study by Bernal et al. (2024) – who make use of the follow-up survey of ESBAM – finds evidence that MNA (both the score and components) may be one of the key mechanisms through which *Pension 65* could affect nutrition-related health outcomes among eligible individuals. With regard to the relationship with mortality, we find that increasing the quality of diet (and, therefore, decreasing the risk of malnutrition) is associated with a reduction in mortality.

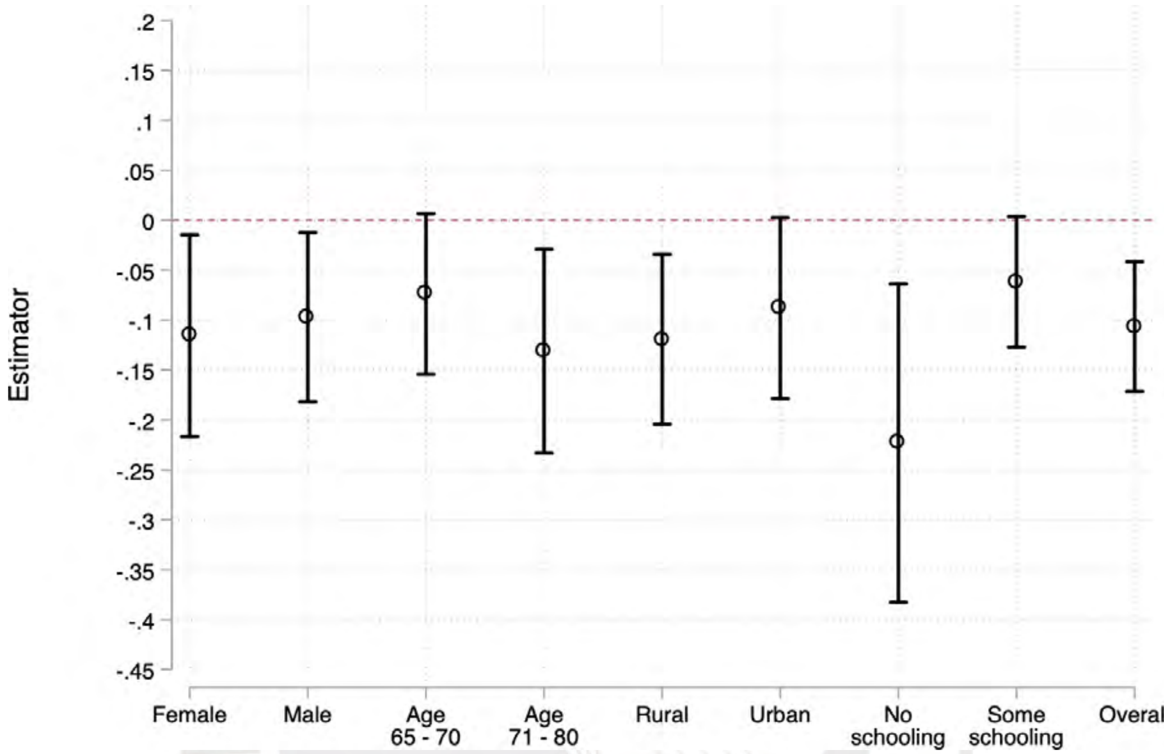
**Heterogeneous effects**

To assess whether the programme may have differential mortality effects for certain groups of individuals, we estimate models based on equation 2.3. We report the estimated ITT coefficients across four distinctive groups (gender, age, area of residence, and education) in Figure 2.4. While the overall effect of the programme in reducing mortality among eligible individuals is statistically significant, we do not find evidence of any specific impact on the groups of younger old adults (aged 65–70), persons residing in urban areas and individuals having some education.[13] The ITT effects are statistically significant for individuals who are female or male, aged 71–80, live in rural areas and have no 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 reduce the mortality rate for these populations, which are already facing a high level of mortality risk. Thus,

[13]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.

the relative survival gains triggered by the programme could be more salient for these groups.

Figure 2.4: Heterogeneous effects on mortality rate




*Notes:* The graph plots the estimated ITT coefficients from equation 2.3 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 *Pension 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.[14] Furthermore, we evaluate whether having more than one older adult at home (and more than one potential recipient) may lead to different programme effects. Still, again, we do not find significant results.[15]

[14]*Juntos* is a conditional cash transfer programme that benefits households with 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 in our sample could be potentially eligible for *Juntos*.

[15]The programme's effect on mortality is 11.1 pp and 11.0 pp for households with one and two eligible individuals, respectively (results are not reported).

**Exposure to health campaigns**

The Ministry of Health in collaboration with *Pension 65* organises campaigns of healthcare services deployed in districts across the year. This collaboration exploits the framework of the public health insurance program *Seguro Integral de Salud (SIS)*, available to individuals residing in households classified as extremely poor or non-extreme poor. While the health campaigns co-organised by the programme and Ministry of Health are designed for programme recipients, all elderly SIS affiliates are eligible to attend. While there is no available data to identify who participated in the health campaigns, we do have administrative data about the roll-out of these campaigns by district and month. In order to capture the potential effects of exposure to health campaigns on mortality, we have constructed a variable indicating the average number of yearly health campaigns deployed in the individual's district of residence to which the individual was exposed during the period 2013-2016.

The results (shown in Table B–11 in the Appendix) indicate that cumulative exposure to district healthcare campaigns is associated with lower mortality rates. Furthermore, the main ITT effect of the programme is practically the same. The reduction in mortality rates due to programme eligibility is 11.2 pp. In contrast, the reduction in mortality rates due to health campaigns is 0.10 pp. Table B–12 reports the results for the survival models.

### 2.5.2 ITT effects with survival models

Survival models are 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 mortality hazard ratio as the dependent variable to obtain our ITT estimates in a comparable setting to the linear models (see equation 2.4). The results are reported in Table 2.4 and are based on a Gompertz type parametric model.[16]

The last column of Table 2.4 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 an 81% lower risk of dying than ineligible individuals (hazard ratio = $exp(-1.680) = 19\%$).

[16]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 B–6 in the Appendix.

Table 2.4: Effect of *Pension 65* on log of mortality hazard rate

| | (1) | (2) | (3) |
|---|---|---|---|
| Intention-to-treat ($\hat{\beta}_1$) | -0.739 | -1.109 | -1.680 |
| | (0.259) | (0.356) | (0.525) |
| | [0.004] | [0.002] | [0.001] |
| Constant ($\hat{\beta}_0$) | -3.771 | -3.845 | -3.878 |
| | (0.203) | (0.283) | (0.319) |
| | [0.001] | [0.001] | [0.001] |
| Bandwidth | +/- 0.330 | +/- 0.2 | +/- 0.150 |
| Observations | 3,885 | 2,104 | 1,598 |
| Percentage Sample | Full sample | 54% | 41% |

*Notes:* The table reports the ITT estimates for the log of mortality hazard rate observed during 4 years (equation 2.4). 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 2.2). The standard errors are indicated in parenthesis. P-values are reported in brackets.

Figure B–4 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 2.3 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 B–9, B–5 and Table B–7 in the Appendix).

### 2.5.3 Potential mechanisms

Among the potential mechanisms behind the effect of the transfer on mortality, we note that Bernal et al. (2024) use the follow-up of the ESBAM survey (fielded between July and September 2015) to estimate the effects of *Pension 65* on nutrition-related health outcomes. They find that the programme impacts 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. Therefore, we could consider them as leading mechanisms for the impact of the pension transfer on reducing mortality (also see Table 2.3). 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 can 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 surveyed in the follow-up. This number is larger than the 3,351 subjects used in Bernal et al. (2024), because we could manually identify respondents whose SISFOH score was missing.

Table B–14 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. (2024). Because the design of the sampling framework involves a very local sample, the authors argue that one could use the full sample without reducing the already small bandwidths. The second set of results shows what the ITT effects of the programme would be if we use the same bandwidth and kernel weighting utilised in our analysis of 4-year mortality (bandwidth equal to 0.150). In this case, the programme may significantly impact increasing cognitive functioning, reporting chronic diseases, self-reported health and healthcare utilisation while reducing obesity and food expenditure per capita at the threshold.[17]

The third set of results shows the ITT effects when we use the non-parametric approach suggested by Calonico et al. (2015) for each outcome (robust with kernel weights and polynomial of degree one and MSE-optimal bandwidths) that is closer to our primary 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), self-reported health and healthcare utilisation, but that it reduces food expenditure per capita at the threshold ($p$=0.082) even when the effect is positive when we employ the entire sample. The survey does not allow us to identify each family member's consumption; therefore, we should interpret the result for food expenditure per capita with caution. Furthermore, we detect a statistically significant increase in household members, which could explain the negative impact on food expenditure per capita. The programme does not show implications for total and household food expenditure under the non-parametric approach.

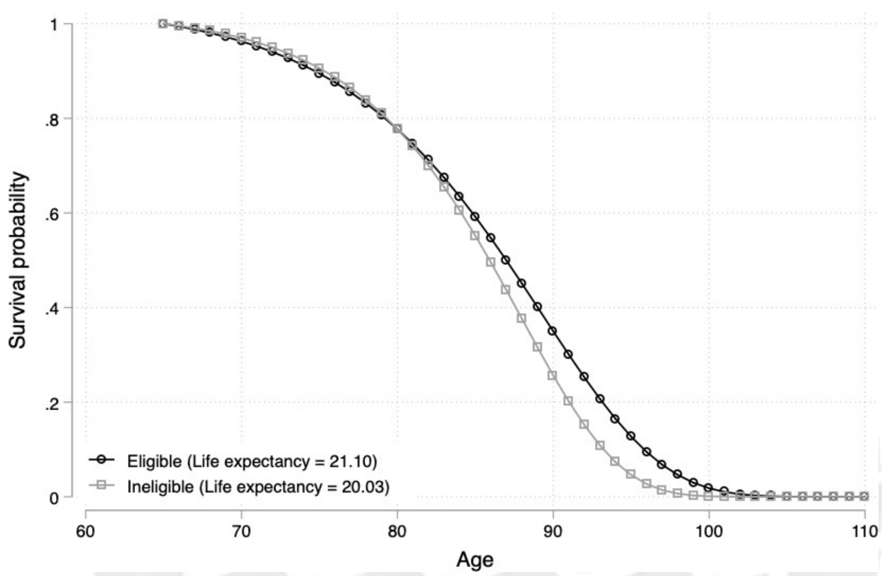
### 2.5.4 Policy impact

A critical policy outcome of our analysis is estimating how much longer a person eligible for the programme could live. Is the *Pension 65* programme able to extend the life of its recipients? If so, then for how long? The structure of our survival data from 2012 to 2016 allows us to use actuarial methods to estimate life tables for eligible and ineligible individuals. We organise the data by year

[17]The programme's positive effect on chronic diseases can be interpreted as having more income to attend healthcare facilities, receive diagnoses of illnesses and be given information to treat them. The significant effect of attending a healthcare centre is consistent with the programme facilitating access to health care through health campaigns.

of observation and age and identify the number of persons dying at each age between 2012 and 2016. 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.[18] We use a Gompertz-type function to estimate survival curves at age 65 for eligible individuals and report the results in Figure 2.5. The estimated curves show that eligible individuals tend to live longer than ineligible individuals, resulting in a difference of 1.07 years in life expectancy.

Figure 2.5: 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 2016 and assumes a Gompertz-type mortality function.

The estimations indicate that ineligible individuals have a life expectancy of 65 equal to 20.03 years, whilst this is 21.10 for eligible individuals. To put these figures into context, the current official life tables for Peru's primary contributory pension system (the Private Pension System, SPP) indicate that the average life expectancy of both sexes at age 65 is 23.43 years. Our estimations suggest 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 5.3% ($= 1.07/20.03$).

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

[18]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 assumes that we treat cohorts between 1932 and 1947 as just one cohort. We use the entire sample to have enough observations to estimate survival functions by age and eligibility condition.

costs are lower than the gains in terms of the value of statistical life (VSL). The VSL can thus be understood as the willingness to pay to reduce the risk of mortality. As explained in Robinson et al. (2019), a policy causing a decrease in mortality over a given period will reduce the number of deaths and increase life expectancy. 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 some studies estimate and/or extrapolate VSL values for other selected countries. Table B–13 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 *Pension 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 8,346 US dollars in 2012. The cost for enabling one more expected year of life is 8,346 dollars. In line with Miglino et al. (2022), we multiply this amount by the life expectancy estimated for eligible individuals (21.10 years) and compare it with the estimates of VSL reported in Table B–13 in the Appendix.[19] The programme cost is 176,111 US dollars, which is lower than any of the VSL estimates for Peru. Indeed, the cost of the programme is only 18% or 28% of the average and median values of VSL, respectively.

A complementary way for reporting the programme's policy impact – 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. We compute augmented individual incomes by adding the pension transfer (125 soles) to the eligible individual's income and find that the income of eligible individuals could increase by 46.7% on average. For consistency, we also estimate the average effect of the programme on mortality, obtaining a variation equal to -38.1%. Thus, the elasticity equals -0.82 (= -38.1%/46.7%) with 95% confidence intervals between -0.3 and -1.3.[20]

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 more developed social security systems. For instance, Miglino et al. (2022) 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

[19]However, there is a difference in the method used to estimate life expectancy. Miglino et al. (2022) 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.

[20]To calculate the variation of income and mortality rate, we have used the observations included in the optimal bandwidth of our main ITT regression (+/- 0.15) and employed triangular kernel weights. The average income varies from 275.2 to 403.7 Soles, while the mortality rate varies from 10.3% to 6.2%.

(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 2-year mortality for male pensioners aged 60 who suffered pension arrears in Russia.

One reason why we obtain a larger elasticity could be 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. This contributes to a higher mortality risk at the programme's start. Thus, the effect of the income transfer could be significant (and more elastic) in preventing death for the very poor. Another potential explanation is that the programme facilitates access to health care through health campaigns, which may contribute to diagnosing and treating illnesses and, consequently, reducing mortality. Indeed, attendance at a health centre is one of the variables identified as an essential mechanism in Section 2.5.3.

## 2.6 Validation, falsification and robustness

In this section, we show evidence for our identification assumptions and robustness. First, we assess the validity of the design by performing a falsification exercise. Second, we show how sensitive the results are to excluding observations, which is very close to the cutoff. Lastly, we further illustrate the robustness of the results by changing the specification of the models and the time of exposure to the programme.

### 2.6.1 Placebo cutoffs

We assess the RDD's validity for estimating the programme's impact at placebo thresholds. To carry out this test, we choose the following thresholds located equidistantly around the actual eligibility cutoff: -0.25, -0.15, -0.075, 0.075, 0.15 and 0.25. Next, we estimate the impact of the programme at placebo thresholds and report the results in Table B–9 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 significance levels. We conclude that the mortality probability and hazard function only change discontinuously at the centred zero threshold.

### 2.6.2 Sensitivity to observations near the cutoff

Another falsification procedure investigates how sensitive the results are to the response of units located very close to the cutoff. The idea is that the empirical effects should not be drastically determined by a few observations 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 eligibility threshold: 0.002, 0.004, 0.006, 0.008 and 0.01. We then estimate the impact, excluding the observations in these intervals, and report the results in Table B–10 in the Appendix. In general, we observe that excluding these observations does not alter the conclusions of the analysis, either in the linear model or in the survival model.

### 2.6.3 Robustness analysis

We analyse the sensitivity of our results to different sizes of bandwidths and other periods to evaluate mortality and different model specifications. Figures B–8 and B–9 in the Appendix show the ITT effects, considering alternative bandwidths 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 B–10 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 in the impact on mortality in the eligible population after the third year of observation. Lastly, Figure B–11 in the Appendix plots the ITT effects for different polynomial orders. Interestingly, the negative impact of the programme on mortality remains in all these specifications.

### 2.6.4 Additional test of continuity of covariates

We run an auxiliary regression to predict the mortality rate based on the covariates previously examined and use this prediction as the left-hand side variable in our ITT regression. This is useful not only for the treatment effect estimate –which should be statistically insignificant– but also for the confidence interval that comes with it. If the confidence interval excludes the main ITT effect estimate, that is very strong evidence that slight imbalances in the covariates could not drive our results. Table B–8 B–8 in the Appendix shows that the ITT effect of predicted mortality is zero and that our primary ITT effect estimate (-0.107) is outside the estimated confidence intervals.[21]

## 2.7 Conclusions

This paper studies the effect of Peru's social pension programme, *Pension 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 extremely poor by the official targeting welfare index, we can 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 essential 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 2012-2016 period.

Analysing mortality over 4 years, we find that the programme can reduce the mortality rate of eligible individuals by about 10.7 percentage points. Furthermore, we compute that *Pension 65* could increase the life expectancy of eligible individuals by one year. The estimated monetary cost associated with improving 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 our analysis focuses 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 the effect of the permanent social pension could be significant (and more elastic) in preventing death for the very poor.

Furthermore, access to healthcare through health campaigns promoted by the programme and

[21]This result is true both when we include all covariates in the regression to predict mortality and when we include only statistically significant covariates chosen in a stepwise regression.

the Ministry of Health may positively impact individual health and, consequently, reduce mortality. While there is no available data identifying the individuals who attend these campaigns, we have identified the importance of these campaigns on the mortality rate through the effect of exposure to campaigns in the district of residence. This is consistent with the findings of a recent paper by Bernal et al. (2024), which analysed the same programme and found that being eligible for *Pension 65* significantly increases the likelihood of attending a healthcare centre.

# Conclusions

This doctoral thesis examines two key issues within Peru's pension systems: the public pension system's regressivity and the effect of social pensions on mortality rates among the elderly in extreme poverty. By analyzing administrative data alongside a specialized survey, significant findings have emerged that offer empirical evidence for creating more equitable and effective public policies.

The first chapter of this thesis focused on evaluating the hypothesis that a public pension system, designed to be progressive, can become regressive due to system regulations and the early mortality of the poorest. To this end, administrative records from the Peruvian pension system from July 1999 to August 2018 were used, providing detailed information on contributions, remuneration, dates of death (where applicable), and the pension application process of affiliates. These data allowed for an analysis of how contributions and life expectancy differences affect the distribution of pension wealth.

The results show that the poorest individuals contribute less and have a shorter life expectancy than those with higher incomes. This generates a regressive effect on the distribution of pension wealth. In particular, it was observed that denying pensions to those who do not meet the minimum requirement of 20 years of contributions has a more significant impact on the system's regressivity than differences in life expectancy. These findings are consistent with previous studies conducted in other countries in the region and developed economies. Still, the novelty of this research lies in demonstrating the combined effect of insufficient contributions and early mortality, highlighting that the former is the primary driver of regressivity.

The policy implications derived from this analysis are clear. Firstly, it is suggested that the contribution rate should be directly linked to income, ensuring that those with lower incomes contribute less, given their shorter life expectancy. Secondly, alternatives are proposed to compensate those who do not meet the minimum contribution requirements. A recent policy in Peru has established alternative minimum contribution thresholds, granting proportional minimum pensions to those who contribute between 10 and 20 years. While this measure mitigates some distributive issues, it cannot fully progress the system.

Due to data limitations, the empirical analysis cannot estimate socioeconomic status using the complete income history over an individual's life cycle. However, using contribution history five years before the legal retirement age is considered an adequate method for estimating SES. Additionally, the truncation of the sample due to the lack of information on individuals who died before July 1999 could underestimate the regressive effects, particularly among the poorest.

The second chapter evaluated the causal impact of the social pension programme Pension 65 on mortality among the elderly living in extreme poverty in Peru. To this end, a specialised survey designed to apply a regression discontinuity design (RDD) was used, enriched with administrative records from the programme and mortality statistics from the national population register from 2012 to 2016. The survey provided detailed information on beneficiaries and non-beneficiaries of the programme, while the administrative records allowed for the verification of eligibility and mortality status of individuals.

The results show that the Pension 65 programme significantly reduces the mortality rate among eligible beneficiaries by 10.7%, equating to an increase in life expectancy of approximately one year. This effect is robust to various validation and falsification tests, and the monetary cost associated with the improvement in life expectancy is estimated to be much lower than the value of a statistical life in Peru, suggesting that the policy is cost-effective.

The estimated income-mortality elasticity is higher than that reported in other studies. This may be attributed to the focus on an extremely poor population that has faced multiple deprivations throughout their lives, including limited access to healthcare, nutrition, and education. These factors increase the risk of mortality, making the effect of monetary transfers more significant in preventing deaths among the poorest.

Additionally, it was identified that health campaigns promoted by the programme and the Ministry of Health may positively impact reducing mortality. However, individual-level data on attendance at these campaigns is not available. Exposure to these campaigns in the district of residence was associated with a reduction in the mortality rate, consistent with recent findings showing that eligibility for Pension 65 increases the likelihood of attending healthcare centres.

Overall, this doctoral thesis has demonstrated that Peru's pension system faces significant equity and effectiveness challenges. On the one hand, the public pension system tends to be regressive due to insufficient contributions among the poorest and differences in life expectancy. On the other hand, social pensions have a positive and cost-effective impact on reducing mortality among the elderly living in extreme poverty.

The policy implications suggest the need for reforms to ensure more significant equity in the pension system, such as implementing income-based differentiated contribution rates and expanding Pension 65 to complement contributory pensions. This research contributes to the academic and policy debate on pension systems, offering evidence-based analysis that can inform the design of more inclusive and effective public policies in Peru and other developing countries.

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# Appendix

# A Appendix Chapter 1

Table A–1: Some parameters in the public PAYG systems for selected countries

| Country | Legal retirement age Male/Female (effective 2017) (1)(2)(3)(4) | Minimum and maximum pension in US, ideally adjusted by PPP |
|---|---|---|
| Argentina | 65 / 60 | For 2015, the minimum monthly pension (based on the 3 components: a basic flat-rate old-age pension, a compensatory pension based on years of contributions and service before July 1994, and an additional pension based on years of contributions since July 1, 1994), was US$ 456.38, and the maximum monthly pension was US$ 3343.5 (based on the 3 components). (11) |
| Brasil | 65 / 60 | The minimum monthly pension is equal to the legal minimum wage. For January 2016, the legal minimum salary was US$ 216.75, therefore, the minimum pension. The maximum pension for January 2016, was US$ 1278.28. (8) and (11) |
| Colombia | 62 / 57 | The minimum pension cannot be less than the current minimum wage or more than 25 times the minimum wages, as established by the Political Constitution. (7) and (11) |

| | | |
|---|---|---|
| Costa Rica | 65 | For the calculation of the pension, the last 240 salaries or accrued income on which contributions have been made, adjusted by the consumer price index, are used as a reference. For each contribution in excess of the 240 quotas, the pension is adjusted by an additional percentage of 0.0833%. If the insured decides to postpone retirement, an additional amount of 0.1333% per month over the average salary is recognized. For 2019, the minimum contributory pension was set at ¢136,865 (US$241) while the upper caps correspond to ¢1,612,851 (US$2,839) without deferral and ¢2,282,184 (US$4,018) with deferral. (6) and (11) |
| Honduras | 65 / 60 | In the IHSS system (El Instituto Hondureño de Seguridad Social), the pension must not be less than 50% or more than 80% of the base contribution salary . The pension is calculated on the basis of the last 180 monthly wages earned or the income used as the monthly contribution base salary, indexed to the month in which the insured person qualifies for the pension. (10) and (11) |
| Panama | 62 / 57 | In 2015, the minimum monthly pension was US$ 245. The minimum monthly old-age pension increases by US$ 10 per month every 5 years (the government can freeze the level of benefits). The maximum monthly social security pension is US$1,500 (US$2,000 with 25 years of contributions and an average monthly salary of US$2,000 for the highest 15 years of contributions or US$2,500 with 30 years of contributions and an average monthly salary of US$2,500 for the highest 20 years of contributions. The maximum monthly pension under the mixed social security system is 500 US$. (9) and (11) |
| Peru | 65 | In 2015, the minimum monthly pension was US$ 128.48 and the maximum monthly pension was US$ 265.44. (11) |

| | | |
|---|---|---|
| Uruguay | 60 | For 2015, the minimum monthly pension was US$ 264.01, and the maximum monthly pension was US$ 1,138.17 (social security and individual account) or US$ 1,683.11 (social security only). As of 2003, for each year of work exceeding 60 years of age , the minimum pension increases by 12% with a cap of 120%. (11) |
| USA | 66 | Minimum pension: Minimum age (age 62), $1,700 per month; full age (age 67), $3,627 per month; maximum age (age 70), $4,555 per month (5). The maximum monthly pension for workers retiring in 2015 at full retirement age is $2,663 ($2,639 in 2016). (11) |
| Chile | 65 / 60 | Social Security: The minimum monthly pension is US$176.25 for those under age 70, US$193.42 for those 70 to 75, and US$206.37 for those 75 or older. (11) |
| Venezuela | 60 / 55 | The minimum pension is the monthly legal minimum wage. The minimum monthly legal minimum wage is $ 1531.46 per month (December 2015). (11) |

*Note: Value of the dollar in local currency by country ranking: 9.42 pesos (argentines), 4.06 reales, 1.00 balboa, 3.23 nuevos soles, 28.90 pesos (uruguayan), 698.85 pesos (chileans), 6.30 bolivares.*

*(1) https://lc.cx/5q03SF*
*(2) https://lc.cx/bn4RQQ*
*(3) https://lc.cx/jvqPDk*
*(4) https://lc.cx/YKMPhu*
*(5) https://lc.cx/JbRxbh*
*(6) https://lc.cx/1pIjKE*
*(7) https://onx.la/f1931*
*(8) https://lc.cx/EwYCuG*
*(9) https://lc.cx/n2l0dG*
*(10) https://lc.cx/QbdEKp*
*(11) https://lc.cx/x6Ioeu*

Table A–2: Labor force in Peru according to age range and poverty status 2023

width=

| Indicator | Up to 20 | 21 to 40 | 41 to 59 | 60 to 64 | 65 to 70 | 71 and more | Total |
|---|---|---|---|---|---|---|---|
| **Extremely poor** | | | | | | | |
| Employed | 37.1% | 71.0% | 79.2% | 69.0% | 73.8% | 49.3% | 65.0% |
| Unemployed | 4.7% | 4.2% | 2.9% | 1.6% | 0.4% | 2.1% | 3.7% |
| Inactive | 58.3% | 24.8% | 17.9% | 29.4% | 25.8% | 48.6% | 31.4% |
| Total in % | 100.0% | 100.0% | 100.0% | 100.0% | 100.0% | 100.0% | 100.0% |
| Population | 267,838 | 576,524 | 304,074 | 47,004 | 42,373 | 60,760 | 1,298,573 |
| Unemp. Rate | 11.1% | 5.5% | 3.5% | 2.3% | 0.5% | 4.0% | 5.3% |
| Participation rate | 41.7% | 75.2% | 82.1% | 70.6% | 74.2% | 51.4% | 68.6% |
| **Non-extremely poor** | | | | | | | |
| Employed | 31.4% | 71.6% | 79.1% | 73.1% | 57.1% | 34.7% | 63.7% |
| Unemployed | 7.2% | 4.5% | 2.8% | 2.5% | 2.6% | 1.2% | 4.3% |
| Inactive | 61.5% | 23.9% | 18.1% | 24.5% | 40.4% | 64.1% | 32.0% |
| Total in % | 100.0% | 100.0% | 100.0% | 100.0% | 100.0% | 100.0% | 100.0% |
| Population | 1,080,268 | 2,500,412 | 1,436,266 | 194,000 | 188,588 | 263,971 | 5,663,504 |
| Unemp. Rate | 18.6% | 6.0% | 3.4% | 3.2% | 4.3% | 3.4% | 6.3% |
| Participation rate | 38.5% | 76.1% | 81.9% | 75.5% | 59.7% | 36.0% | 68.0% |
| **Non-poor** | | | | | | | |
| Employed | 34.0% | 78.3% | 84.1% | 75.6% | 59.4% | 35.0% | 69.6% |
| Unemployed | 5.5% | 3.7% | 2.2% | 1.4% | 1.6% | 0.8% | 3.1% |
| Inactive | 60.5% | 18.0% | 13.7% | 23.0% | 39.0% | 64.2% | 27.3% |
| Total in % | 100.0% | 100.0% | 100.0% | 100.0% | 100.0% | 100.0% | 100.0% |
| Population | 2,893,005 | 7,788,547 | 5,625,975 | 1,017,169 | 937,865 | 1,235,846 | 19,498,407 |
| Unemp. Rate | 13.8% | 4.5% | 2.5% | 1.8% | 2.6% | 2.3% | 4.3% |
| Participation rate | 39.5% | 82.0% | 86.3% | 77.0% | 61.0% | 35.8% | 72.7% |

Table A–3: Main Regulations Governing the Peruvian Pension System

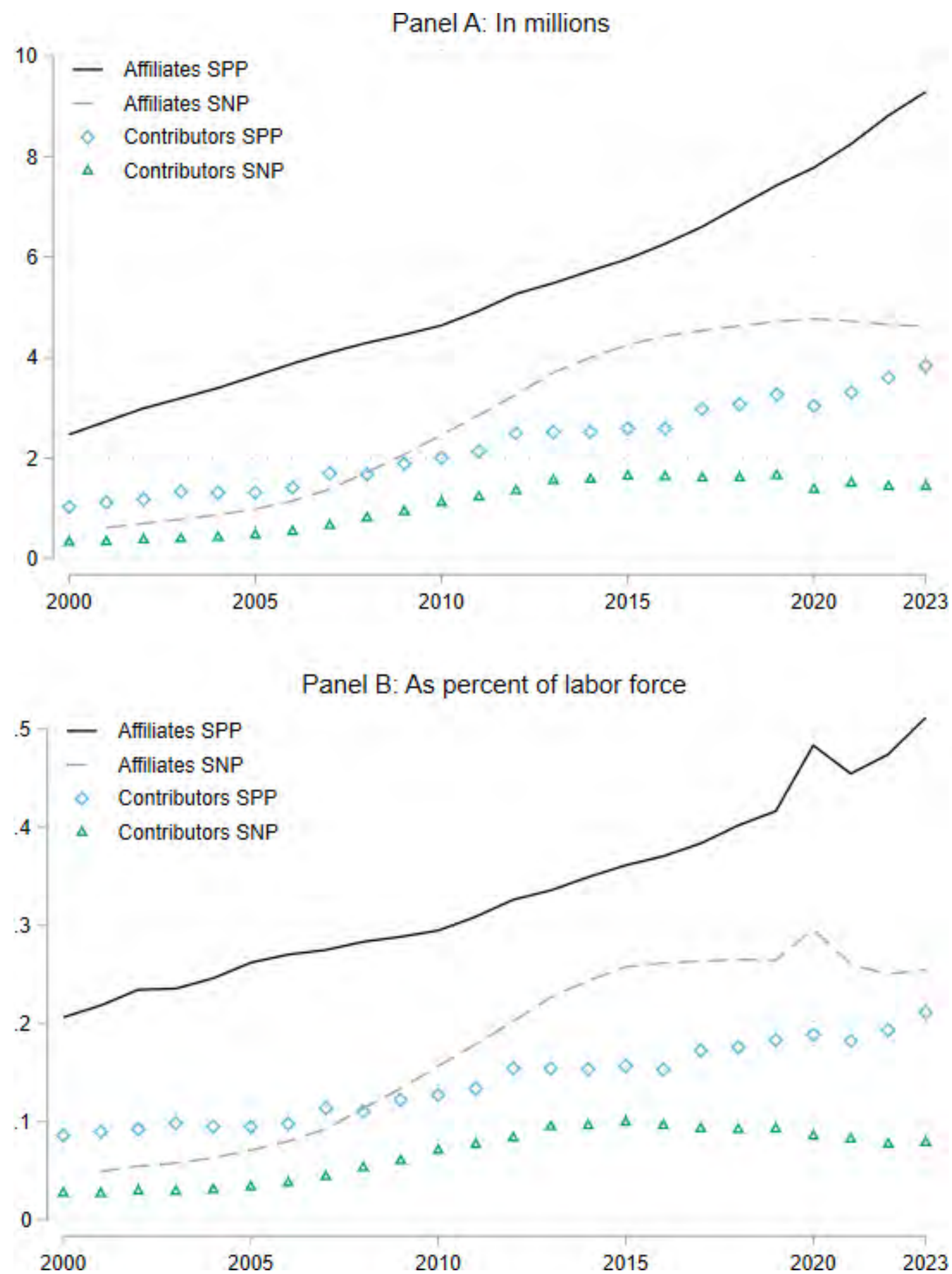
| Law/Decree | Description | Effective Since |
|---|---|---|
| Law No. 19990 | Establishes the National Pension System (SNP). Created in 1973, it regulates retirement, disability, widowhood, and orphanhood pension schemes. The system is funded through contributions from workers and employers and is administered by the National Pension Normalization Office (ONP). | Since 05/01/1973 |
| Law No. 20530 | Establishes the pension and compensation regime for public sector employees. Known as the "Cédula Viva", this system was closed to new affiliates in 2004, but continues to provide benefits to those who were affiliated before that date. | Since 02/28/1974 |

| Law/Decree | Description | Effective Since |
|---|---|---|
| Supreme Decree No. 001-77-TR | Regulation of Law No. 19990. Details the provisions and procedures for the implementation of the National Pension System Law. Includes rules for affiliation, contribution calculations, benefits, and procedures for recognition and payment of pensions. | Since 01/03/1977 |
| Law No. 24640 | Establishes the Military Police Pension Fund (CPMP), which regulates the pension and compensation regime for members of the Armed Forces and the National Police of Peru. | Since 12/26/1986 |
| Supreme Decree No. 002-DE/CCFF | Regulation of Law No. 24640. Details the provisions and procedures for the implementation of the Military Police Pension Fund, including rules for affiliation, contribution calculations, benefits, and procedures for recognition and payment of pensions. | Since 06/28/1988 |
| Law No. 25897 | Establishes the Private Pension System (SPP). Introduced in 1993, it allows workers to choose between the SNP and the SPP, which is managed by private pension fund administrators (AFP). | Since 12/06/1993 |
| Law No. 27617 | Modification of Law No. 19990. Introduces changes to pension calculation and other administrative aspects of the system. Adjusts pension calculation formulas, eligibility requirements, and establishes mechanisms to improve the system's sustainability. | Since 09/01/2002 |
| Law No. 28449 | Closes the regime of Law No. 20530 for new affiliates. Establishes that no new incorporations will be allowed to the pension and compensation regime established by Law No. 20530, known as "Cédula Viva". | Since 12/30/2004 |
| Law No. 28791 | Allows access to early retirement pensions under certain conditions. Establishes the circumstances under which workers can access a pension before the official retirement age, facilitating early retirement in specific cases. | Since 07/01/2006 |

| **Law/Decree** | **Description** | **Effective Since** |
|---|---|---|
| Law No. 29426 | Labor Reinsertion and Formalization Law. Establishes benefits and facilities for the reintegration of contributors to the National Pension System. Includes measures to encourage labor formalization and the reintegration of workers who have ceased contributing to the system. | Since 10/14/2009 |
| Supreme Decree No. 081-2011-PCM | Creates the social program Pensión 65, aimed at elderly people in extreme poverty who do not receive a pension from the public or private system. Provides a non-contributory pension to ensure a minimum income and improve their quality of life. | Since 10/16/2011 |
| Law No. 29903 | Reform of the Private Pension System (SPP). Introduces changes aimed at improving the efficiency and sustainability of the SPP, including mandatory affiliation for new workers, and enhances the regulatory framework for AFPs. | Since 11/01/2012 |
| Law No. 30003 | Modifies Law No. 19990 to allow for proportional pensions. Aimed at workers who have not completed the required years of contributions for a full pension but have made significant contributions. Sets the basis for calculating these pensions proportionally to the years contributed. | Since 05/17/2013 |
| Supreme Decree No. 080-2013-EF | Regulation of the procedure for issuing contribution recognition certificates. Establishes the procedures for workers to obtain a certificate of their contributions to the National Pension System, necessary for various pension-related procedures. | Since 12/30/2013 |
| Supreme Decree No. 018-2013-TR | Regulation of the procedure for the recognition and transfer of contributions to the National Pension System. Establishes procedures for workers to transfer their contributions between the National and Private Pension Systems (SPP). | Since 01/01/2014 |
| Supreme Decree No. 021-2013-EF | Modification of the Regulation of Law No. 19990. Updates procedures and establishes new provisions to improve the management of the National Pension System. Includes measures to streamline pension procedures and enhance service to the insured. | Since 01/01/2014 |

| Law/Decree | Description | Effective Since |
|---|---|---|
| Chief Resolution No. 064-2015/SIS | Approves the Procedures Manual of the National Pension System. Details the procedures and processes for managing pensions within the framework of the SNP, including affiliation, benefit calculation, and dispute resolution. | Since 07/01/2015 |
| Legislative Decree No. 1242 | Establishes the possibility of voluntarily contributing to the National Pension System to complete the minimum contribution time needed to access a pension. Allows workers to make additional contributions to meet the eligibility requirements for a pension. | Since 11/10/2015 |
| Law No. 30683 | Modification of Law No. 24640. Introduces changes in the pension and compensation regime of the Military Police Pension Fund, improving the conditions and benefits for its affiliates. | Since 10/27/2017 |
| Law No. 31301 | Modifies various provisions of Law No. 19990 related to the calculation and eligibility for pensions of the National Pension System, aiming to improve conditions and benefits for pensioners. Among the main benefits are: the reduction of the retirement age for mothers with minor children, the recognition of incomplete contribution periods, and the increase of minimum pensions. | Since 09/23/2021 |

Figure A–1: Affiliates and contributors in SNP and SPP, 2000-2023




*Notes:* The figure is based on administrative data from the SNP and SPP and survey data from the National Household Survey (ENAHO).

Table A–4: Main statistics of pension schemes in Peru (2023)

| Variable | SPP | SNP | Pension 65 | CPMP | Law 20530 |
|---|---|---|---|---|---|
| Millions of Soles: | | | | | |
| Contributions revenues | 14,792 | 4,507 | | 692 | 11 |
| Pension payroll | | 5,952 | 838 | 2,709 | 4,466 |
| Government transfers | | 7 92 | | 2,306 | |
| Reserves fund | | 136,354 | | | 37,133 |
| SPP pension fund | 122,806 | | | | |
| As % of GDP: | | | | | |
| Contributions revenues | 1.50 | 0.41 | | 0.08 | 0 |
| Pension payroll | | 0.64 | 0.10 | 0.31 | 0.51 |
| Government transfers | | 0.01 | | 0.27 | |
| Reserves fund | | 15.67 | | | 4.27 |
| SPP pension fund | 12.46 | | | | |
| Population: | | | | | |
| Pensioners | 202,107 | 590,968 | 568,599 | 78,727 | 216,717 |
| Affiliates | 9,286,247 | 4,716,085 | | 191,492 | |
| Contributors | 3,839,547 | 1,437,799 | | 191.492 | 1,993 |
| Pensioners (% population 65 and older ) | 7.39 | 21.61 | 20.80 | 2.88 | 7.93 |
| Contributors (% affiliates) | 41.35 | 30.00 | | 100.00 | |
| Affiliates (% labor force) | 51.20 | 29.00 | | 1.00 | |
| Contributors (% labor force) | 19.00 | 9.00 | | 1.00 | 0.00 |

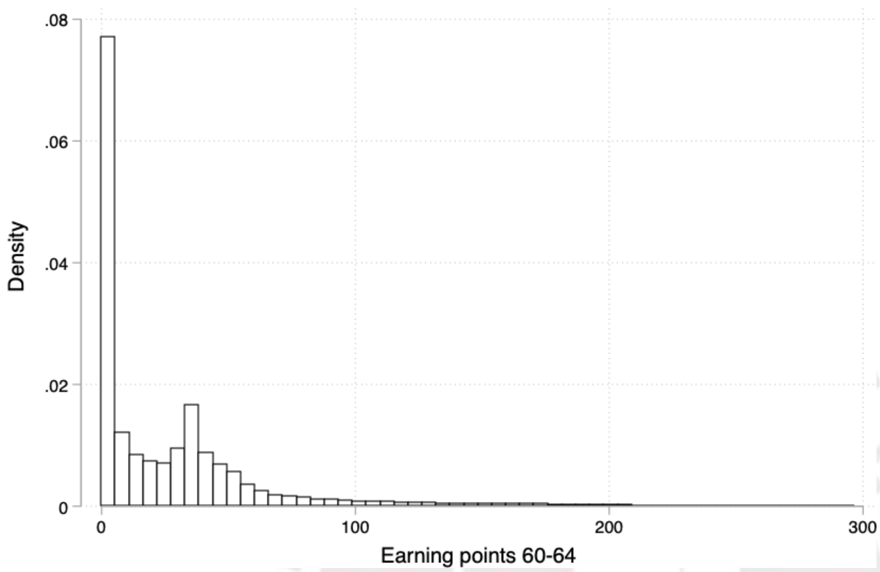
*Notes:* The table is based on administrative data from the SNP and SPP and survey data from the National Household Survey (ENAHO).

Table A–5: Force labor covered by the SNP

| **Age** | **Labor force (a)** | **Occupied (b)** | **SNP Affiliates (c)** | **(c)/(a)** | **(c)/(b)** |
|---|---|---|---|---|---|
| 25 or less | 3,692,599 | 3,298,529 | 393,868 | 11% | 12% |
| 26-30 | 2,354,459 | 2,225,258 | 561,109 | 24% | 25% |
| 31-40 | 4,343,800 | 4,197,195 | 1,384,977 | 32% | 33% |
| 41-50 | 3,785,932 | 3,676,333 | 1,043,206 | 28% | 28% |
| 50-65 | 3,939,479 | 3,848,290 | 1,065,199 | 27% | 28% |
| 66-70 | 560,394 | 542,117 | 143,430 | 26% | 26% |
| 71 and above | 568,671 | 553,804 | 124,295 | 22% | 22% |
| **Total** | **18,116,268** | **17,245,604** | **4,716,085** | **26%** | **27%** |

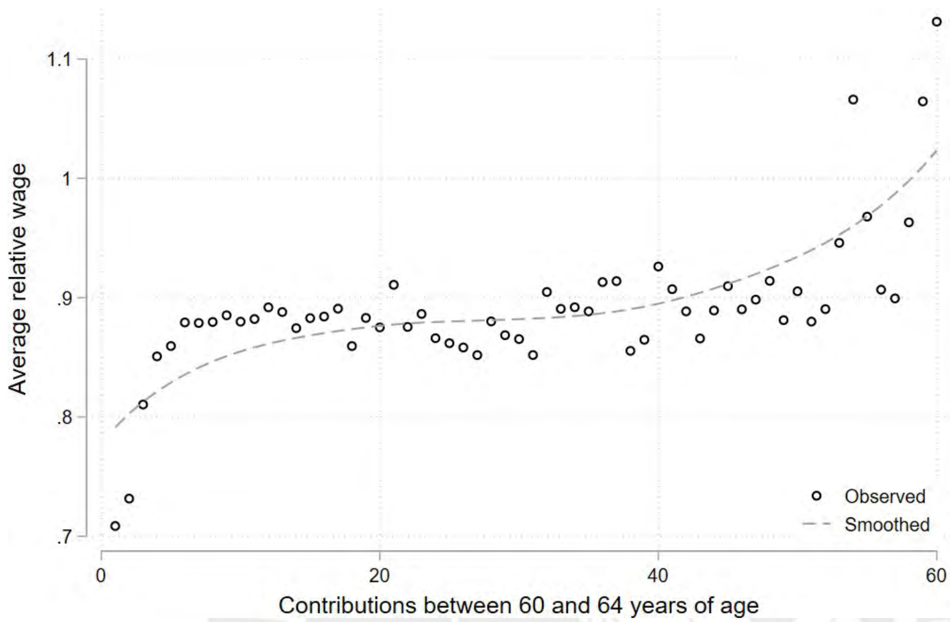
Note: The table is based on administrative data from the SNP and survey data from the National Household Survey (ENAHO).

Figure A–2: Distribution of accumulated earning points




*Notes:* The figure plots the distribution of accumulated earning points.

Figure A–3: Average relative wage and contributions between 64 and 65 years old




*Notes:* The figure plots the average relative age (earning points) and contributions between 60 and 64 years old.

Table A–6: Density and average relative income by cohort, age and SES (Quartile=1)

| | | Cohorts | | |
|---|---|---|---|---|
| | | **1939-1943** | **1944-1948** | **1949-1952** |
| **Age at contribution** | **Variable** | | | |
| 47-50 | Average relative income | | | 0.86 |
| | Density | | | 0.15 |
| 51-54 | Average relative income | | 0.92 | 0.87 |
| | Density | | 0.21 | 0.13 |
| 55-59 | Average relative income | 0.68 | 0.76 | 0.76 |
| | Density | 0.11 | 0.11 | 0.07 |
| 60-64 | Average relative income | 0.14 | 0.14 | 0.14 |
| | Density | 0.00 | 0.00 | 0.00 |
| Total | Average relative income | 0.45 | 0.67 | 0.73 |
| | Density | 0.04 | 0.08 | 0.07 |

*Note:* The table is based on administrative data from the SNP. Density is defined as the percentage of contributions made by a person for each year of age. Relative income is the earning point defined in Section 4.1.

Table A–7: Density and average relative income by cohort, age and SES (Quartile=2)

| | | Cohorts | | |
|---|---|---|---|---|
| | | 1939-1943 | 1944-1948 | 1949-1952 |
| **Age at contribution** | **Variable** | | | |
| 47-50 | Average relative income | | | 0.83 |
| | Density | | | 0.06 |
| 51-54 | Average relative income | | 0.80 | 0.76 |
| | Density | | 0.08 | 0.07 |
| 55-59 | Average relative income | 0.65 | 0.69 | 0.69 |
| | Density | 0.19 | 0.11 | 0.11 |
| 60-64 | Average relative income | 0.55 | 0.61 | 0.63 |
| | Density | 0.14 | 0.15 | 0.13 |
| Total | Average relative income | 0.58 | 0.67 | 0.71 |
| | Density | 0.16 | 0.12 | 0.10 |

*Note:* The table is based on administrative data from the SNP. Density is defined as the percentage of contributions made by a person for each year of age. Relative income is the earning point defined in Section 4.1.

Table A–8: Density and average relative income by cohort, age and SES (Quartile=3)

| | | Cohorts | | |
|---|---|---|---|---|
| | | 1939-1943 | 1944-1948 | 1949-1952 |
| **Age at contribution** | **Variable** | | | |
| 47-50 | Average relative income | | | 0.71 |
| | Density | | | 0.31 |
| 51-54 | Average relative income | | 0.66 | 0.68 |
| | Density | | 0.39 | 0.37 |
| 55-59 | Average relative income | 0.64 | 0.64 | 0.66 |
| | Density | 0.64 | 0.54 | 0.53 |
| 60-64 | Average relative income | 0.64 | 0.65 | 0.65 |
| | Density | 0.71 | 0.75 | 0.76 |
| Total | Average relative income | 0.64 | 0.65 | 0.67 |
| | Density | 0.68 | 0.60 | 0.53 |

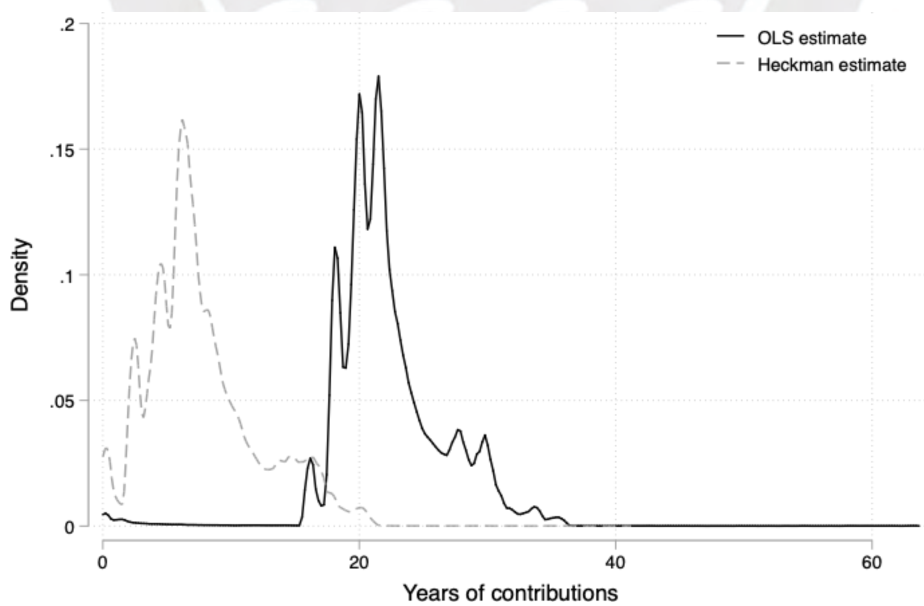
*Note:* The table is based on administrative data from the SNP. Density is defined as the percentage of contributions made by a person for each year of age. Relative income is the earning point defined in Section 4.1.

Table A–9: Density and average relative income by cohort, age and SES (Quartile=4)

| | | Cohorts | | |
|---|---|---|---|---|
| | | **1939-1943** | **1944-1948** | **1949-1952** |
| **Age at contribution** | **Variable** | | | |
| 47-50 | Average relative income | | | 1.20 |
| | Density | | | 0.57 |
| 51-54 | Average relative income | | 1.28 | 1.25 |
| | Density | | 0.62 | 0.64 |
| 55-59 | Average relative income | 1.53 | 1.33 | 1.31 |
| | Density | 0.74 | 0.75 | 0.78 |
| 60-64 | Average relative income | 1.53 | 1.42 | 1.38 |
| | Density | 0.82 | 0.88 | 0.89 |
| Total | Average relative income | 1.53 | 1.36 | 1.30 |
| | Density | 0.79 | 0.78 | 0.75 |

*Note:* The table is based on administrative data from the SNP. Density is defined as the percentage of contributions made by a person for each year of age. Relative income is the earning point defined in Section 4.1.

Figure A–4: Years of contributions estimated (not applications)




*Notes:* The figure shows the difference caused by not considering the selection bias in estimating the contributions of those who did not submit a pension claim.

Table A–10: Heckman two-stage estimation

| | (1) | (2) | (3) |
|---|---|---|---|
| Regression equation | | | |
| Contributions Observed | 1.422*** | 1.483*** | |
| | (316.86) | (305.23) | |
| Death=1 | | 2.254*** | -0.739*** |
| | | (14.55) | (-6.24) |
| Female=1 | | -3.004*** | -2.608*** |
| | | (-35.14) | (-42.35) |
| Selection equation | | | |
| Cont. Obs. 60-64 | 0.0214*** | 0.0215*** | 0.0174*** |
| | (107.40) | (107.64) | (82.89) |
| Contributions Observed | -0.00144 | -0.000737 | |
| | (-1.79) | (-0.91) | |
| Death=1 | | 0.00152 | -0.292*** |
| | | (0.15) | (-28.05) |
| Female=1 | | -0.133*** | -0.121*** |
| | | (-24.30) | (-21.47) |
| Constant | -0.759*** | -0.724*** | -0.0487* |
| | (-199.94) | (-173.41) | (-2.30) |
| mills | | | |
| lambda | 16.04*** | 16.37*** | 8.761*** |
| | (329.87) | (302.90) | (54.12) |
| *N* | 277,227 | 277,227 | 277,227 |

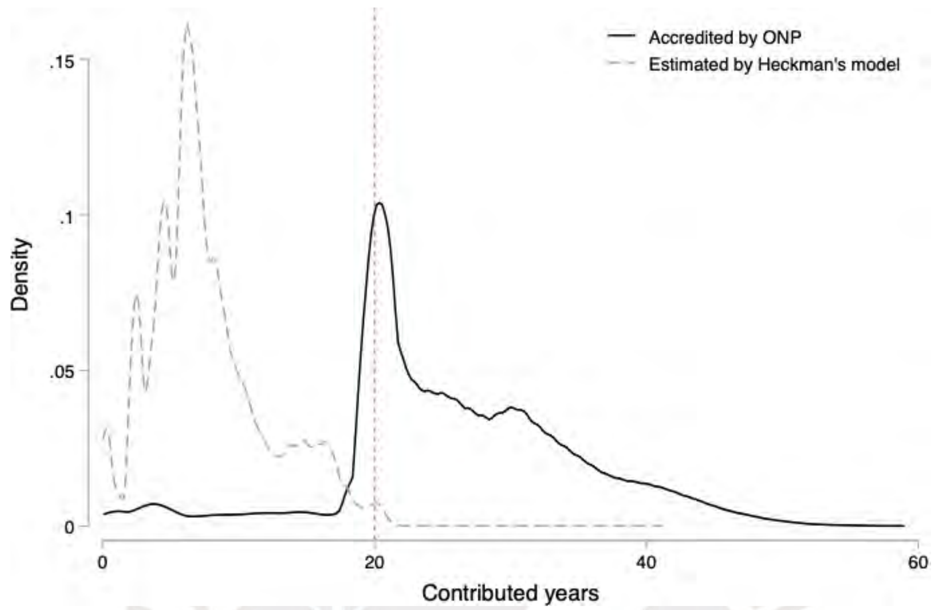
*t* statistics in parentheses.

Dichotomous "Death" refers to death after the age of 65.

Model 3 includes cohort fixed effects and their interaction with observed contributions.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure A–5: Distribution of accumulated contributions at the end of working life




*Notes:* The figure shows the distribution of observed and estimated inputs using a Heckman model.

Table A–11: Contributed years

| Quartile | Mean | P25 | P50 | P75 |
|---|---|---|---|---|
| 1 | 10.0 | 4.5 | 6.5 | 10.5 |
| 2 | 9.9 | 4.8 | 6.8 | 11.3 |
| 3 | 17.6 | 9.1 | 20 | 23.2 |
| 4 | 24.8 | 16.0 | 24.3 | 33 |
| Total | 15.6 | 6.2 | 11.9 | 23 |

*Notes:* The table is based on administrative data from the SNP and Heckman estimation.

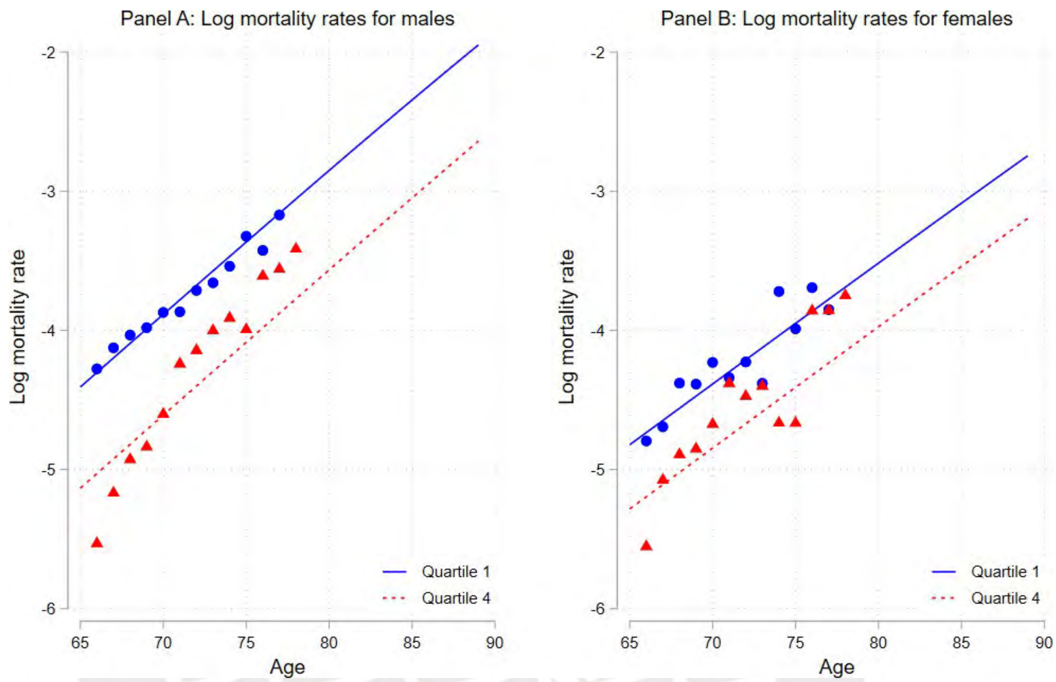
Table A–12: Gompertz regression (log relative-hazard form)

| | Female | Male |
|---|---|---|
| Quartile= 1 | 0.463*** | 0.730*** |
| | (0.0462) | (0.0249) |
| Quartile= 2 | 0.459*** | 0.550*** |
| | (0.0450) | (0.0241) |
| Quartile= 3 | 0.189*** | 0.202*** |
| | (0.0447) | (0.0270) |
| Quartile= 4 | -5.325*** | -5.184*** |
| | (0.0405) | (0.0232) |
| Gamma | 0.088*** | 0.105*** |
| | (0.0041) | (0.0024) |
| Obs. | 89,340 | 187,519 |
| *AIC* | 42,736 | 117,381 |
| Log-Likelihood | -21,363 | -58,686 |
| chi2 | 159.7.3 | 1125.5 |

S.E. in parenthesis.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure A–6: Gompertz approximations and empirical mortality in the first and fourth quartile, 1999-2018



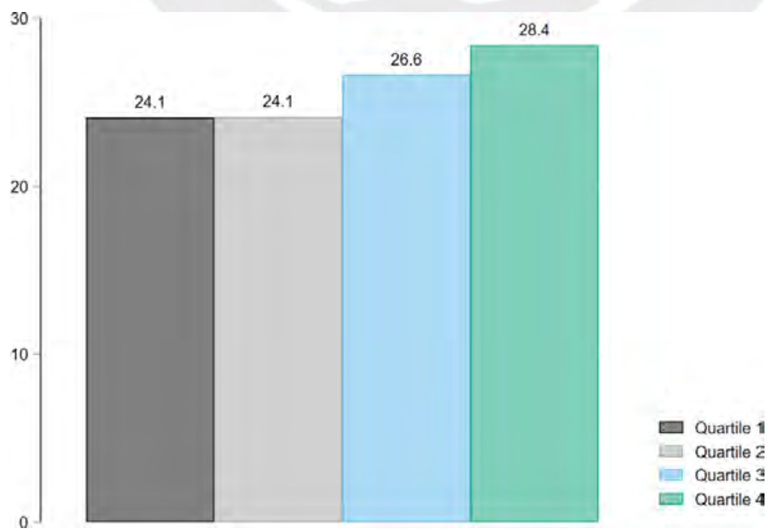

*Notes:* The figure shows empirical mortality, and that is estimated using the Gompertz model.

Table A–13: Life expectancy according to source, age and sex.

| | Gompertz | Peruvian population | Gap |
|---|---|---|---|
| | **Age=65** | | |
| Males | 86.3 | 81.9 | 4.4 |
| Females | 90.7 | 84.7 | 6.0 |
| | **Age=70** | | |
| Males | 87.3 | 83.4 | 3.9 |
| Females | 91.6 | 85.8 | 5.8 |
| | **Age=80** | | |
| Males | 90.6 | 87.7 | 2.9 |
| Females | 94.4 | 89.3 | 5.1 |

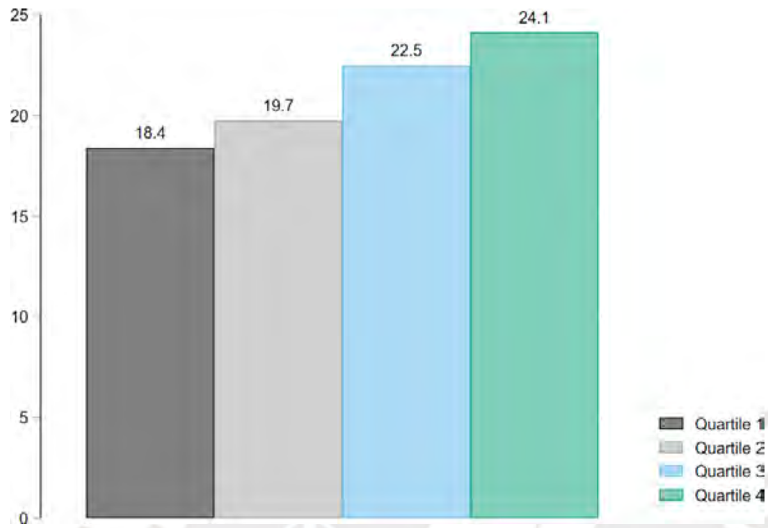
*Notes:* In Gompertz, a survival model is estimated without differentiating by quartiles. The life expectancy of the Peruvian population is estimated for INEI (sf).

Figure A–7: Females: Life expectancy at age 65



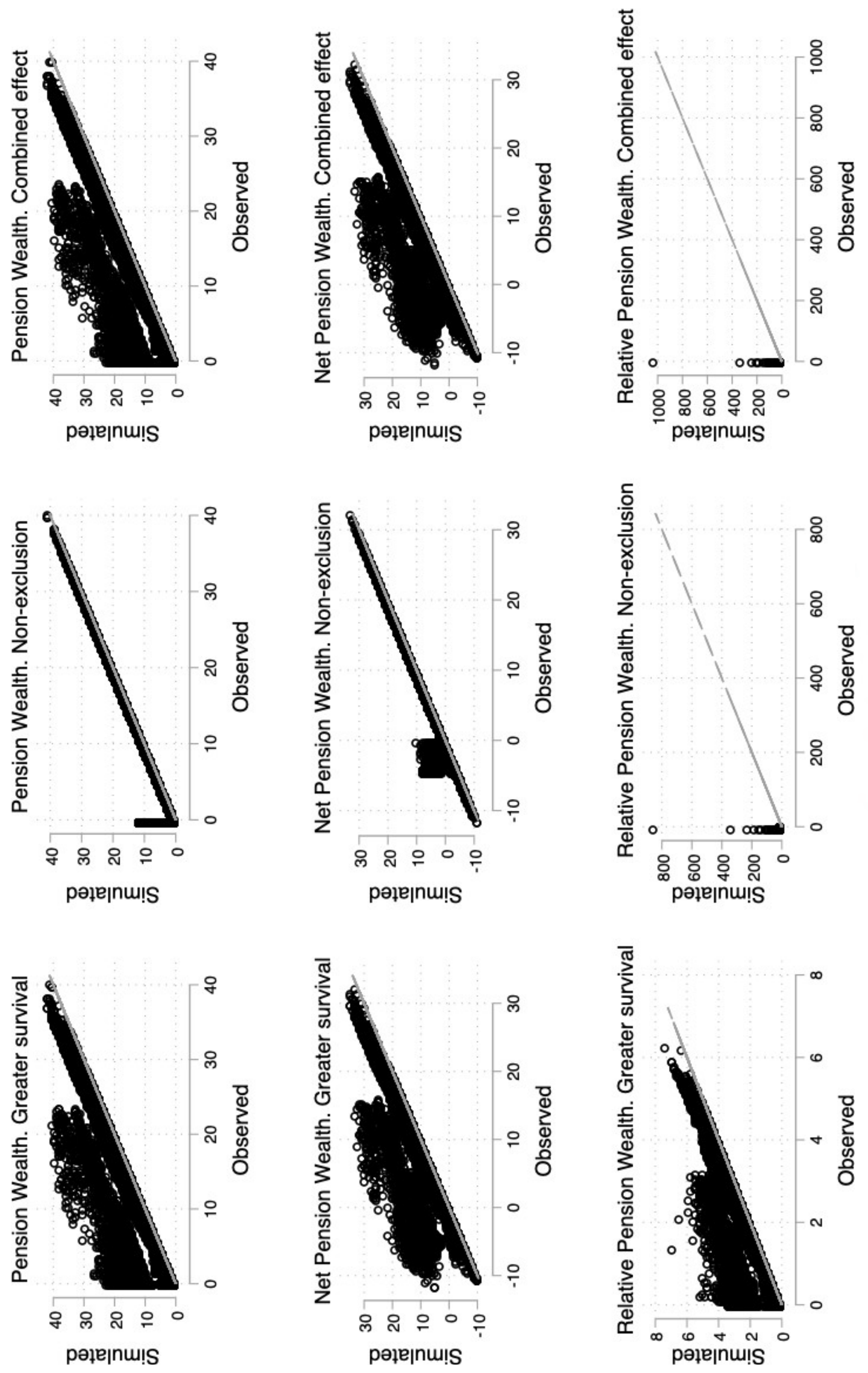

*Notes:* The figure plots the residual life expectancy by quartile.

Figure A–8: Males: Life expectancy at age 65




*Notes:* The figure plots the residual life expectancy by quartile.

Figure A–9: Effects of simulations




*Notes:* The figure shows the effect of the simulations for the outcome variables considered.

Table A–14: Pension wealth and contributions in millions

| Quartile | N | Pension wealth | Contributions | Net pension wealth |
|---|---|---|---|---|
| Q1 | 69,085 | 2,454 | 2,902 | -447 |
| Q2 | 69,237 | 1,959 | 3,654 | -1,695 |
| Q3 | 69,285 | 6,353 | 4,503 | 1,849 |
| Q4 | 69,278 | 10,564 | 5,249 | 5,316 |
| Total | 276,885 | 21,332 | 16,308 | 5,023 |

*Notes:* The table is based on administrative data from the SNP.

Table A–15: Average effect on pension wealth by quartiles by males

| Quartile | Baseline | Greater survival(1) | Non-exclusion(2) | Combined effect(3) |
|---|---|---|---|---|
| | **Pension wealth (PW)** | | | |
| **Quartile** | **Baseline** | **Greater survival(1)** | **Non-exclusion(2)** | **Combined effect(3)** |
| 1 | 3.4 | 4.2 | 7.7 | 9.7 |
| | (0.03) | (0.04) | (0.02) | (0.03) |
| 2 | 2.2 | 2.8 | 6.8 | 8.3 |
| | (0.02) | (0.03) | (0.01) | (0.02) |
| 3 | 7.1 | 7.9 | 9.7 | 10.7 |
| | (0.03) | (0.03) | (0.02) | (0.02) |
| 4 | 12.6 | 12.6 | 13.7 | 13.7 |
| | (0.03) | (0.03) | (0.03) | (0.03) |
| Total | 6.3 | 6.8 | 9.4 | 10.6 |
| | (0.02) | (0.02) | (0.01) | (0.01) |
| | **Net pension wealth (NPW)** | | | |
| **Quartile** | **Baseline** | **Greater survival(1)** | **Non-exclusion(2)** | **Combined effect(3)** |
| 1 | -0.4 | 0.4 | 3.9 | 5.9 |
| | (0.03) | (0.03) | (0.02) | (0.02) |
| 2 | -1.5 | -1.0 | 3.0 | 4.5 |
| | (0.02) | (0.02) | (0.01) | (0.01) |
| 3 | 2.4 | 3.2 | 5.0 | 6.0 |
| | (0.03) | (0.03) | (0.02) | (0.02) |
| 4 | 6.5 | 6.5 | 7.6 | 7.6 |
| | (0.03) | (0.03) | (0.02) | (0.02) |
| Total | 1.7 | 2.2 | 4.8 | 6.0 |
| | (0.01) | (0.02) | (0.01) | (0.01) |
| | **Relative pension wealth (RPW)** | | | |
| **Quartile** | **Baseline** | **Greater survival(1)** | **Non-exclusion(2)** | **Combined effect(3)** |
| 1 | 0.6 | 0.7 | 1.9 | 2.5 |
| | (0.005) | (0.006) | (0.003) | (0.003) |
| 2 | 0.4 | 0.5 | 1.8 | 2.2 |
| | (0.004) | (0.005) | (0.004) | (0.005) |
| 3 | 1.3 | 1.5 | 2.1 | 2.3 |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| 4 | 2.0 | 2.0 | 2.3 | 2.3 |
| | (0.005) | (0.005) | (0.008) | (0.008) |
| Total | 1.1 | 1.2 | 2.0 | 2.3 |
| | (0.003) | (0.003) | (0.003) | (0.003) |

*Notes:* The table is based on administrative data from the SNP. Standard errors are reported in parenthesis. (1) the individuals of lower SES are assigned higher survival, which we consider by assuming that survival is the same for everyone and corresponds to the highest quartile; (2) everyone receives a pension, meaning that the individuals with contributions below the threshold receive a hypothetical pension proportional to the contributions made and whose maximum value corresponds to the minimum legal pension; (3) the joint effect of (1) and (2).

Table A–16: Average effect on pension wealth by quartiles by females

| | **Pension wealth (PW)** | | | |
|---|---|---|---|---|
| **Quartile** | **Baseline** | **Greater survival**$^{(1)}$ | **Non-exclusion**$^{(2)}$ | **Combined effect**$^{(3)}$ |
| 1 | 2.6 | 2.9 | 8.4 | 9.6 |
| | (0.04) | (0.05) | (0.03) | (0.03) |
| 2 | 2.0 | 2.4 | 7.4 | 8.6 |
| | (0.03) | (0.04) | (0.02) | (0.02) |
| 3 | 8.0 | 8.8 | 11.1 | 12.0 |
| | (0.04) | (0.04) | (0.02) | (0.02) |
| 4 | 14.0 | 14.0 | 15.5 | 15.5 |
| | (0.05) | (0.05) | (0.04) | (0.04) |
| Total | 6.8 | 7.2 | 10.7 | 11.5 |
| | (0.03) | (0.03) | (0.02) | (0.02) |
| | **Net pension wealth (NPW)** | | | |
| **Quartile** | **Baseline** | **Greater survival**$^{(1)}$ | **Non-exclusion**$^{(2)}$ | **Combined effect**$^{(3)}$ |
| 1 | -0.8 | -0.4 | 5.0 | 6.3 |
| | (0.04) | (0.04) | (0.03) | (0.03) |
| 2 | -1.3 | -1.0 | 4.0 | 5.2 |
| | (0.03) | (0.03) | (0.02) | (0.02) |
| 3 | 3.5 | 4.2 | 6.5 | 7.4 |
| | (0.03) | (0.03) | (0.02) | (0.02) |
| 4 | 8.2 | 8.2 | 9.7 | 9.7 |
| | (0.04) | (0.04) | (0.03) | (0.03) |
| Total | 2.5 | 2.9 | 6.4 | 7.2 |
| | (0.02) | (0.02) | (0.01) | (0.01) |
| | **Relative pension wealth (RPW)** | | | |
| **Quartile** | **Baseline** | **Greater survival**$^{(1)}$ | **Non-exclusion**$^{(2)}$ | **Combined effect**$^{(3)}$ |
| 1 | 0.5 | 0.5 | 2.4 | 2.8 |
| | (0.007) | (0.008) | (0.004) | (0.004) |
| 2 | 0.4 | 0.5 | 2.3 | 2.6 |
| | (0.007) | (0.007) | (0.046) | (0.055) |
| 3 | 1.6 | 1.7 | 2.5 | 2.7 |
| | (0.007) | (0.008) | (0.011) | (0.011) |
| 4 | 2.3 | 2.3 | 2.7 | 2.7 |
| | (0.007) | (0.007) | (0.005) | (0.005) |
| Total | 1.2 | 1.3 | 2.5 | 2.7 |
| | (0.004) | (0.005) | (0.010) | (0.012) |

*Notes:* The table is based on administrative data from the SNP. Standard errors are reported in parenthesis. (1) the individuals of lower SES are assigned higher survival, which we consider by assuming that survival is the same for everyone and corresponds to the highest quartile; (2) everyone receives a pension, meaning that the individuals with contributions below the threshold receive a hypothetical pension proportional to the contributions made and whose maximum value corresponds to the minimum legal pension; (3) the joint effect of (1) and (2).

Table A–17: Average effect on pension wealth by quartiles by cohorts 1939-1943

| | **Pension wealth (PW)** | | | |
|---|---|---|---|---|
| **Quartile** | **Baseline** | **Greater survival(1)** | **Non-exclusion(2)** | **Combined effect(3)** |
| 1 | 6.9 | 8.4 | 10.1 | 12.5 |
| | (0.12) | (0.14) | (0.10) | (0.11) |
| 2 | 3.2 | 3.9 | 6.2 | 7.7 |
| | (0.05) | (0.05) | (0.04) | (0.04) |
| 3 | 8.1 | 9.3 | 9.1 | 10.4 |
| | (0.05) | (0.05) | (0.05) | (0.05) |
| 4 | 12.4 | 12.4 | 12.6 | 12.6 |
| | (0.08) | (0.08) | (0.07) | (0.07) |
| Total | 7.2 | 8.1 | 9.1 | 10.4 |
| | (0.04) | (0.04) | (0.03) | (0.03) |

| | **Net pension wealth (NPW)** | | | |
|---|---|---|---|---|
| **Quartile** | **Baseline** | **Greater survival(1)** | **Non-exclusion(2)** | **Combined effect(3)** |
| 1 | 2.5 | 4.0 | 5.6 | 8.0 |
| | (0.10) | (0.12) | (0.08) | (0.09) |
| 2 | -1.0 | -0.2 | 2.1 | 3.6 |
| | (0.04) | (0.05) | (0.03) | (0.04) |
| 3 | 3.2 | 4.4 | 4.3 | 5.6 |
| | (0.05) | (0.05) | (0.04) | (0.04) |
| 4 | 6.1 | 6.1 | 6.3 | 6.3 |
| | (0.07) | (0.07) | (0.07) | (0.07) |
| Total | 2.4 | 3.2 | 4.2 | 5.5 |
| | (0.03) | (0.03) | (0.03) | (0.03) |

| | **Relative pension wealth (RPW)** | | | |
|---|---|---|---|---|
| **Quartile** | **Baseline** | **Greater survival(1)** | **Non-exclusion(2)** | **Combined effect(3)** |
| 1 | 1.1 | 1.3 | 2.0 | 2.5 |
| | (0.018) | (0.020) | (0.011) | (0.012) |
| 2 | 0.6 | 0.7 | 1.5 | 1.9 |
| | (0.008) | (0.010) | (0.055) | (0.066) |
| 3 | 1.6 | 1.8 | 1.9 | 2.1 |
| | (0.010) | (0.010) | (0.008) | (0.008) |
| 4 | 1.9 | 1.9 | 2.0 | 2.0 |
| | (0.011) | (0.011) | (0.011) | (0.011) |
| Total | 1.3 | 1.4 | 1.8 | 2.0 |
| | (0.006) | (0.006) | (0.018) | (0.022) |

*Notes:* The table is based on administrative data from the SNP. Standard errors are reported in parenthesis. (1) the individuals of lower SES are assigned higher survival, which we consider by assuming that survival is the same for everyone and corresponds to the highest quartile; (2) everyone receives a pension, meaning that the individuals with contributions below the threshold receive a hypothetical pension proportional to the contributions made and whose maximum value corresponds to the minimum legal pension; (3) the joint effect of (1) and (2).

Table A–18: Average effect on pension wealth by quartiles by cohorts 1944-1948

| | **Pension wealth (PW)** | | | |
|---|---|---|---|---|
| **Quartile** | **Baseline** | **Greater survival$^{(1)}$** | **Non-exclusion$^{(2)}$** | **Combined effect$^{(3)}$** |
| 1 | 4.0 | 4.8 | 8.3 | 10.2 |
| | (0.05) | (0.06) | (0.04) | (0.04) |
| 2 | 2.2 | 2.8 | 7.1 | 8.6 |
| | (0.03) | (0.03) | (0.02) | (0.02) |
| 3 | 8.8 | 9.8 | 10.8 | 11.9 |
| | (0.04) | (0.04) | (0.03) | (0.02) |
| 4 | 15.1 | 15.1 | 15.5 | 15.5 |
| | (0.04) | (0.04) | (0.04) | (0.04) |
| Total | 7.5 | 8.0 | 10.4 | 11.5 |
| | (0.02) | (0.03) | (0.02) | (0.02) |
| | **Net pension wealth (NPW)** | | | |
| **Quartile** | **Baseline** | **Greater survival$^{(1)}$** | **Non-exclusion$^{(2)}$** | **Combined effect$^{(3)}$** |
| 1 | 0.1 | 1.0 | 4.4 | 6.4 |
| | (0.04) | (0.05) | (0.03) | (0.03) |
| 2 | -1.4 | -0.9 | 3.4 | 4.9 |
| | (0.02) | (0.03) | (0.01) | (0.01) |
| 3 | 3.9 | 4.9 | 5.9 | 7.0 |
| | (0.03) | (0.03) | (0.02) | (0.02) |
| 4 | 8.5 | 8.5 | 8.9 | 8.9 |
| | (0.03) | (0.03) | (0.03) | (0.03) |
| Total | 2.7 | 3.3 | 5.6 | 6.8 |
| | (0.02) | (0.02) | (0.01) | (0.01) |
| | **Relative pension wealth (RPW)** | | | |
| **Quartile** | **Baseline** | **Greater survival$^{(1)}$** | **Non-exclusion$^{(2)}$** | **Combined effect$^{(3)}$** |
| 1 | 0.7 | 0.8 | 2.0 | 2.5 |
| | (0.008) | (0.009) | (0.004) | (0.004) |
| 2 | 0.5 | 0.6 | 1.9 | 2.4 |
| | (0.005) | (0.007) | (0.005) | (0.005) |
| 3 | 1.7 | 1.8 | 2.2 | 2.5 |
| | (0.007) | (0.007) | (0.012) | (0.012) |
| 4 | 2.3 | 2.3 | 2.4 | 2.4 |
| | (0.005) | (0.005) | (0.014) | (0.014) |
| Total | 1.3 | 1.4 | 2.2 | 2.4 |
| | (0.004) | (0.004) | (0.005) | (0.005) |

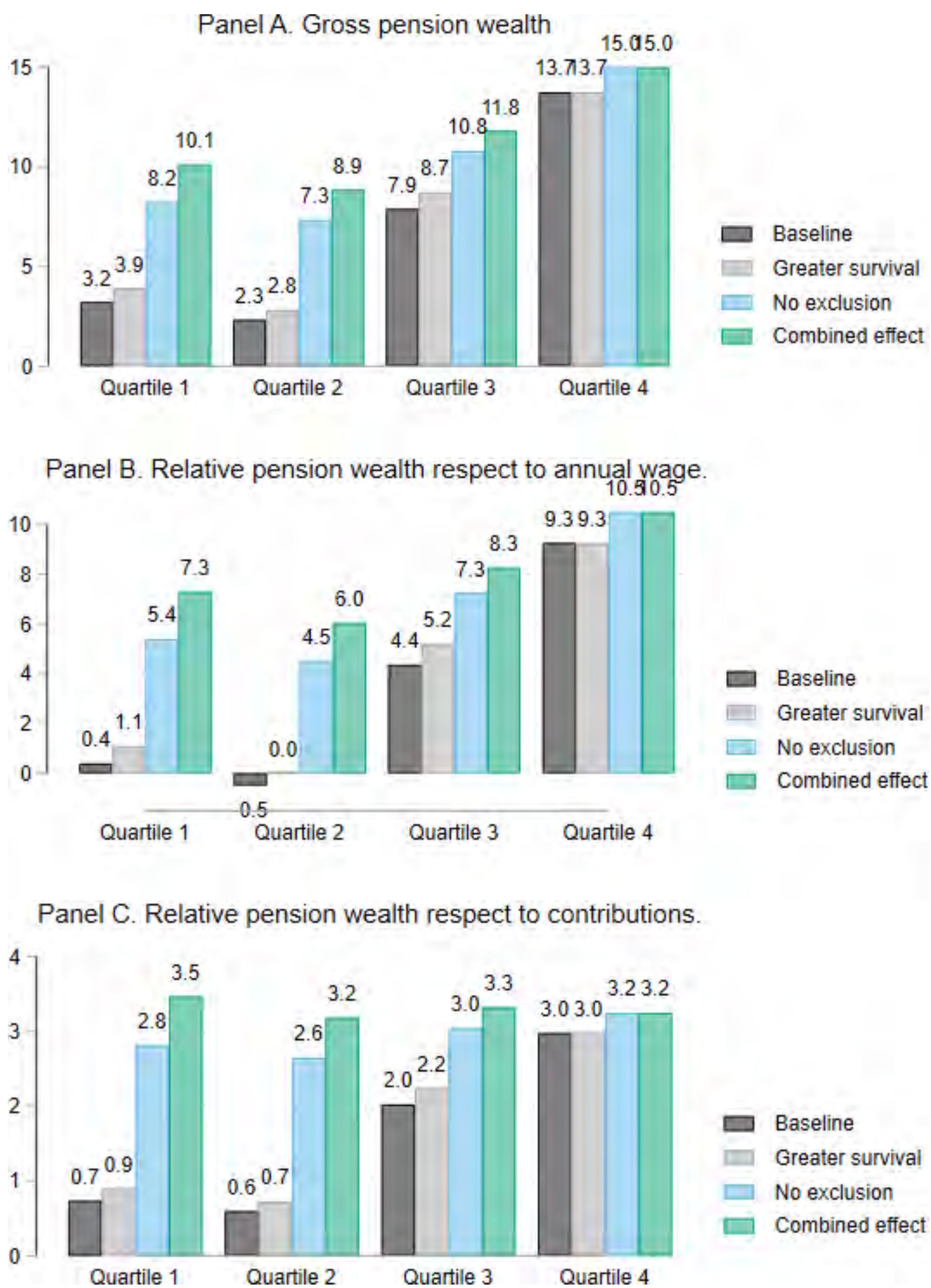
*Notes:* The table is based on administrative data from the SNP. Standard errors are reported in parenthesis. (1) the individuals of lower SES are assigned higher survival, which we consider by assuming that survival is the same for everyone and corresponds to the highest quartile; (2) everyone receives a pension, meaning that the individuals with contributions below the threshold receive a hypothetical pension proportional to the contributions made and whose maximum value corresponds to the minimum legal pension; (3) the joint effect of (1) and (2).

Table A–19: Average effect on pension wealth by quartiles by cohorts 1949-1952

| Quartile | Baseline | Greater survival(1) | Non-exclusion(2) | Combined effect(3) |
|---|---|---|---|---|
| | **Pension wealth (PW)** | | | |
| 1 | 1.7 | 2.0 | 7.2 | 8.7 |
| | (0.02) | (0.03) | (0.01) | (0.02) |
| 2 | 1.6 | 1.9 | 7.3 | 8.6 |
| | (0.02) | (0.03) | (0.01) | (0.02) |
| 3 | 6.2 | 6.6 | 10.4 | 11.0 |
| | (0.03) | (0.04) | (0.02) | (0.02) |
| 4 | 11.7 | 11.7 | 13.8 | 13.8 |
| | (0.04) | (0.04) | (0.03) | (0.03) |
| Total | 5.4 | 5.6 | 9.7 | 10.6 |
| | (0.02) | (0.02) | (0.01) | (0.01) |
| | **Net pension wealth (NPW)** | | | |
| **Quartile** | **Baseline** | **Greater survival(1)** | **Non-exclusion(2)** | **Combined effect(3)** |
| 1 | -1.7 | -1.4 | 3.8 | 5.4 |
| | (0.02) | (0.02) | (0.01) | (0.01) |
| 2 | -1.8 | -1.5 | 3.9 | 5.2 |
| | (0.02) | (0.02) | (0.01) | (0.01) |
| 3 | 1.8 | 2.2 | 6.0 | 6.7 |
| | (0.03) | (0.03) | (0.01) | (0.01) |
| 4 | 6.2 | 6.2 | 8.3 | 8.3 |
| | (0.03) | (0.03) | (0.02) | (0.02) |
| Total | 1.2 | 1.5 | 5.5 | 6.4 |
| | (0.02) | (0.02) | (0.01) | (0.01) |
| | **Relative pension wealth (RPW)** | | | |
| **Quartile** | **Baseline** | **Greater survival(1)** | **Non-exclusion(2)** | **Combined effect(3)** |
| 1 | 0.3 | 0.4 | 2.1 | 2.6 |
| | (0.004) | (0.005) | (0.002) | (0.002) |
| 2 | 0.3 | 0.4 | 2.2 | 2.6 |
| | (0.005) | (0.006) | (0.006) | (0.007) |
| 3 | 1.2 | 1.3 | 2.4 | 2.6 |
| | (0.007) | (0.007) | (0.008) | (0.008) |
| 4 | 1.9 | 1.9 | 2.5 | 2.5 |
| | (0.006) | (0.006) | (0.003) | (0.003) |
| Total | 1.0 | 1.0 | 2.3 | 2.6 |
| | (0.003) | (0.004) | (0.003) | (0.003) |

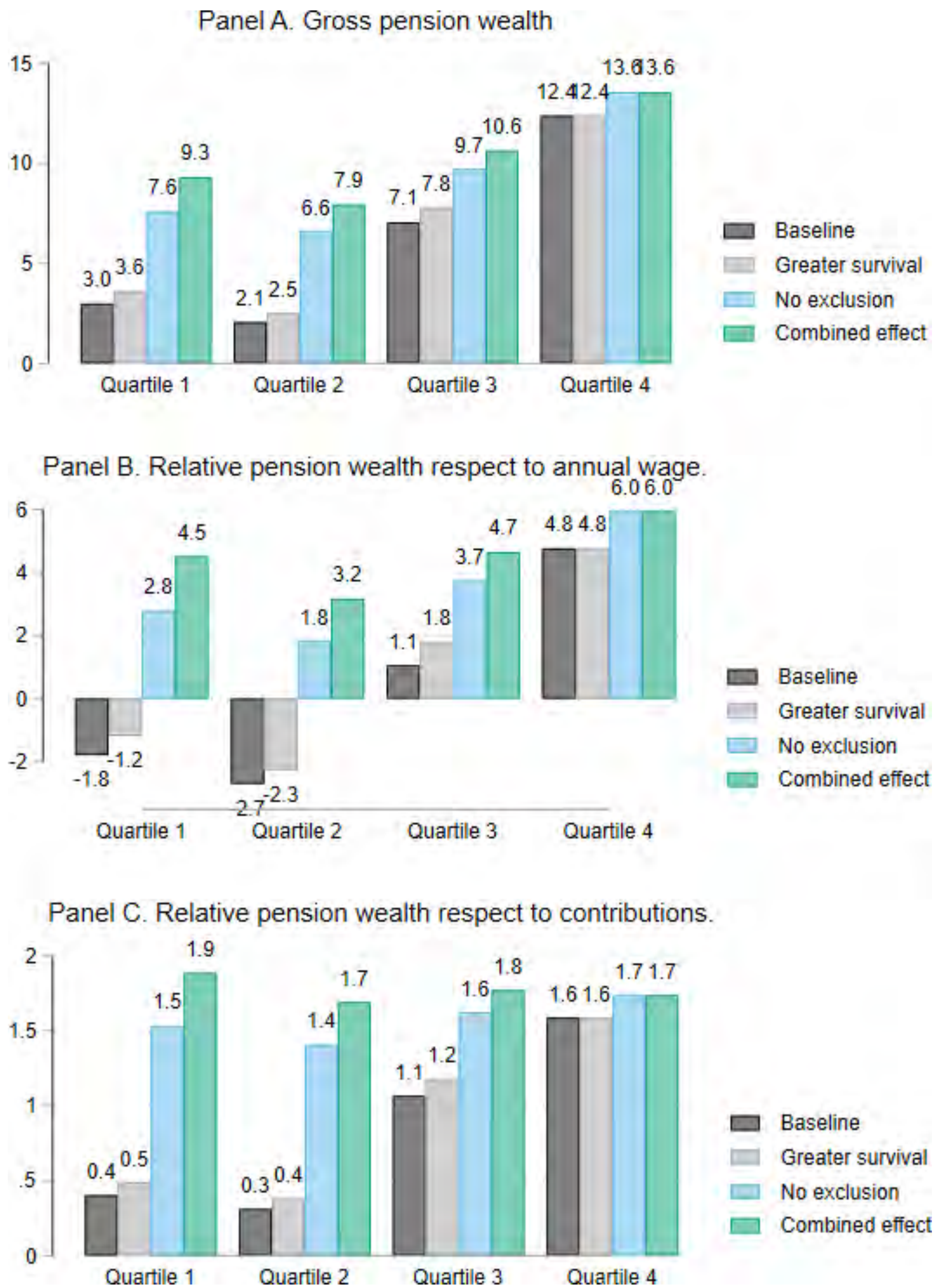
*Notes:* The table is based on administrative data from the SNP. Standard errors are reported in parenthesis. (1) the individuals of lower SES are assigned higher survival, which we consider by assuming that survival is the same for everyone and corresponds to the highest quartile; (2) everyone receives a pension, meaning that the individuals with contributions below the threshold receive a hypothetical pension proportional to the contributions made and whose maximum value corresponds to the minimum legal pension; (3) the joint effect of (1) and (2).

Figure A–10: Robustness $r = 0.01$



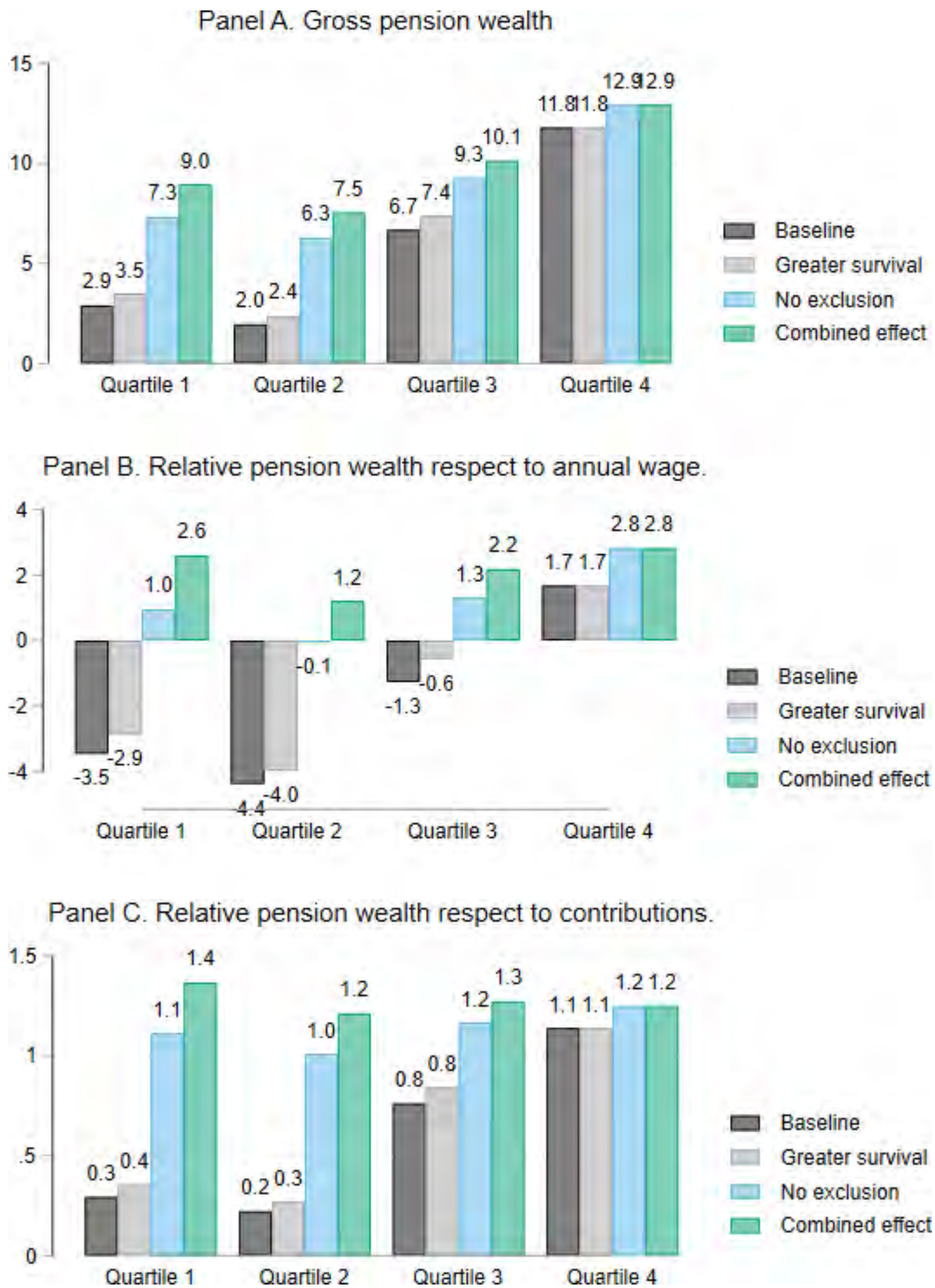

*Notes:* The figure shows the effect of the simulations per outcome variable according to quartiles.

Figure A–11: Robustness $r = 0.03$



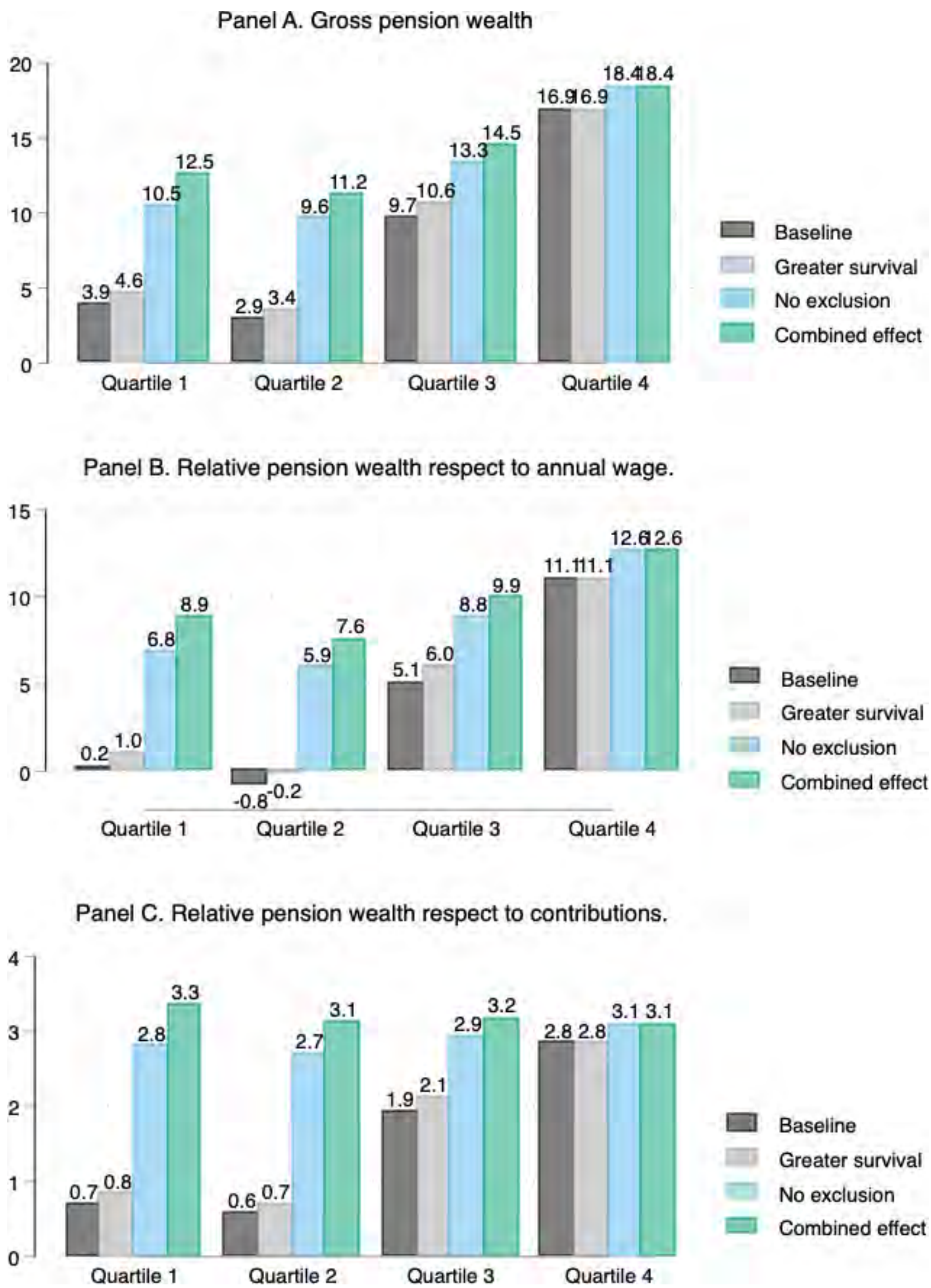

*Notes:* The figure shows the effect of the simulations per outcome variable according to quartiles.

Figure A–12: Robustness $r = 0.04$



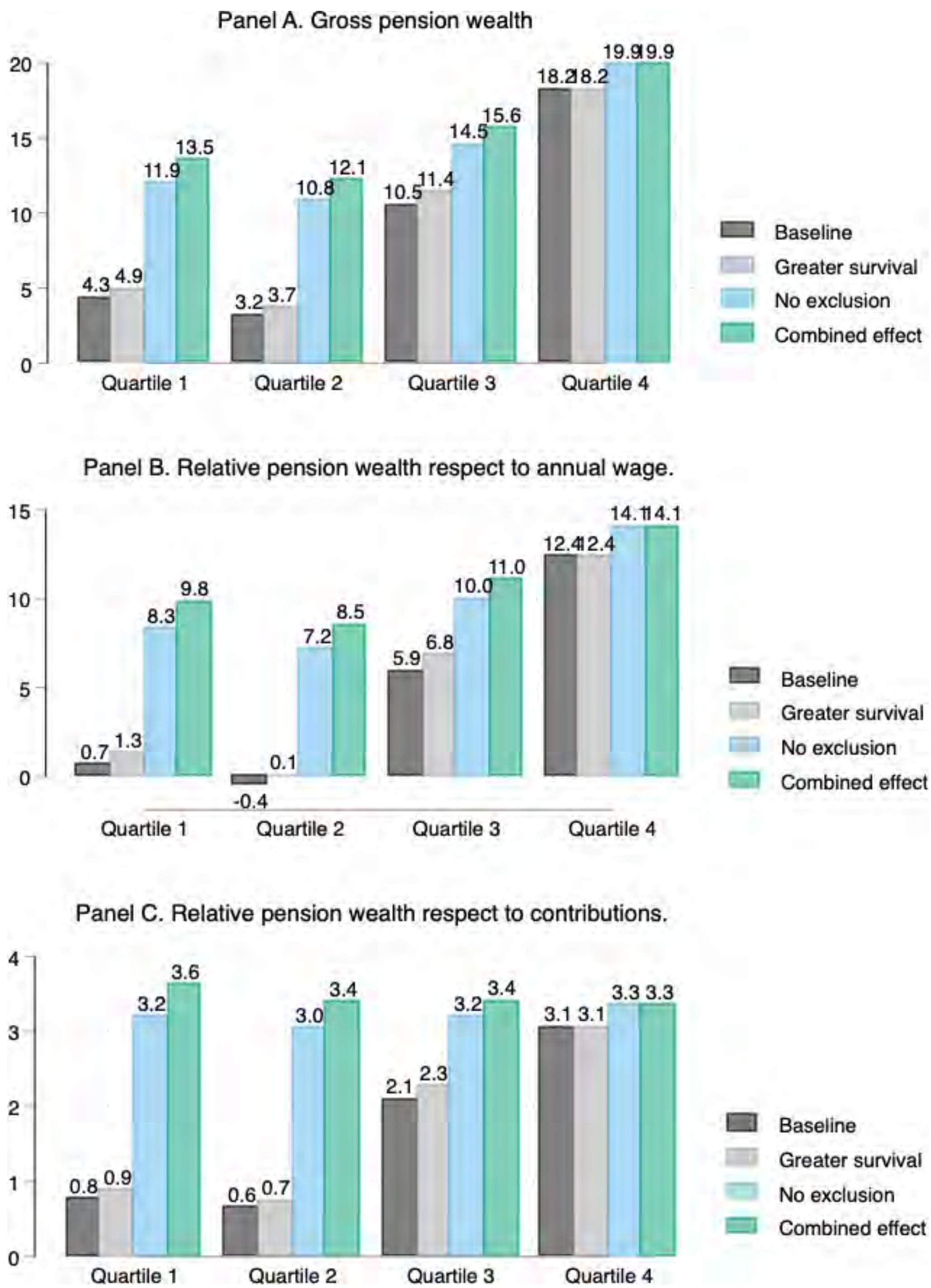

*Notes:* The figure shows the effect of the simulations per outcome variable according to quartiles.

Figure A–13: Weibull



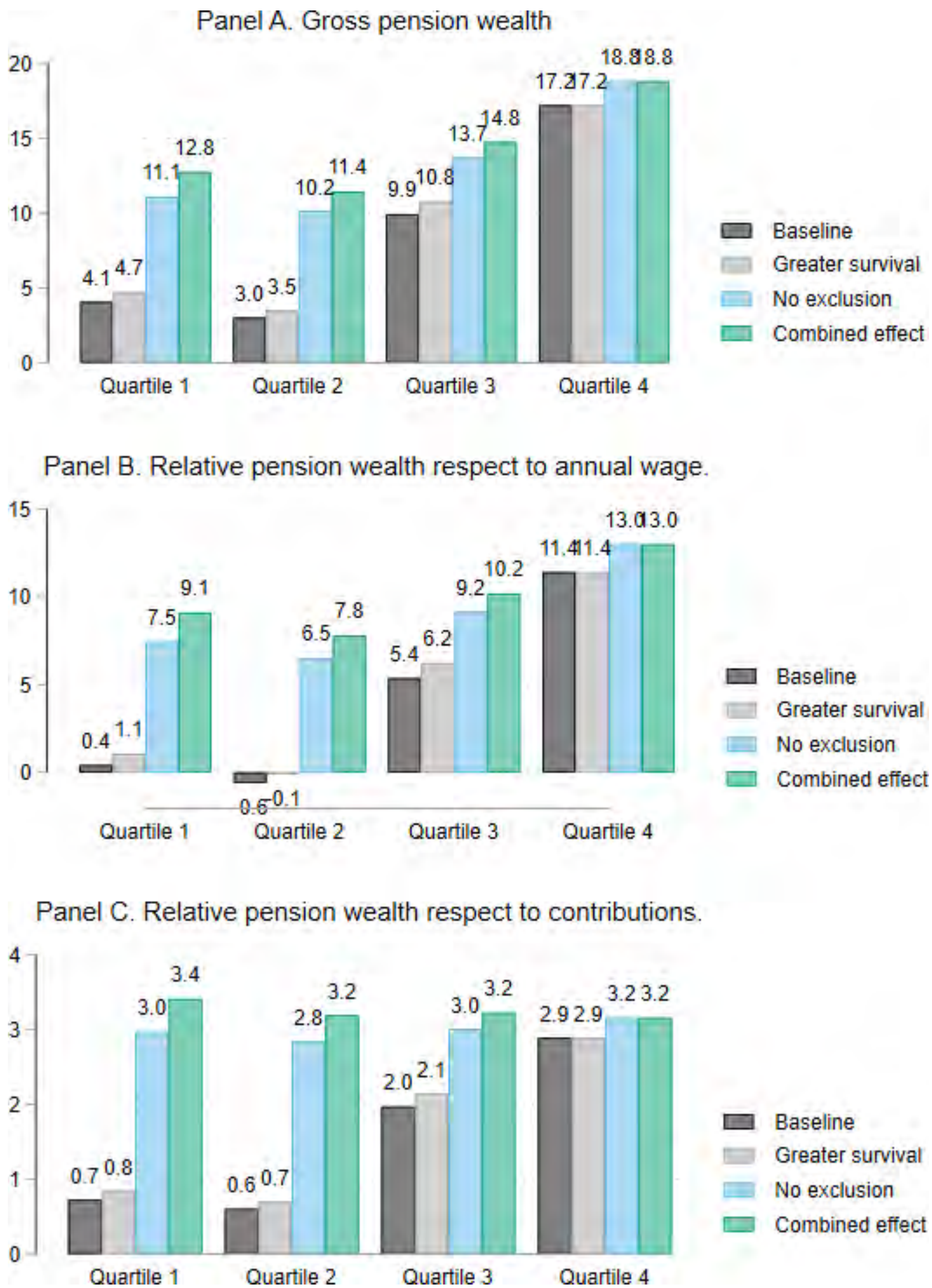

*Notes:* The figure shows the effect of the simulations per outcome variable according to quartiles.

Figure A–14: Exponential




*Notes:* The figure shows the effect of the simulations per outcome variable according to quartiles.

Figure A–15: Log logistic




*Notes:* The figure shows the effect of the simulations per outcome variable according to quartiles.

# B Appendix Chapter 2

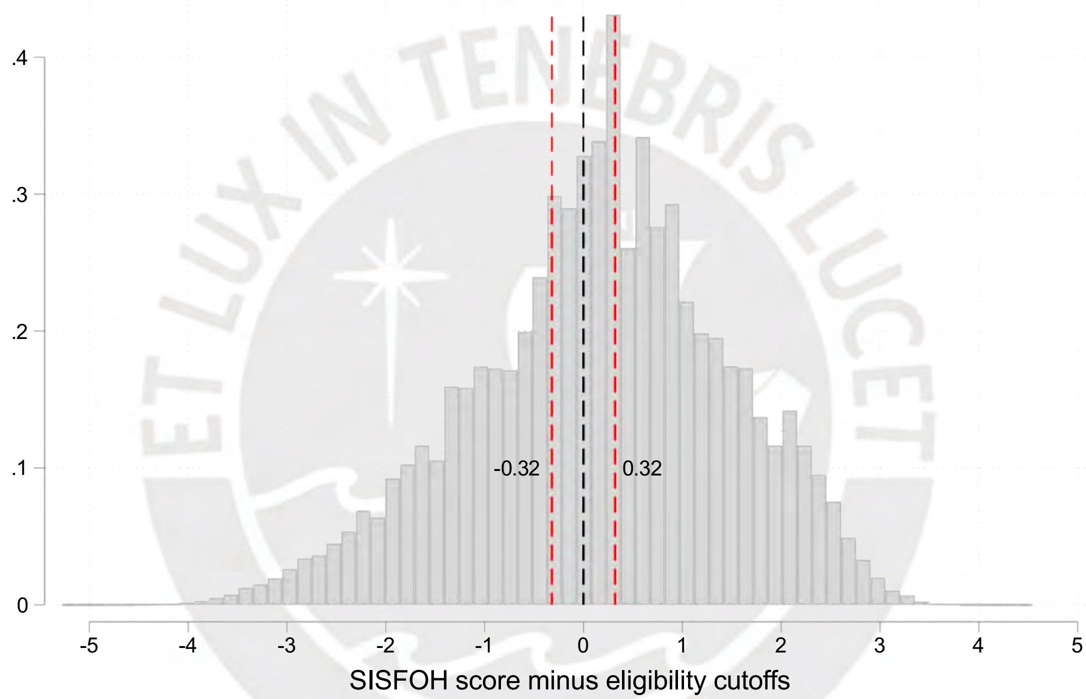
Table B–1: Definition of variables

| 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 cut-offs 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 cut-offs 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 centimeters. |
| Calf circumference (CC) | Calf circumference in centimetres. |
| Cognitive functioning | Is a score (0-13) computed from the points assigned to correct answers for 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 worst or much worst. |
| 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 up them. Second, we re-scale this value to obtain an index ranging between 0 an 1. Thus, larger values imply better perceived health. |

Table B–2: Definition of variables

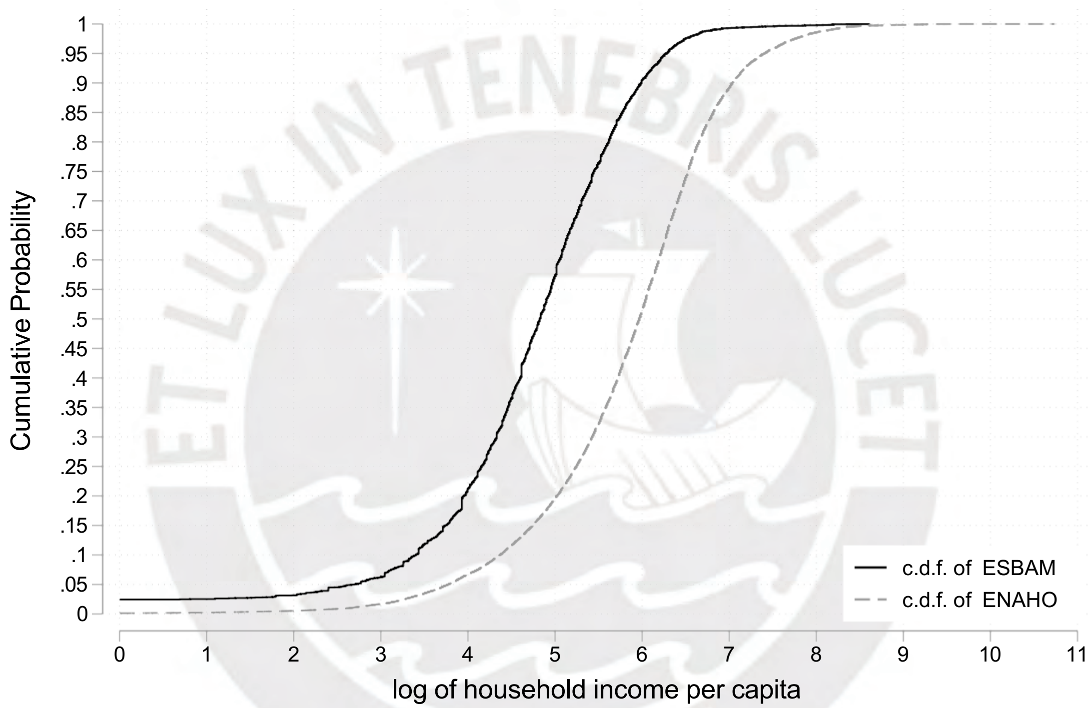
| Variable | Definition |
|---|---|
| Mini Nutritional Assessment (MNA) score | Is a score measuring the quality of diet and the risks of under-nutrition and malnutrition among old individuals. The scores originally ranged from 0 to 30, but the available information in ESBAM allows us to compute a score 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) eating 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, bu 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. |

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–3: Distribution of observations in sample

| | **Overall** | | | **Eligible** | | | **Ineligible** | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Mean** | **SD** | **N** | **Mean** | **SD** | **N** | **Mean** | **SD** | **N** |
| ***Key variable*** | | | | | | | | | |
| Dead (0/1) | 0.085 | 0.280 | 3,885 | 0.083 | 0.276 | 2,525 | 0.090 | 0.287 | 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 or missing key information, the sample size is set to 3,885 individuals.

Table B–4: Distribution of observations in optimal selected sample

| | Overall | | | Eligible | | | Ineligible | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Mean** | **SD** | **N** | **Mean** | **SD** | **N** | **Mean** | **SD** | **N** |
| ***Key variable*** | | | | | | | | | |
| Dead (0/1) | 0.091 | 0.287 | 1,598 | 0.078 | 0.269 | 688 | 0.100 | 0.300 | 910 |
| Running variable | 0.012 | 0.083 | 1,598 | -0.075 | 0.037 | 688 | 0.078 | 0.033 | 910 |
| Treated (0/1) | 0.424 | 0.494 | 1,598 | 0.875 | 0.331 | 688 | 0.084 | 0.277 | 910 |
| ***Covariates*** | | | | | | | | | |
| Male (0/1) | 0.544 | 0.498 | 1,598 | 0.557 | 0.497 | 688 | 0.534 | 0.499 | 910 |
| Age | 71.468 | 4.353 | 1,598 | 71.506 | 4.261 | 688 | 71.440 | 4.424 | 910 |
| High blood pressure (0/1) | 0.340 | 0.474 | 1,579 | 0.403 | 0.491 | 683 | 0.292 | 0.455 | 896 |
| Anaemia (0/1) | 0.302 | 0.459 | 1,568 | 0.284 | 0.451 | 675 | 0.316 | 0.465 | 893 |
| Weight (Kg.) | 56.124 | 10.538 | 1,574 | 56.939 | 10.766 | 679 | 55.505 | 10.324 | 895 |
| Abdominal obesity (0/1) | 0.360 | 0.480 | 1,598 | 0.386 | 0.487 | 688 | 0.341 | 0.474 | 910 |
| Arm span (cm.) | 156.460 | 10.390 | 1,580 | 156.832 | 10.660 | 681 | 156.178 | 10.177 | 899 |
| Mid-upper arm circum. (cm.) | 26.408 | 3.257 | 1,580 | 26.916 | 3.158 | 681 | 25.022 | 3.279 | 899 |
| Calf circum. (cm.) | 31.891 | 3.087 | 1,575 | 32.283 | 3.111 | 679 | 31.628 | 3.045 | 896 |
| Cognitive functioning (0-13) | 10.752 | 2.037 | 1,574 | 10.994 | 1.940 | 679 | 10.569 | 2.090 | 895 |
| Chronic diseases (0-13) | 0.999 | 1.307 | 1,598 | 1.097 | 1.369 | 688 | 0.924 | 1.252 | 910 |
| Good health (0/1) | 0.577 | 0.494 | 1,594 | 0.588 | 0.492 | 687 | 0.568 | 0.496 | 907 |
| MNA score (0-19) | 11.918 | 2.755 | 1,541 | 12.162 | 2.539 | 661 | 11.735 | 2.896 | 880 |
| Alcohol (0/1) | 0.197 | 0.398 | 1,596 | 0.181 | 0.385 | 687 | 0.210 | 0.408 | 909 |
| Tobacco (0/1) | 0.196 | 0.397 | 1,594 | 0.186 | 0.390 | 687 | 0.204 | 0.403 | 907 |
| Juntos (0/1) | 0.116 | 0.320 | 1,598 | 0.122 | 0.328 | 688 | 0.111 | 0.314 | 910 |

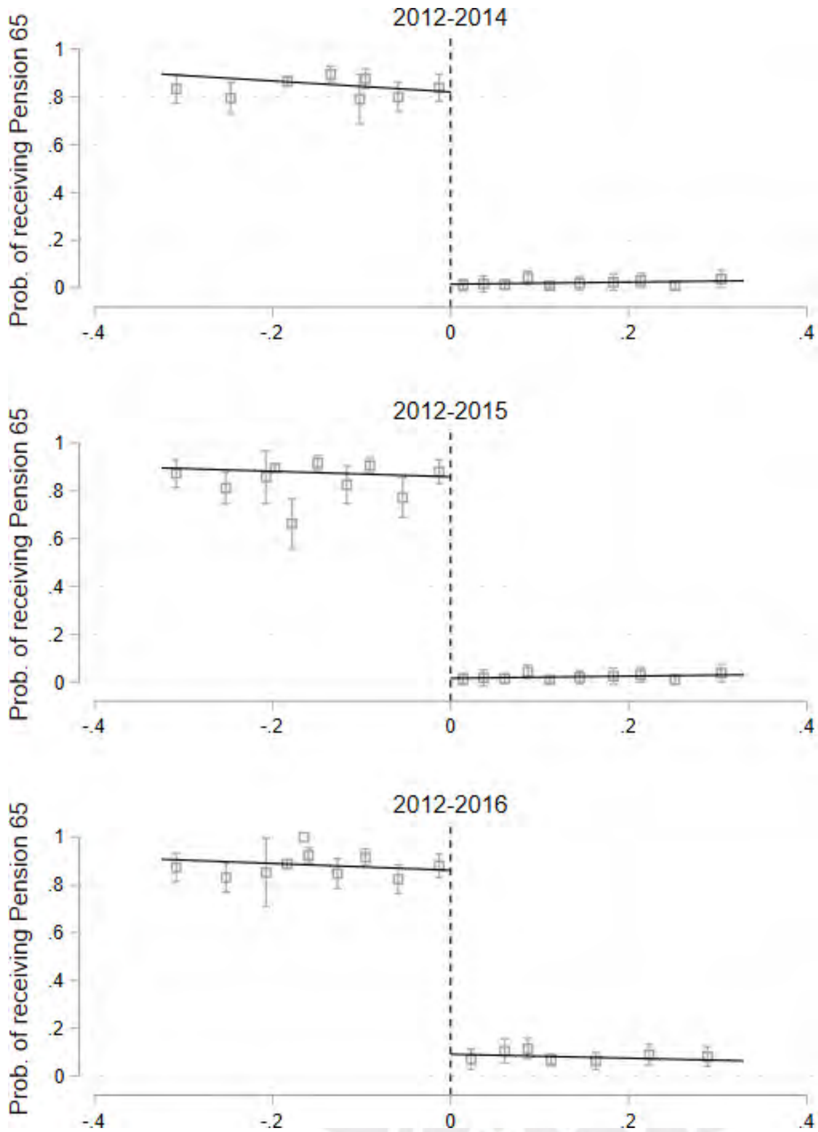
*Notes:* The sample is composed of individuals observed in the baseline of the 2012 ESBAM survey within the optimal bandwidth of +/-0.150 around the eligibility threshold, resulting in a sample size of 1,598 individuals.The optimal bandwidth is obtained from the point estimation model as suggested by Calonico et al. (2015)

Table B–5: Cumulative number of *Pension 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 |

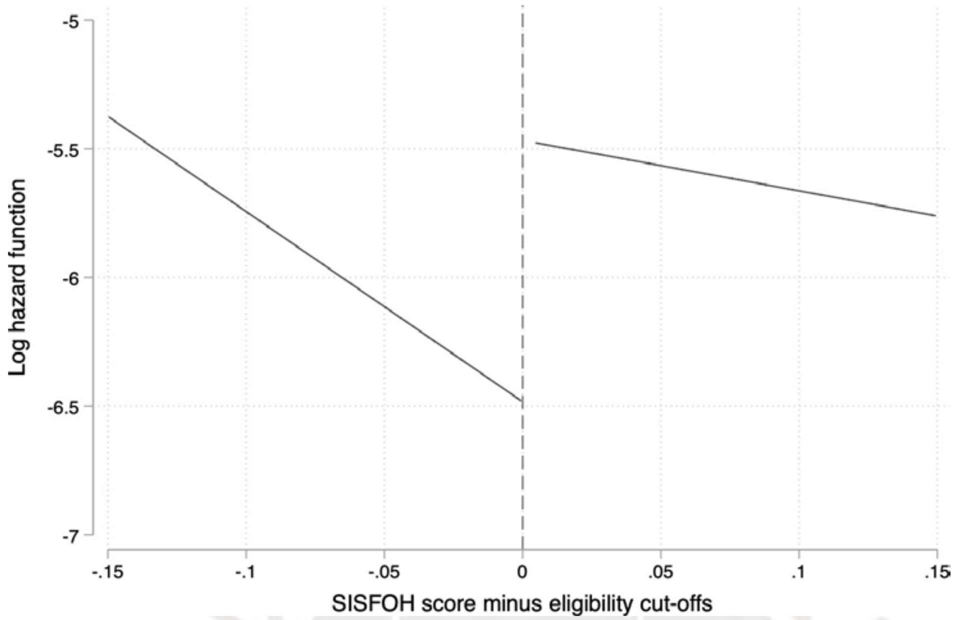
*Notes:* The first and second columns indicate the number of individuals who have survived until December of each year by the eligibility condition measured at the baseline (i.e. according to the SISFOH rules of 2012). The third column shows the accumulated number of individuals each year who have received 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 *Pension 65* recipient at different evaluation periods




*Notes:* The graphs plots the probability of receiving *Pension 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.

Figure B–4: Intention-to-treat in survival model




*Notes:* The graph plots the log of the hazard ratio of mortality observed over 4 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 B–6: Effect of *Pension 65* on log of mortality hazard rate under alternative functions

| Model | ITT Estimator | 95% C.I. | |
|---|---|---|---|
| Cox | -1.679 | -2.900 | -0.458 |
| Exponential | -1.671 | -2.698 | -0.645 |
| Weibull | -1.680 | -2.711 | -0.648 |

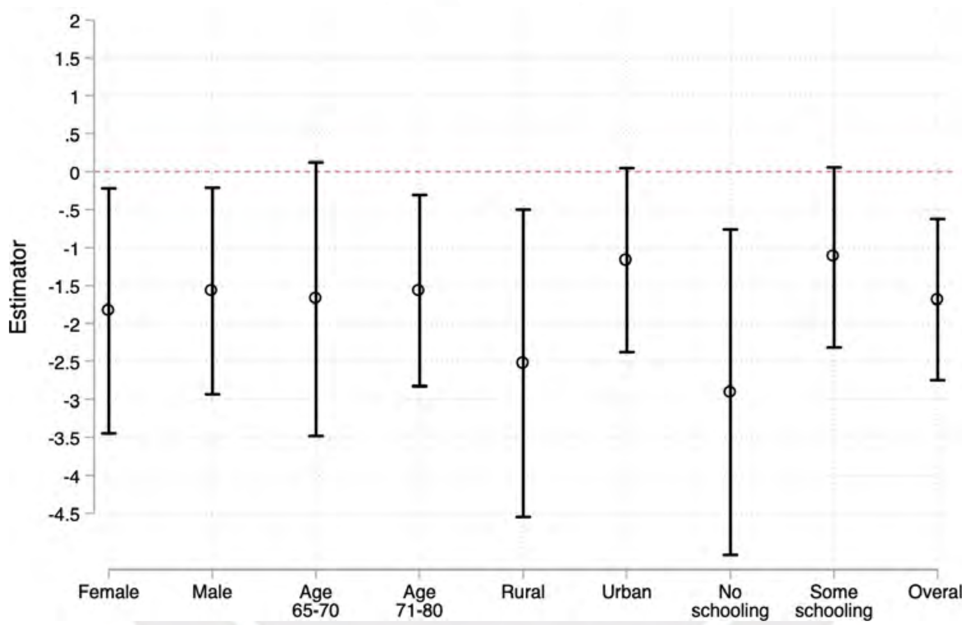
*Notes:* The table reports the ITT estimates for the log of mortality hazard rate observed over 4 years (equation 2.4). The estimators correspond to a non-parametric version (Cox model) and two parametric models (Exponential and Weibull). The models use triangular kernel, local linear polynomial and the optimal bandwidth for point estimation as suggested by Calonico et al. (2015) (obtained in the Table 2.2).

Table B–7: Effect of *Pension 65* on log of mortality hazard rate including covariates

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| ITT | -1.680*** | -1.595*** | -1.302** | -1.748*** | -1.682*** |
| | (0.525) | (0.529) | (0.549) | (0.579) | (0.592) |
| Male | | 0.373* | 0.656*** | 0.727*** | 0.683*** |
| | | (0.195) | (0.248) | (0.251) | (0.253) |
| Age | | 0.124*** | 0.089*** | 0.086*** | 0.092*** |
| | | (0.021) | (0.021) | (0.022) | (0.022) |
| High blood pressure | | | 0.465** | 0.421* | 0.441* |
| | | | (0.225) | (0.232) | (0.228) |
| Anaemia | | | 0.409** | 0.464** | 0.493** |
| | | | (0.196) | (0.198) | (0.199) |
| Weight | | | 0.041** | 0.045** | 0.042** |
| | | | (0.021) | (0.021) | (0.021) |
| Abdominal obesity | | | 0.370 | 0.378 | 0.472* |
| | | | (0.271) | (0.276) | (0.278) |
| Arm span | | | -0.004 | -0.012 | -0.014 |
| | | | (0.014) | (0.014) | (0.014) |
| Mid-upper arm circ. (MUAC) | | | -0.184*** | -0.164*** | -0.161*** |
| | | | (0.060) | (0.060) | (0.060) |
| Calf circumference (CC) | | | -0.096** | -0.087** | -0.085** |
| | | | (0.043) | (0.044) | (0.041) |
| Cognitive functioning | | | -0.151*** | -0.118*** | -0.120*** |
| | | | (0.039) | (0.040) | (0.041) |
| Chronic diseases | | | | 0.078 | 0.081 |
| | | | | (0.064) | (0.065) |
| Health today | | | | -0.341 | -0.357 |
| | | | | (0.235) | (0.237) |
| Nutrition score (MNA) | | | | -0.060 | -0.066 |
| | | | | (0.052) | (0.052) |
| Alcohol | | | | | 0.535** |
| | | | | | (0.238) |
| Tobacco | | | | | -0.027 |
| | | | | | (0.235) |
| Constant | -3.878*** | -13.099*** | -3.690 | -2.870 | -3.170 |
| | (0.319) | (1.625) | (2.771) | (2.900) | (2.870) |
| Observations | 1598 | 1598 | 1533 | 1503 | 1501 |

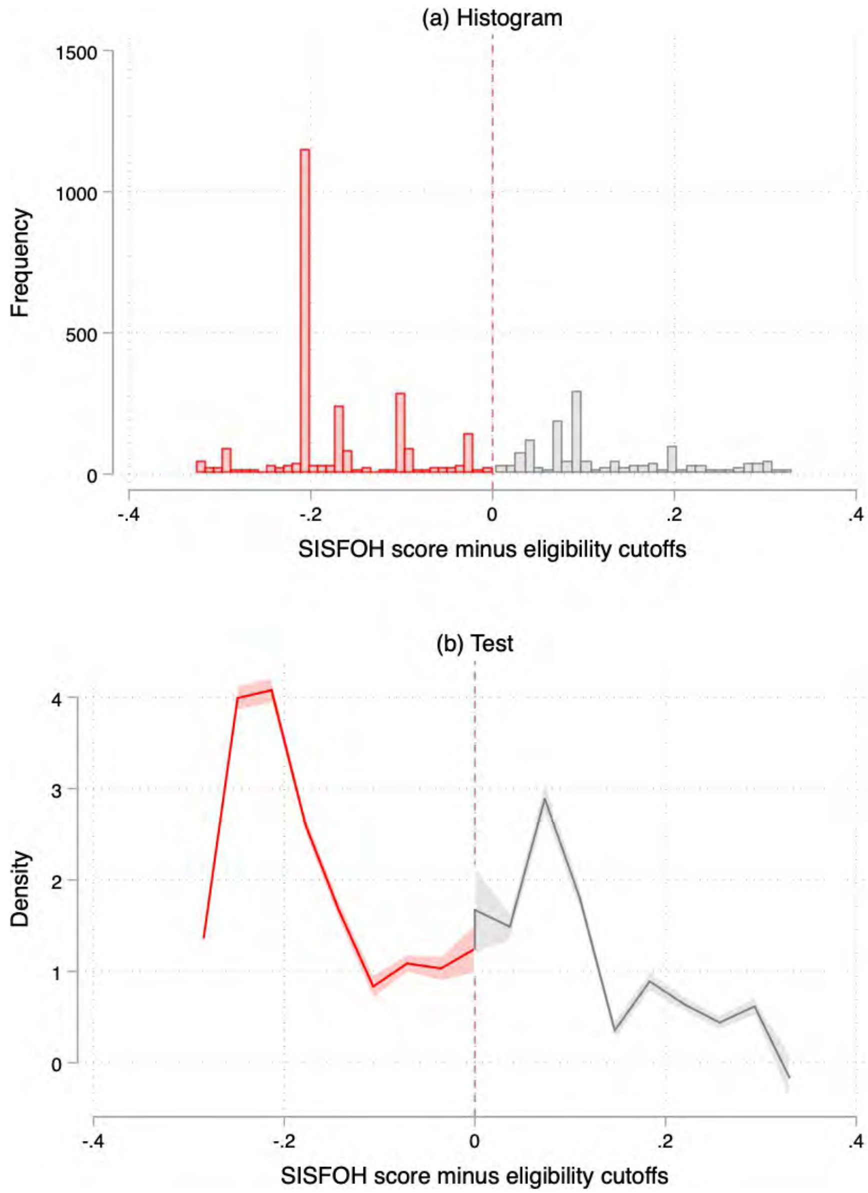
*Notes:* The table reports the ITT estimates for the log of mortality hazard rate observed over 4 years (equation 2.4), including covariates related to the mortality risk. The estimator corresponds to a Gompertz-type model. The models use triangular kernel, local linear polynomial and the optimal bandwidth for point estimation as suggested by Calonico et al. (2015) (obtained in Table 2.2). The standard errors are indicated in parentheses. *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$ indicate statistically significance levels.

Figure B–5: Heterogeneous effects on the log of mortality hazard rate



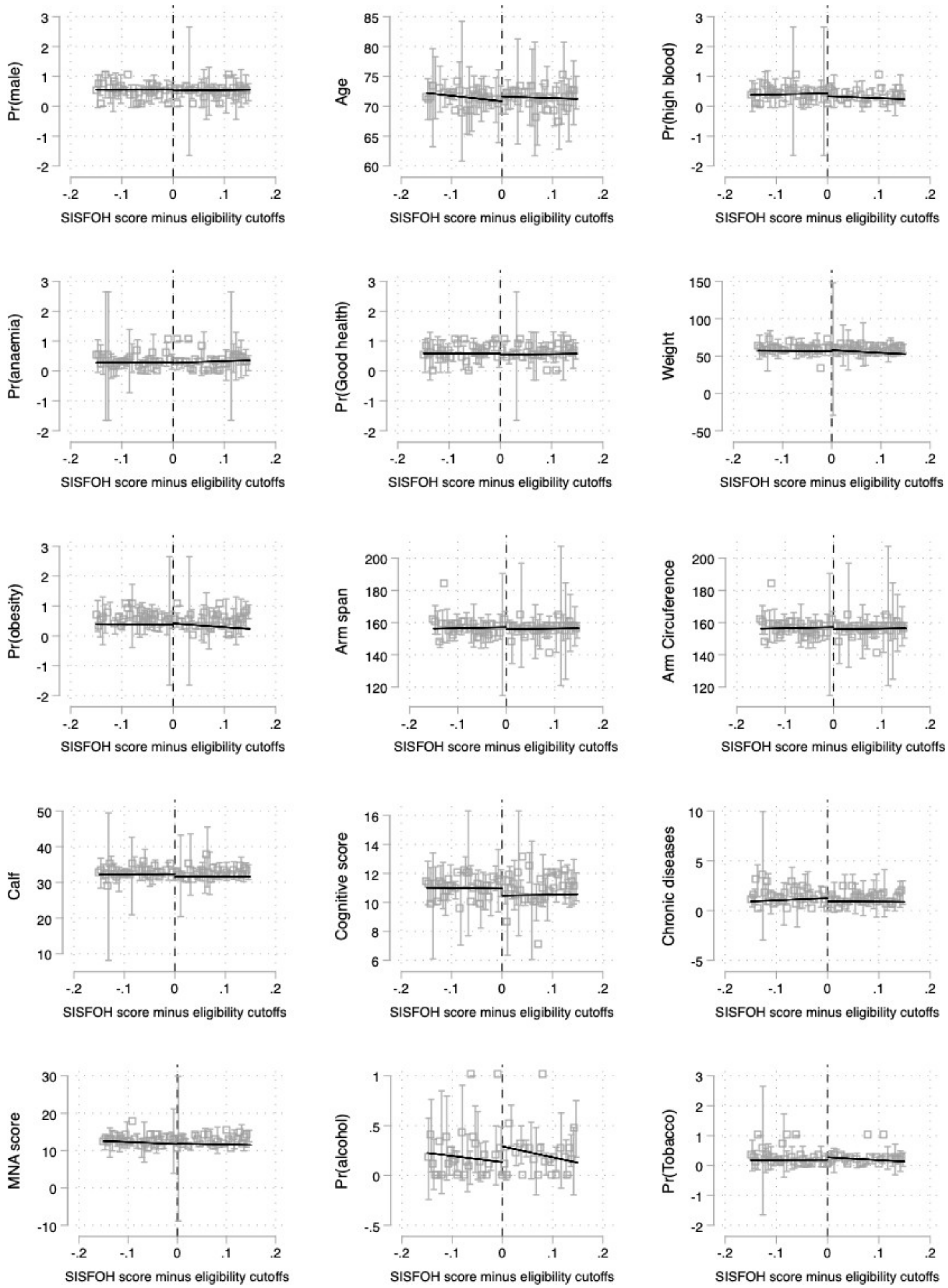

*Notes:* The graph plots the estimated ITT coefficients from equation 2.4 for four distinctive demographic groups (by sex, age, area, and education) and the overall effect. The vertical lines indicate 95% confidence intervals.

Figure B–6: 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 B–7: 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 B–9: ITT effects under alternative cutoffs

| Alternative cut-offs (x100) | Optimal bandwidth | OLS model | | Survival model | |
|---|---|---|---|---|---|
| | | ITT | P-value | ITT | P-value |
| -25 | 0.093 | -0.001 | 0.999 | 0.041 | 0.957 |
| -15 | 0.126 | -0.027 | 0.536 | -0.288 | 0.550 |
| -7.5 | 0.047 | -0.171 | 0.147 | -1.966 | 0.088 |
| 0 | 0.145 | -0.114 | 0.011 | -0.846 | 0.009 |
| 7.5 | 0.172 | 0.026 | 0.418 | 0.326 | 0.329 |
| 15 | 0.086 | 0.010 | 0.868 | 0.126 | 0.847 |
| 25 | 0.060 | 0.011 | 0.883 | 0.113 | 0.924 |

*Notes:* The table reports the ITT effects estimated for equations 2.2 and 2.4 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 B–8: Testing the effect of *Pension 65* on actual and predicted mortality

| | (1) | (2) | (3) |
|---|---|---|---|
| Intention-to-treat ($\hat{\beta}_1$) | -0.107 | -0.011 | -0.006 |
| | (0.033) | (0.012) | (0.012) |
| | [0.001] | [0.352] | [0.595] |
| 95% Conf. Interval | (-0.172, -0.042) | (-0.034, 0.012) | (-0.030, 0.017) |
| Bandwidth | +/- 0.150 | +/- 0.093 | +/- 0.093 |
| Observations | 1,598 | 762 | 762 |

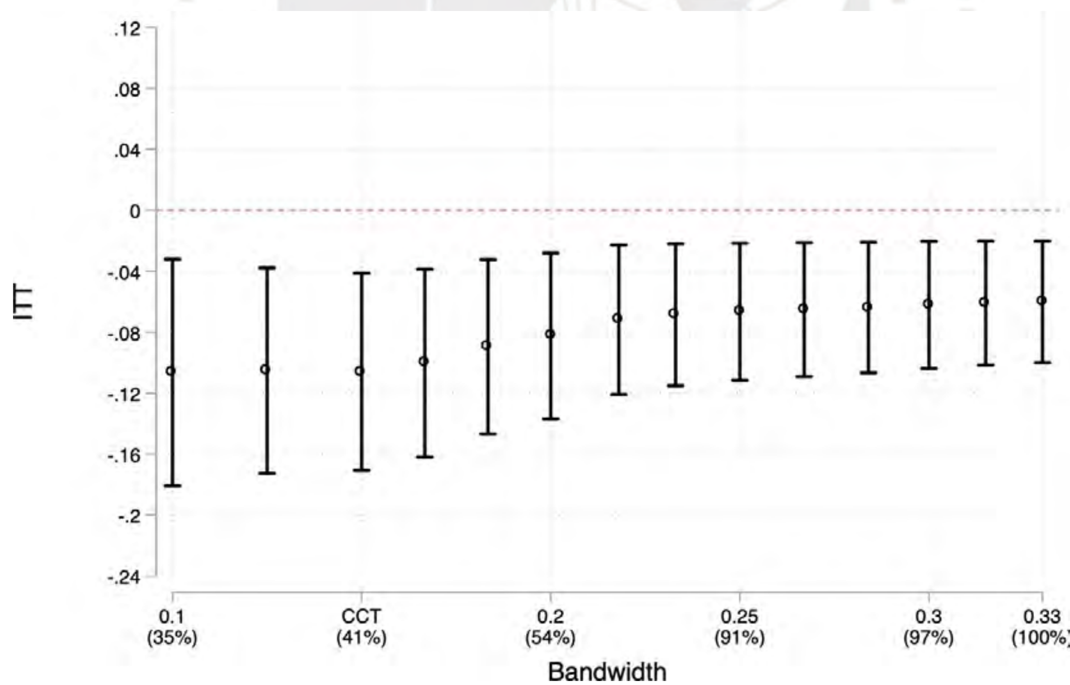
*Notes:* The table reports the ITT estimates for mortality observed in 4 years (Equation 2.2). The models use triangular kernel and local linear polynomial. The first column reports the ITT effect of our main model on actual mortality (column 3 of Table 2.2), while columns 2 and 3 report the ITT effect on predicted mortality. In the second column, the mortality rate has been predicted using all the predetermined covariates that were employed in the balance test. In the third column, the mortality rate has been predicted using only those covariates that were statistically significant (using a stepwise regression). The optimal bandwidth for point estimation is used, 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.

Table B–10: Sensitivity to observations near the cutoff (donut hole approach)

| Donut-hole Radius (x1000) | Excluded Obs. | | OLS Model | | Survival Model | |
|---|---|---|---|---|---|---|
| | Left | Right | ITT | p-value | ITT | p-value |
| 0 | 0 | 0 | -0.107 | 0.001 | -1.672 | 0.001 |
| 2 | 7 | 0 | -0.106 | 0.002 | -1.625 | 0.002 |
| 4 | 11 | 0 | -0.105 | 0.002 | -1.597 | 0.003 |
| 6 | 16 | 18 | -0.117 | 0.001 | -1.682 | 0.002 |
| 8 | 16 | 20 | -0.121 | 0.001 | -1.711 | 0.002 |
| 10 | 17 | 21 | -0.122 | 0.001 | -1.719 | 0.002 |

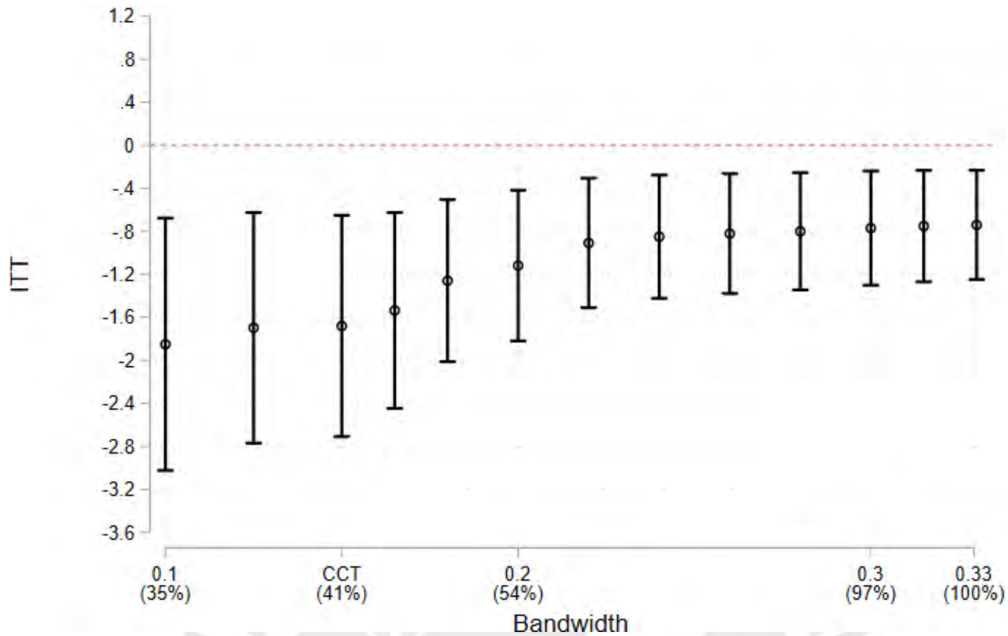
*Notes:* The table reports the ITT effects estimated for equations 2.2 and 2.4 excluding observations around cut-off. All the estimated models use triangular kernel, and the optimal bandwidth for point estimation as suggested by Calonico et al. (2015) (obtained in the Table 2.2). The standard errors are clustered by the Primary Sampling Unit (PSU) of the sampling framing.

Figure B–8: ITT effects by alternative bandwidths



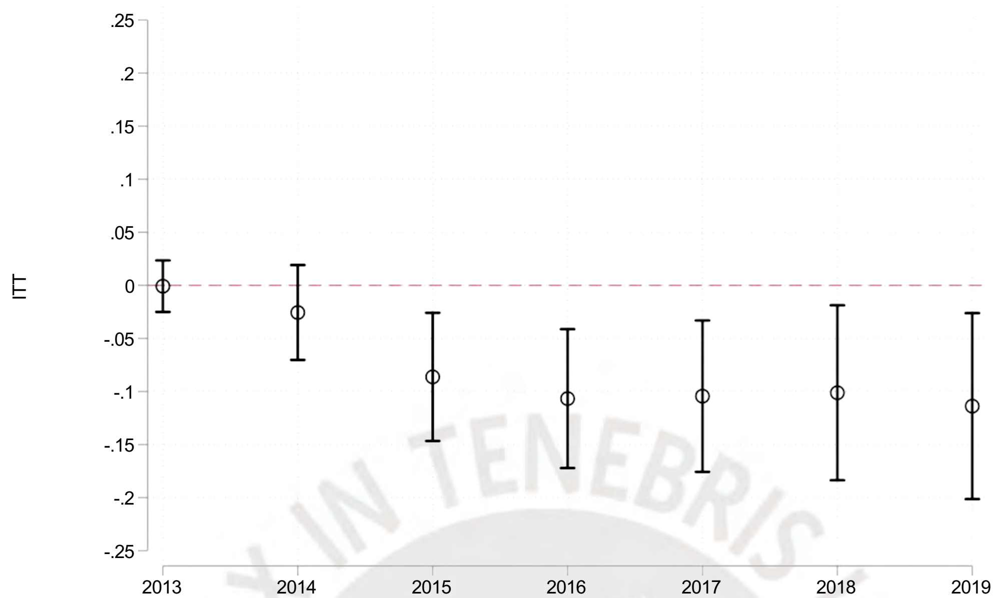

*Notes:* This figure plots the ITT effects estimated for equation 2.2 for alternative bandwidths. All the estimated models use triangular kernel and local linear polynomial. The horizontal axis shows the percentage of the sample employed for each estimated model. CCT corresponds to the optimally estimated bandwidth proposed by Calonico et al. (2015). The vertical lines indicate 95% confidence intervals.

Figure B–9: ITT effects on the log of mortality hazard ratio by alternative bandwidths



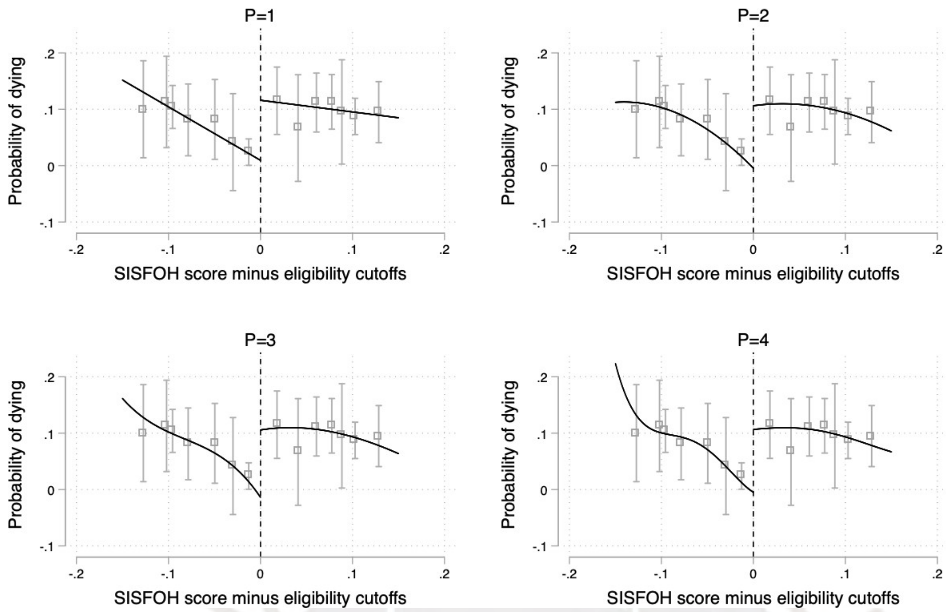

*Notes:* This figure plots the ITT effects estimated for equation 2.4 for alternative bandwidths. All the estimated models use triangular kernel and local linear polynomial. The horizontal axis shows the percentage of the sample employed for each estimated model. CCT corresponds to the optimally estimated bandwidth proposed by Calonico et al. (2015). The vertical lines indicate 95% confidence intervals.

Figure B–10: ITT effects by period of observed mortality




*Notes:* This figure plots the ITT effects estimated for equation 2.2 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 2.2). The vertical lines indicate 95% confidence intervals.

Figure B–11: ITT estimator assuming different order of polynomials




*Notes:*: This figure plots the ITT effects estimated for equation 2.2 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.

Table B–11: Effect of *Pension 65* on mortality rate

| | (1) | (2) |
|---|---|---|
| Intention-to-treat ($\hat{\beta}_1$) | -0.107 | -0.112 |
| | (0.033) | (0.034) |
| Health campaigns in the district | | -0.010 |
| | | (0.002) |
| Constant | 0.116 | 0.142 |
| | (0.028) | (0.031) |
| Observations | 1,598 | 1,598 |

*Notes:* The table reports the ITT estimates for mortality observed in 4 years (Equation 2.2). The models use triangular kernel and local linear polynomial. The first column shows our main model. The second model includes the average number of yearly health campaigns conducted by the Ministry of Health in the individual's district of residence, to which the individual was exposed during the period 2013-2016. The optimal bandwidth for point estimation is used, 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.

Table B–12: Effect of *Pension 65* on log mortality hazard rate

| | (1) | (2) |
|---|---|---|
| Intention-to-treat ($\hat{\beta}_1$) | -1.680 | -1.741 |
| | (0.525) | (0.531) |
| Health campaigns in the district | | -0.237 |
| | | (0.074) |
| Constant | -3.878 | -3.450 |
| | (0.319) | (0.349) |
| Observations | 1,598 | 1,598 |

*Notes:* The table reports the ITT estimates for mortality observed in 4 years (Equation 2.2). The first column shows our main model. The second model includes the average number of yearly health campaigns conducted by the Ministry of Health in the individual's district of residence, to which the individual was exposed during the period 2013-2016. The optimal bandwidth for point estimation is used, 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.

Table B–13: 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 Dollars. Robinson et al. (2019) extrapolate VSL estimates of USD using different base values and income elasticity ($\varepsilon$). The base value multiplies the Gross National Income (GNI) per capita, while the $\varepsilon$ 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 $\gamma$, 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.

Table B–14: ITT effects of *Pension 65* on various outcomes (2015 follow-up sample)

| Outcomes | All sample Effect | N | Bandwidth 0.150 Effect | N | Non-parametric Effect | N |
|---|---|---|---|---|---|---|
| High blood pressure | 0.091 | 3,494 | -0.164 | 1,434 | -0.284* | 1,235 |
| Anaemia | -0.246*** | 3,454 | -0.011 | 1,417 | 0.228 | 469 |
| Weight | 0.127 | 3,478 | -0.111 | 1,426 | -0.294 | 644 |
| Abdominal obesity | 0.118 | 3,512 | -0.229 | 1,444 | -0.498* | 473 |
| Arm span | 0.014 | 3,481 | -0.065 | 1,429 | 0.265 | 469 |
| Mid-upper arm circ. (MUAC) | 0.322*** | 3,496 | 0.096 | 1,435 | 0.250* | 1,828 |
| Calf circumference (CC) | 0.260*** | 3,492 | -0.110 | 1,435 | -0.093 | 689 |
| Depression symptoms | -0.237*** | 3,511 | -0.154 | 1,444 | 0.239 | 476 |
| Cognitive functioning | 0.333*** | 3,449 | 0.387*** | 1,422 | -0.058 | 443 |
| Chronic diseases | 0.356*** | 3,512 | 0.567*** | 1,444 | -0.052 | 449 |
| Nutrition score (MNA) | 0.307*** | 3,354 | -0.002 | 1,374 | -0.148 | 621 |
| Health today | 0.131 | 3,506 | 0.233* | 1,441 | -0.008 | 481 |
| Health compared to last year | 0.292*** | 3,503 | 0.333** | 1,441 | 0.267* | 1,247 |
| Health compared to other people | 0.197** | 3,455 | 0.091 | 1,420 | 0.022 | 1,220 |
| Subjective health index | 0.246*** | 3,454 | 0.226* | 1,419 | 0.100 | 649 |
| Attended health centre | 0.347*** | 2,474 | 0.716*** | 1,016 | 0.570** | 476 |
| Indiv. health expenditure | 0.106 | 3,512 | 0.172 | 1,444 | 0.157 | 1,856 |
| Indiv. medicine expenditure | 0.120** | 3,512 | 0.127 | 1,444 | 0.098 | 3,037 |
| Working hours | -0.298*** | 3,512 | -0.109 | 1,444 | -0.102 | 1,322 |
| Working | -0.311*** | 3,512 | -0.096 | 1,444 | -0.068 | 1,243 |
| Household expenditure | 0.544*** | 3,512 | 0.034 | 1,444 | -0.071 | 1,322 |
| Household food expenditure | 0.486*** | 3,512 | -0.102 | 1,444 | -0.203 | 743 |
| Expenditure per capita | 0.332*** | 3,494 | -0.222 | 1,436 | -0.495 | 634 |
| Food expenditure per capita | 0.382*** | 3,494 | -0.318** | 1,436 | -0.418* | 654 |
| Number of household members | 0.276*** | 3,512 | 0.459*** | 1,444 | 0.396*** | 3,507 |

*Notes*: The table reports the ITT effects of *Pension 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.