Authors' post-print version.

Olivera, J., Andreoli, F., Leist, A. K., & Chauvel, L. (2018) Inequality in old age cognition across the world. *Economics & Human Biology*, 29, 179-188.

https://doi.org/10.1016/j.ehb.2018.03.002

# Inequality in old age cognition across the world

**Javier Olivera** (🖂)
Luxembourg Institute of Socio-Economic Research (LISER), &
Department of economics, Pontificia Universidad Catolica del Peru
11, Porte des Sciences, L-4366 Belval, Luxembourg. e-mail: javier.olivera@liser.lu

**Francesco Andreoli**
Luxembourg Institute of Socio-Economic Research (LISER)
11, Porte des Sciences, L-4366 Belval, Luxembourg. e-mail: francesco.andreoli@liser.lu

**Anja Leist**
University of Luxembourg, Institute for Research on Socio-Economic Inequality (IRSEI)
11, porte des Sciences. L-4366 Belval, Luxembourg. e-mail: anja.leist@uni.lu

**Louis Chauvel**
University of Luxembourg, Institute for Research on Socio-Economic Inequality (IRSEI)
11, porte des Sciences. L-4366 Belval, Luxembourg. e-mail: louis.chauvel@uni.lu

**Abstract.** Although cohort and country differences in average cognitive levels are well established, identifying the degree and determinants of inequalities in old age cognitive functioning could guide public health and policymaking efforts. We use all publicly available and representative old age surveys with comparable information to assess inequalities of cognitive functioning in six distinctive age groups of 29 countries. We document that cognitive inequalities in old age are largely determined by earlier educational inequalities as well as gender differential survival rates. For example, a one percentage point increase in the Gini index of past education is associated with an increase of 0.45 percentage points in the Gini index of delayed recall and 0.23 percentage points in the Gini of immediate recall. Results are robust to a variety of alternative explanations and persist even after controlling for gender-related biases in survival rates. Furthermore, we find evidence that unequal opportunities for education -captured by differences in parental background and gender- also have significant effects on inequality of old age cognition.

**Keywords**: Cognition functioning, inequality, old age, education, inequality of opportunity
**JEL codes**: I14, I24, J14

## 1 Introduction

Intact cognitive functioning in old age refers to attention, thinking, understanding, learning, decision-making and problem solving. It is fundamental to "an individual's ability to engage in activities, accomplish goals and successfully negotiate the world" (Blazer et al. 2015, p. 2). From an economic perspective, cognitive abilities are an indicator of accumulated human capital that depreciates over time, although the individual can take limited measures for cognitive maintenance or repairing (McFadden 2008). In particular, at older ages, higher starting levels of cognitive functioning are even more important, as processes of cognitive aging lead to declines in cognitive functioning. Intact cognitive functioning is related to autonomy, quality of life and active aging, whereas cognitive impairment or dementia goes along with increased disability and higher health expenditures (Bonsang et al. 2012).

Many studies have focused on measuring the level of cognitive functioning and its determinants (Leist and Mackenbach 2014), and phenomena regarding cohort and country differences in average cognitive levels, such as the Flynn effect and associations to economic development are well established (Skirbekk et al. 2013, Skirbekk et al. 2012, Rindermann 2008). However, little is known regarding the inequalities in cognitive functioning in old age.

We argue that the degree and determinants of old age cognitive inequalities may provide important information for public health and policymaking efforts. Knowing about the potential of education to increase cognitive reserve (Chen 2016, Banks and Mazzonna 2012, Meng and D'Arcy 2012, Singh-Manoux et al. 2011, Glymour et al. 2008, Lee et al. 2003), the distribution of cognitive functioning in old age may reflect undeveloped potential for cognitive functioning due to early-life educational inequalities and lack of educational opportunities. Therefore, high inequality in old age cognition may be associated with low average levels of old age cognition. Given the high costs of cognitive impairment and dementia (Prince et al. 2015, Handels et al. 2013) and its importance for health expenditures, it is expected that high inequality of cognitive functioning may undermine the sustainability of healthcare. Further, considering the importance of cognitive functioning for financial decision making and financial outcomes (Christelis 2010, Smith et al. 2010), inequalities in cognition may exacerbate the inequality of wealth due to poor financial planning and investment decisions. Indeed, a recent study by Lusardi et al. (2017) shows that financial literacy can explain about 30-40% of wealth inequality in the U.S.

In a broader perspective, inequality of old age cognitive functioning can be related as well to the distribution of wellbeing among old people. In fact, cognitive functioning may determine key dimensions for this population group, such as autonomy, mental health, and planning ability, among others. Educational inequalities have been shown to have long-run consequences on hampering equality of opportunity for accumulation of resources over the life course (Attewell and Newman 2010, Roemer 1998).

In this paper, we analyze current inequalities in old age cognitive functioning around the world. Our goal is to assess the extent to which educational inequalities experienced at young age have long-run effects on inequality in cognitive functioning experienced in old age. We condition our results for the role of survival rates on cognition because differential survival rates may further aggravate today's inequalities due to gender-unbalanced accessibility to education often observed in older cohorts (Weber et al. 2014). In our baseline estimation we find that a one percent increase in educational inequalities is associated to a positive and significant increase in inequality in cognitive functioning in late age that ranges from 0.10 to 0.45 percentage points depending on the cognitive functioning indicator. The effects are consistent in significance and size across a variety of robustness checks, involving the way in which inequalities are measured and changes in inequalities correctly identified. Results are also robust to the effects of unfair differences in parental background and gender.

Our investigations are based on a variety of available data sources, including survey data, population projections and the historical distribution of educational attainment, drawn from 29 countries with diverse economic development levels in four continents. The selection of countries is mostly based on the availability of survey representative data measuring cognitive functioning among old individuals. The main results show evidence of significant long-term effects of past educational inequalities on inequalities in old age cognitive functioning observed today. In addition, we show that the relative higher life expectancy of women may contribute to increase cognitive inequality. All in all, we also bring new evidence that countries that experienced a large gender gap in education are showing higher old age cognitive inequalities.

## 2 Data

For the measurement of inequality of old-age cognition we use survey data from 29 countries for years 2008-2015, with most of the surveys (23 out of 29) taken between 2011 and 2015. The complete list of countries, years and surveys are reported in Table 1. The selection of these countries is based on the public availability of the data, comparability of cognitive tests and national representativeness of the sample. All these surveys are specialized studies focused on the elderly population (generally aged 50+) that can be considered sister studies of the Health and Retirement Survey (HRS). Altogether, these surveys represent about 61% of the world's 50+ population.

Table 1. List of surveys with old age cognitive tests

| Survey/Dataset | Version/release | Country and year of interview |
|---|---|---|
| SHARE | Waves 5-6, release 6.0.0 | Austria (2015), Germany (2015), Sweden (2015), Netherlands (2013), Spain (2015), Italy (2015), France (2015), Denmark (2015), Greece (2015), Switzerland (2015), Belgium (2015), Israel (2015), Czech Republic (2015), Poland (2015), Luxembourg (2015), Hungary (2011), Portugal (2015), Slovenia (2015), Estonia (2015), Croatia (2015) |
| ELSA | Wave 7, v0 | UK (2014) |
| TILDA | Wave 1, v1.6 | Ireland (2010) |
| HRS | Wave 2014, v1.0 | United States (2014) |
| SAGE | Wave 1 | China (2009), Ghana (2007), Russia (2008), South Africa (2007) |
| LASI | Pilot | India (2010) |
| MHAS | Wave 4 | Mexico (2015) |

Note: In 22 countries the data were collected within one calendar year, while in 7 countries (U.S., U.K., Ireland, China, Ghana, Russia and South Africa) the data were collected during more than one calendar year. In U.S. 95% of the analyzed sample was collected during 2014 and 5% during 2015. In U.K. 79% was collected during 2014 and 21% during 2015. In Ireland the collection took place in the period 18-10-2009 to 22-02-2011 (the database does not specify the date of interview of each respondent) so approximately 70% of the sample was collected in 2010. In China 37%, 5%, 45% and 13% of the sample were collected in 2007, 2008, 2009 and 2010, respectively. In Ghana 67% and 33% of the sample were collected in 2007 and 2008. In Russia 23%, 48% and 8% of the sample were collected in 2007, 2008 and 2010, respectively. In South Africa 92% and 8% of the sample were collected in 2007 and 2008. For these 7 countries the year between parentheses corresponds to the year were more observations were collected.

The surveys presented in Table 1 provide harmonized measures of cognitive function, assessing *immediate memory* (number of correctly recalled answers to a 10-word list read out loud by the interviewer), *delayed recall memory* (number of correctly recalled words of the same word list after a delay), *average memory* (average of both memory tests) and *verbal fluency* (number of animals named in one minute). These types of measures are routinely utilized in studies about later-life cognition (e.g. Rohwedder and Willis 2010, Banks and Mazzona 2012, de Grip 2015, Guven and Lee 2015). The respondents are divided in 6 age groups (50-54, 55-59, 60-64, 65-69, 70-74 and 75-79) within each country, which results in a sample of 174 synthetic individuals (country-cohort points). Inequalities are measured for each of these groups.

Some details about the choice of some surveys are worth mentioning. We use the Study on Global Ageing and Adult Health (SAGE) survey for China instead of the China Health and Retirement Longitudinal Study (CHARLS) survey because the former includes the verbal fluency test, and the latter does not include it. The wave 2 (2012) of the Irish Longitudinal Study on Ageing (TILDA) was available at the time of writing, but the design weights were not publicly available. Therefore, we use TILDA wave 1 (2010). The Mexican Health and Aging Study (MHAS) utilizes a memory test with a list of eight instead of 10 words as is the case in the other countries. Given that the Gini index of inequality of cognitive functioning is our main variable of study, the different size of the word list is factorized by the formula to compute the index. Other potential old age surveys were not included due to weak comparability. For example, the Japanese Study of Aging and Retirement (JSTAR) does not include the test of verbal fluency, and the New Zealand Longitudinal Study of Aging (NZLSA) categorizes the number of words of the verbal fluency test in 7 intervals, which does not allow to compute a Gini comparable to the other countries.

## 3 Measurement of inequality

### 3.1 Inequality of educational attainment

The inequality of education is measured with the Gini index (Atkinson 1970), which is bounded between 0 and 1. A larger index indicates more inequality. We compute the Gini of years of education in the year when each particular country-age group point (observed in the old age cognition survey) was aged 25-29. For example, the age group 65-69 of a country with survey year in 2015 has a Gini of cognition computed for that group in 2015, while its corresponding Gini of education is measured with the educational distribution of the 25-29 age group in 1975. For this procedure we need historical data about the distribution of education within age groups for each country. This information is drawn from the Barro-Lee dataset of educational attainment 1950-2010 (Barro and Lee 2013). This dataset reports the distribution of educational attainment in 5-year age groups between 1950 and 2010 and has been extensively used in human capital dynamics, economic growth and educational inequality studies (Castello and Doménech 2002, Harttgen and Klasen 2012).

The distribution of educational attainment in the Barro-Lee data (BL data) includes seven categories: no education, incomplete primary, complete primary, incomplete secondary, complete secondary, incomplete tertiary and complete tertiary. In addition, the database reports the average years of education spent in primary, secondary and tertiary levels. The studies by Castello and Doménech (2002), Thomas et al. (2001) and Checchi (2004), with small differences, compute educational Gini indexes with this data by using the following formula:

$$Gini = \left(\frac{1}{\bar{y}}\right) \sum_{i=2}^{n} \sum_{j=i}^{i-1} p_i p_j \, |y_i - y_j|, \qquad (1)$$

$y_i, y_j$ : Cumulative average of education years of each educational level,

$n$ : Number of educational levels,

$p_i, p_j$ : Shares of population in certain educational level,

$\bar{y}$ : Average educational attainment.

Thomas et al. (2001) use 7 categories of educational level (*n=7*), which are no education, complete and incomplete primary, complete and incomplete secondary and complete and incomplete tertiary education, while Castello and Doménech (2002) use 4 categories. Given that the BL dataset does not report average years of schooling for incomplete levels of education, Thomas et al. (2001) use another source for duration of education levels and assume that incomplete education levels were half of the years of the subsequent level. For this paper, we utilize the newest version of the BL data (version 2.0 with updates as of Feb-2016) and we have access - from the authors of the BL data - to the theoretical duration of each educational level per country and year.[1]

The study by Benaabdelaali et al. (2012) use the same formula for the Gini index and the seven educational levels in the BL data, but they do not rely on external data for educational level durations. Instead, they assume that males and females show the same average years of schooling in each level. Castello and Doménech (2002) use BL data and compute Gini indices of educational attainment with a formula employing four educational levels, i.e. no education, primary, secondary and tertiary education. They do not need to rely on any other data source to

[1] An alternative dataset of historical educational attainment is the one constructed by Cohen and Soto (2007) which reports educational attainments for 95 countries, every ten years from 1960 to 2010. The database displays the average years of education of the population aged 15+, 25+, 25-64 and by 5-year age groups. Likewise, the Wittgenstein Centre Data Explorer includes projections of educational attainment for 1970-2100 in 195 countries by sex and 5-year age groups. These data cannot be used because information for individuals aged 25-29 in 1960 is missing therein.

compute Gini indices. In general, all these papers show that educational inequality is negatively related to average years of education and educational inequality is declining over time.

### 3.2 Inequality in levels of education

The approaches previously mentioned provide estimates of inequality of educational attainment under the assumption that attainment is cardinally measurable. Attainment is nevertheless bounded from above. Increasing school attainment in a country, for instance by promoting larger participation to secondary and tertiary education, would raise average attainment in the population as well as decrease attainment gaps (since attainment of those in tertiary education cannot systematically grow with average schooling attainment expansion). This change in the school attainment distribution would mechanically reduce inequalities.

One alternative is to focus on *inequality in the distribution of levels of education,* i.e. in number of years effectively completed (the levels) within the education system, irrespective of educational attainment. Barro and Lee (2013) report the theoretical duration in years of each educational level. We let $l$ indicate a given level of education. It is measured by natural numbers with $l = 0$ for lack of formal education and $l_p, l_s$ and $l_t$ be the theoretical duration of primary, secondary and tertiary education (reported in years, corresponding to the highest level achievable by a given cohort in a given country), respectively. The data also include information on the probability of not attending any form of education ($p_1$), the probability of attending some primary education or completing it ($p_2$ and $p_3$), the probability of attending some secondary education or completing it ($p_4$ and $p_5$) and the probability of attending some tertiary education or completing it ($p_6$ and $p_7$). The level of education can be treated as a count variable which takes values on $l = 1, \dots, l_t$, each indicating the level accomplished. For instance, $l = 4$ is for attending grades 1 to 4 in primary education without completing it (in most of the countries, primary education ends at fifth grade), while $l = l_p$ if only primary education is completed.

The probability of accessing education level $l$ or larger can be represented by the cumulative distribution of achieved levels, $F(l)$. This distribution is constructed under the assumption that the population is uniform distributed within each education levels. For primary education, for instance, the cumulative distribution function writes $F(0) = p_1$, $F\left(l_p\right) = p_1 + p_2 + p_3$ and $F(l) = p_1 + \frac{l}{l_p - 1} p_2$ for any $l = 1, \dots, l_p$. The cumulative distribution function is hence a step function with uniform increments across levels in either primary, secondary or tertiary education. The distribution $F(l)$ is qualitatively equivalent to the distribution of a counting indicator. In our case, the indicator counts the education levels $l$ achieved by a target population. Understanding inequality in levels of education boils down to evaluating the distribution of cumulative probabilities $(0), \dots, F(l), \dots, F(l_t)$ associated to attained years of education.

An intuitive measure of inequality in education levels is the Gini index of attained years of education, $Gini(F)$, which is the Gini mean difference of attained years of education divided by the average number of completed years in education:

$$Gini(F) = \frac{\sum_{l=0}^{l_t - 1} F(l)\big(1 - F(l)\big)}{\sum_{l=0}^{l_t - 1} 1 - F(l)} \qquad (2)$$

The $Gini(F)$ index has interesting properties. It is normalized so that $Gini(F) = 0$ if and only if years of attained education coincide across the population. In sharp contrast with most of the indices inspired by income inequality literature (such as the Gini index of years of education by Thomas et al. 2001) the *average* level of education cannot be targeted as a relevant egalitarian objective (as it would be the average income). Differently from the analysis of income inequality, basic inequality-reducing rich-to-poor income transfers (that are mean preserving) are not sufficient to reach the egalitarian distribution of education attainments. The $Gini(F)$ index internalizes this feature of the data, and offers a consistent and normatively sound inequality indicator for assessing inequality using counting scores for educational achievement.

Furthermore, $Gini(F) \approx 1$ only when $F(l) \approx 1$ and constant for all $l \leq l_t - 1$, implying that a large fraction of the population has not even attained first year of primary education and only a small fraction of the population has completed tertiary education. Instead, $Gini(F) \in (0,1)$ for the case in which a small proportion of the population has not achieved any level of education while a large majority of the population has completed tertiary education. The three cases are different, and the $Gini(F)$ index correctly distinguish among them.[2] The index is also sensitive to the distribution of increments in completed years of schooling. In fact, increments in

[2] Consider hypothetical cases in BL data (reporting $n = 7$ education levels). In the first case, $Gini(F) = 0$ because $F(l)\big(1 - F(l)\big) = 0$ at any $l$. The second case occurs, for instance, if $p_1 = 0.99$ and $p_7 = 0.01$ and $p_l = 0$ otherwise. In this case, $F(l) = 0.99$ and $F(l)\big(1 - F(l)\big) = 0.0099$ for all $l \leq 6$. It follows that $Gini(F) = \frac{0.0693}{0.07} = 0.99$. Instead, the third case occurs, for instance, if $p_1 = 0.01$ and $p_7 = 0.99$ and $p_l = 0$ otherwise. In this case, $F(l) = 0.01$ and $F(l)\big(1 - F(l)\big) = 0.0099$ for all $l \leq 6$. It follows that $Gini(F) = \frac{0.0693}{6.93} = 0.01$.

education below the median (implying an increase of $1 - F(l)$ and a symmetric decrease of $F(l)$ thus reducing the product $F(l)\big(1 - F(l)\big)$ when $F(l) < 0.5$) are generally accompanied by a reduction in overall inequality compared to increments in education taking place above the median.

We use $Gini(F)$ as our preferred measure of educational inequality. Overall, this measure is strongly associated with $Gini$ index in Thomas et al. (2001) (correlation is 99%). This is not surprising: when $F$ is *continuous* (as it is the case for population models of income distributions) indices like the ones in equations (1) and (2) are qualitatively equivalent (Yitzhaki 1998). Yet, the equivalence breaks down when the population distribution of the data is not continuous, as it is the case for the underlying variable counting levels of education achieved. The $Gini(F)$ index has to be preferred in this case. As a robustness check, we also consider the Thomas et al. (2001) $Gini$ index of inequality in educational attainment as the main treatment variable. In Table A1 in the appendix we report averages of the distribution of $Gini(F)$ indices by country and by age group based on the BL dataset.

### 3.3 Inequality of cognition in old age

We exploit the specific counting nature of the cognitive functioning indicators (memory scores) to construct appropriate inequality measures of cognition in old age. The memory scores reported in the surveys are counts of the number of correct word recalls from a list of 10 words. The verbal fluency score counts the number of animal names over a given amount of time. We measure inequality in cognition by the degree of inequality in the distribution of scores of memory tests across the population.

Let $X_i$ be the count of correctly recalled items by individual $i$ ($i = 1, \dots, N$) for a given memory test. The count score takes on values $X_i = k$, with $k = 0,1, \dots, K$, the maximal number of correctly recalled items. For instance, $K = 10$ in the immediate recall memory indicator. Based on these data, we can calculate the country-age group specific probability that exactly $k$ out of $K$ items are correctly recalled, denoted by $p_k = \sum_{i:X_i=k} w_i$, where $w_i$ is individual $i$ weight. The empirical cumulative distribution (cdf) of counts is $F(k) = \sum_{j=0}^{k} p_j$. The average cognitive functioning score in the sample, $\mu$, can be directly expressed as a function of the cdf as follows: $\mu = \sum_{k=0}^{K} p_k k = K - \sum_{k=0}^{K-1} F(k) = \sum_{k=0}^{K-1} 1 - F(k)$.[3]

The concept of unequal distribution of cognitive functioning is not well-defined as it is the case for income inequality: first, the distribution of cognitive functioning scores is bounded above and below; second, the notion of inequality decreasing (rich to poor) transfers does not straightforwardly apply to the distribution of cognitive functioning scores. Rather, one can refer to improvements and deteriorations in the distribution of cognitive functioning across the population. We hence define an index of inequality of cognition, $I(F)$, implicitly from an underlying welfare function $W(F)$, which measures societal well-being that stems from the overall distribution of cognitive functioning in the society. The function $W$ only depends on the cumulative distribution function of cognitive functioning. Welfare, inequality and average memory scores are tied one to the other according to the usual decomposition $W(F) = \mu\big(1 - I(F)\big)$.[4]

Building on Aaberge et al. (2015), we propose a social welfare function that is rank dependent: social welfare represents the preferences of a social planner that is concerned with the extent of well-being stemming from cognitive functioning score (represented by the count measures) and the proportion of population enjoying that well-being ($F$). We denote social welfare by $W(F) = \sum_{k=0}^{K} \Gamma(1 - F(k))$, where $\Gamma$ is a *distortion* function which assigns different weights to different ranks of the cognitive functioning score distribution function. The function $\Gamma$ should satisfy some desirable properties. Consider first the case of an improvement in the distribution of cognitive functioning scores in the society, implying that $1 - F$ increases. Improvements in memory are definitely good for societal well-being, which amounts to require that $\Gamma$ *is increasing in* $1 - F$. For instance, a linear well-being function $\Gamma$ (i.e., $\Gamma(t) = t$) would imply that $W(F) = \mu$, which is increasing in memory improvements.

A second condition that we require is that societal well-being increases more if the improvement in old-age cognition occurs at the bottom of the cognitive functioning score distribution (where $1 - F$ is relatively high) rather than at the top (where $1 - F$ is relatively low). This amounts to additionally require that $\Gamma$ *is convex in* $1 - F$.

[3] To see that $\mu = \sum_{k=0}^{K} 1 - F(k)$, it is sufficient to note that $F$ is a step function with increments $p_k$. The area below the survival function $1 - F$ is hence an appropriate estimator of the counts expectation.

[4] In the context of income inequality the value of *W(F)* must increase with the mean income and decrease with the level of inequality, encapsulating the trade-off between efficiency and equity (Lambert 2001).

There are many examples of functions $\Gamma$ that are increasing and convex. In this study, we consider the parametric family $\Gamma(t) = t^{\alpha}$, with $\alpha \geq 1$. Larger values of $\alpha$ are associated to welfare evaluations that are more sensitive to the incidence of low old-age cognitive abilities in the population. The associated inequality index is:

$$I(F) = 1 - \frac{\sum_{k=0}^{K-1}\left(1-F(k)\right)^{\alpha}}{\mu}. \qquad (3)$$

Our preferred measure of inequality is a Gini-type indicator of inequality, which is obtained by setting $\alpha = 2$. We hence refer to Gini of cognition in the remainder of the paper as the reference measure of inequality for cognitive functioning (based on the memory and verbal fluency test). The interest and innovativeness of the index $I(F)$ lies on the idea of assessing inequality in cognition through the lenses of the counting approach (see Aaberge et al. 2015). This approach explicitly recognizes that the average memory score $\mu$, (interesting for comparing the memory affluence across populations) does not generally coincide with the egalitarian outcome. Differently from standard (income) inequality indices (e.g. Gini, Atkinson and entropy measures), mean-preserving progressive transfers of outcomes (such as rich-to-poor transfers) converging to $\mu$ may not suffice to reduce inequality in cognition to its minimum $I(F) = 0$, while they suffice to eliminate income inequality. In fact, the egalitarian distribution is only achieved when all individuals display the same cognitive score $k$ (that can be a very low cognitive level) rather than $\mu$, which might not be an *admissible* score. This makes the welfare measure $W(F)$, and the implied inequality indicators in (3), normatively relevant in this context.

In the robustness section, we additionally consider specifications of the index in (3) where $\alpha = 3, 5, 10$. Estimates of inequality in cognitive functioning scores across countries and reference cohorts are reported in table A1 in the appendix.

## 4 Methods

The effects of past educational inequalities on old age cognitive inequality are assessed with Linear (OLS) regressions. The age-group (i.e. the synthetic individual) is the unit of analysis, and the regressions employ the following model specification:

$$I_{c,i} = \alpha_c + \beta_1 Gini_{c,i,t} + \beta_2 \left(S_{c,i,t,female} - S_{c,i,t,male}\right) + \varepsilon_{c,i}, \qquad (4)$$

where $t$ indicates the calendar year when the synthetic individual $i$ was aged 25-29. The dependent variable $I_{c,i}$ is our proposed inequality index of cognitive functioning in (3), measured within the synthetic cohort *c,i* around the survey year[5]. The term $Gini_{c,i,t}$ is our proposed *Gini inequality index of past education* for the age-group *c,i* measured in the year *t* the group was aged 25-29. Baseline results are obtained by measuring the Gini of past education by the inequality in educational level distribution measured by the $Gini(F)$. We produce results with alternative indicators of inequality of past education as robustness checks. The terms $S_{c,i,t,female}$ and $S_{c,i,t,male}$ indicate the survival probability of the female (or male) age-group *c,i* measured in the year *t* the group was aged 25-29. The baseline model always includes country-specific fixed effects.

Regarding the survival rate of a given age-group observed in the survey is the expected survival probability of this group when they were aged 25-29. So, the survival rate is the probability of surviving from age 25-29 to the current age of the age-group and it is specific to each age-group in order to take cohort differences into account. We chose the reference age group 25-29 because the decisions on educational investment have already been taken for most of the individuals at that age.

Regarding the computation of survival rates, we utilize the series of life table survivors of the United Nations World Population Prospects 1950-2100 (2015). In more detailed terms, the survival rate (by sex and total) is measured back in the year the group was aged 25-29. This measures the probability that the individuals aged 25-29 in the past will survive until the current age of the age-group. The following formula is employed:

$$S_{c,i,t} = \left(l_{25+x,t} + l_{30+x,t}\right) / \left(l_{25,t} + l_{30,t}\right) \qquad (5)$$

The subscript *t* indicates the year the age-group *i* was aged 25-29, and the subscript *c* stands for country. The term $l_{25,t}$ is extracted from a period life table and indicates the number of surviving individuals at age 25 in year *t*, and the term $l_{25+x,t}$ is the number of individuals who

[5] The survey year considered for each country is indicated in Table 1.

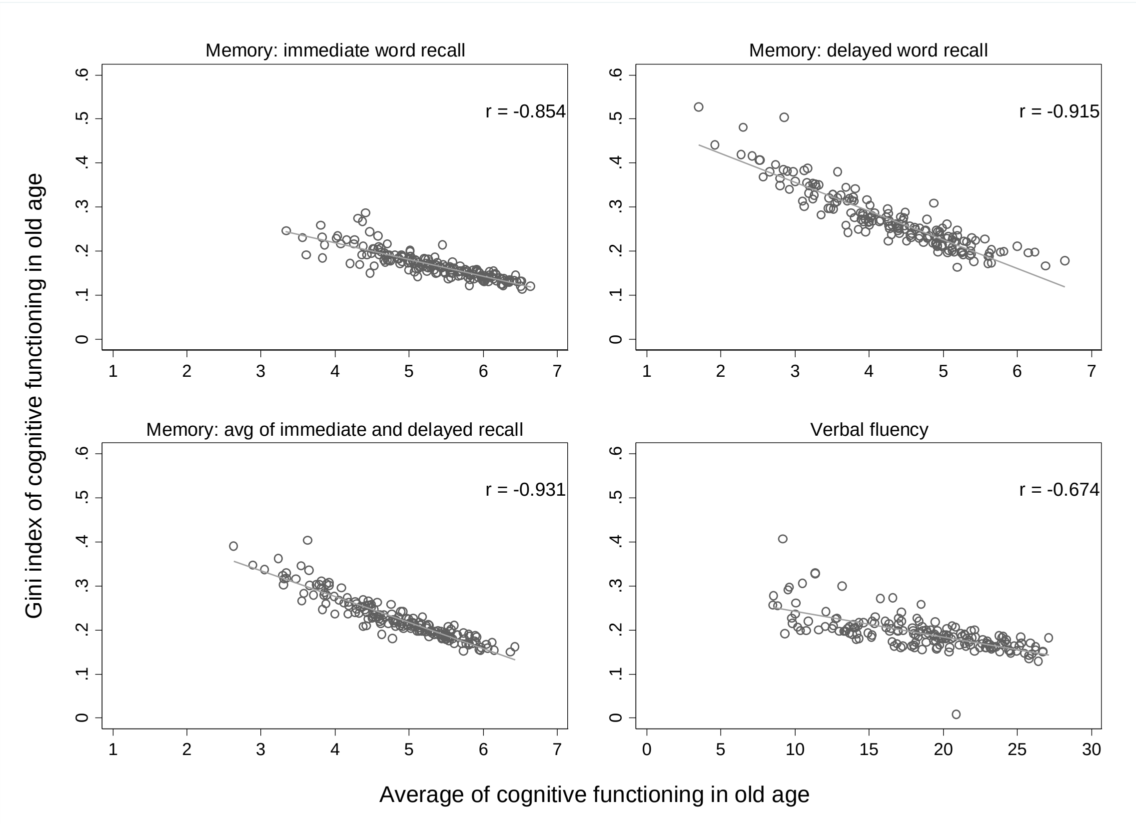
will survive up to the target age $25 + x$. Both terms $l_{25,t}$ and $l_{30,t}$ are employed in order to take into account the number of survivors in the 5-year age group.

# 5 Results

## 5.1 Main results

Raw correlations recover a negative association between the average score of cognition and inequality of cognition (Figure 1). So, age-group observations with a higher level of cognitive functioning are more likely to have a more equitable distribution of cognitive abilities in old age. This resembles the negative relationship found between educational inequality and average years of education in other studies (such as Castelló and Doménech 2002, and Thomas et al. 2001). The descriptive statistics can be consulted in the appendix.

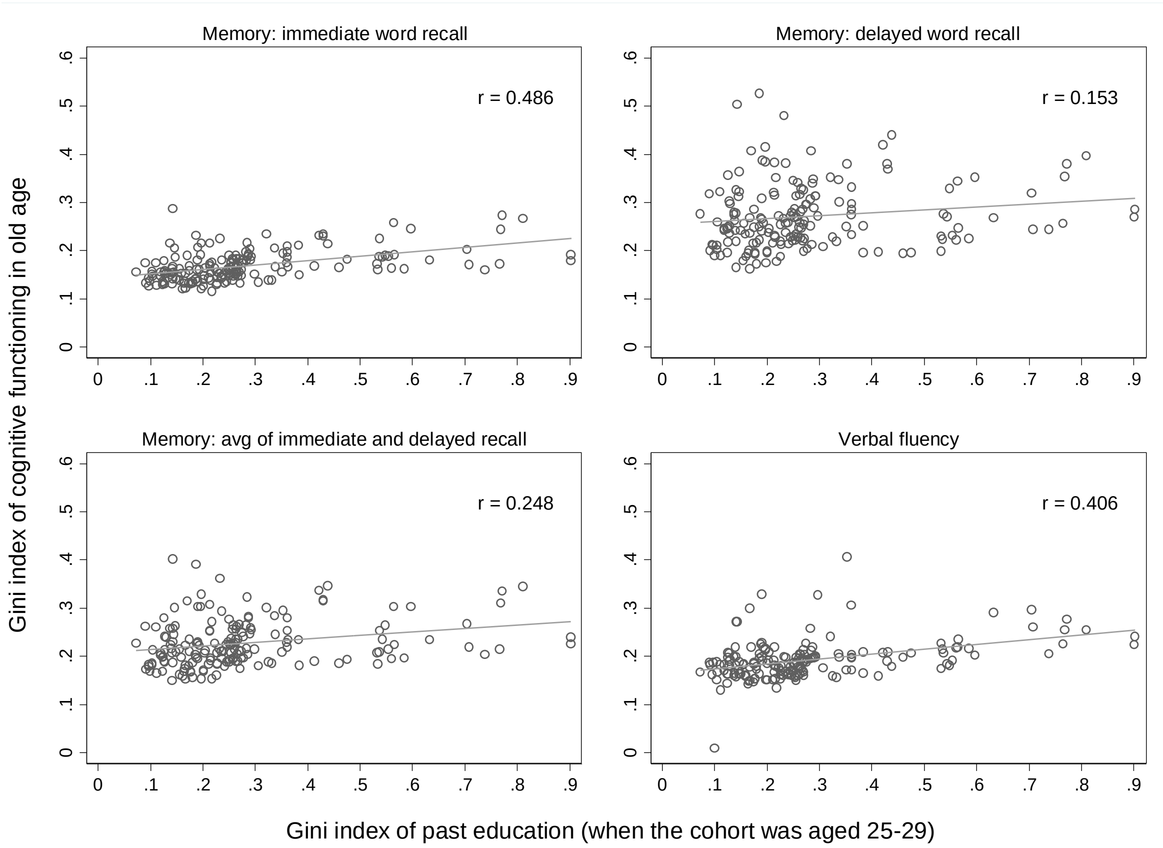
Figure 1. Gini index and mean of cognitive functioning in old age




Note: each observation represents a particular age group in a country. There are 6 age groups and 29 countries, and hence the sample consists of 174 observations. The information corresponds mostly to years 2011-2015.

Our first key findings are shown in Figure 2. We find statistically significant and positive associations between educational inequalities experienced in the past and inequalities in old age cognition measured in the present. The strength of this association is more important in the case of immediate memory and verbal fluency.

Figure 2. Gini indices of cognitive functioning in old age and past education




Note: each observation represents a particular age group in a country. There are 6 age groups and 29 countries, and hence the sample consists of 174 observations. The information corresponds mostly to years 2011-2015.

The positive relationship between inequalities in education and cognition is confirmed in linear regressions that include age group survival rates and dummy variables for countries. By including country fixed effects, we account for unobserved differences across countries at diverse development stages considered in our sample. The estimates reported in Table 2 are identified by variability across cohorts within the same country. We estimate that a one-point increase in educational Gini is associated with an increase of 0.28, 0.61, 0.45 and 0.15 points in the Gini of immediate memory, delayed memory, average memory and verbal fluency, respectively. These estimates are reduced once we introduce differential survival rates (male minus female survival rates) in the regression models. Here, a larger relative surviving probability of women – who are in general less educated than men – is associated with a higher level of cognitive inequality. The estimates for this variable imply that if the relative deficit of survival of males were cancelled out (i.e. males and females would have the same surviving rate), the effect of a one percent change in educational inequalities on inequality in cognitive functioning at old age scales down to 0.24, 0.45, 0.34 and 0.10 for immediate memory, delayed memory, average memory and verbal fluency, respectively.

Table 2. Linear estimates of old age cognitive inequality

| Variables | Gini of immediate memory | | Gini of delayed memory | | Gini of average memory | | Gini of verbal fluency | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Gini of past education | 0.282*** | 0.235*** | 0.607*** | 0.449*** | 0.448*** | 0.342*** | 0.146*** | 0.104** |
| | (0.054) | (0.061) | (0.113) | (0.102) | (0.085) | (0.081) | (0.040) | (0.042) |
| Survival rate (female - | | 0.116** | | 0.395*** | | 0.267*** | | 0.103 |
| male) | | (0.050) | | (0.080) | | (0.063) | | (0.078) |
| Constant | 0.089*** | 0.090*** | 0.102*** | 0.103*** | 0.102*** | 0.102*** | 0.151*** | 0.152*** |
| | (0.015) | (0.013) | (0.032) | (0.022) | (0.024) | (0.017) | (0.011) | (0.010) |
| Observations | 174 | 174 | 174 | 174 | 174 | 174 | 174 | 174 |
| R-squared | 0.678 | 0.697 | 0.650 | 0.702 | 0.673 | 0.717 | 0.749 | 0.758 |

Note: there are 6 age-groups and 29 countries, and therefore the sample consists of 174 synthetic units that are formed by age group and country. The information corresponds to the period 2008-2015, but mostly to year 2015 (114 observations). All regressions include dummy variables for countries. Robust standard errors are clustered by country and are reported in parentheses. Significance levels are ** p<0.05, *** p<0.01.

## 5.2 Robustness checks

The first robustness check concerns our response variable, inequality in cognitive functioning at old age. We report in Table 3, estimates of the effect of a change in the Gini of past education on inequality of memory scores, using different degrees of sensitivity for low memory scores in the population (parameter $\alpha$ in equation (3)). The results confirm findings in Table 2: the effect of an increase of one percentage point in the Gini of past education is associated with a positive and significant increase in inequality in cognitive functioning. Effects are increasing in sensitivity to low cognitive functioning scores, but the size of the effect is never larger than one. The largest impact throughout various specifications is on the Gini of delayed memory, consistently with Table 2.

Table 3. Regression results with different sensitivity to lower parts of the distribution of cognition

| Variables | Gini of immediate memory | Gini of delayed memory | Gini of average memory | Gini of verbal fluency |
|---|---|---|---|---|
| $\boldsymbol{\alpha = 2}$ (baseline) | | | | |
| Gini of past education | 0.235*** | 0.449*** | 0.342*** | 0.104** |
| | (0.061) | (0.102) | (0.081) | (0.042) |
| R-squared | 0.697 | 0.702 | 0.717 | 0.758 |
| $\boldsymbol{\alpha = 3}$ | | | | |
| Gini of past education | 0.346*** | 0.634*** | 0.500*** | 0.136** |
| | (0.089) | (0.140) | (0.116) | (0.054) |
| R-squared | 0.696 | 0.718 | 0.727 | 0.769 |
| $\boldsymbol{\alpha = 5}$ | | | | |
| Gini of past education | 0.466*** | 0.767*** | 0.649*** | 0.162** |
| | (0.120) | (0.161) | (0.145) | (0.064) |
| R-squared | 0.687 | 0.741 | 0.739 | 0.779 |
| $\boldsymbol{\alpha = 10}$ | | | | |
| Gini of past education | 0.601*** | 0.740*** | 0.731*** | 0.183** |
| | (0.159) | (0.145) | (0.153) | (0.076) |
| R-squared | 0.670 | 0.769 | 0.759 | 0.786 |

Note: The unit of the analysis of the Ordinal Least Square (OLS) regressions is the synthetic unit formed by age group and country. There are 6 age groups and 29 countries, and therefore the sample consists of 174 observations. Inequality in cognitive functioning computed according to the index $I(F)$ of equation (3). The parameter $\alpha$ refers to the level of the sensitivity of the inequality index to individuals located in the bottom of the distribution. Larger values of $\alpha$ are associated to welfare evaluations that are more sensitive to the incidence of low old-age cognitive abilities in the population. Inequality in past education is measured by the index $Gini(F)$ of equation (2). Every regression controls for country fixed effects, the gender-based difference in survival rates and includes a constant. Robust standard errors are clustered by country and are in parentheses. Significance levels are * p<0.10, ** p<0.05, *** p<0.01.

The second robustness check we consider involves the treatment variable, the inequality in past education. We replicate estimates of the baseline regression, while using the $Gini$ index of educational attainment of equation (1). Estimates (see Table 4, panel A) coincide with those in the baseline regressions, based on our preferred measure of educational inequality.

Table 4. Additional robustness checks

| Variables | Gini of immediate memory | Gini of delayed memory | Gini of average memory | Gini of verbal fluency |
|---|---|---|---|---|
| *A. Using Gini index* $\mathbf{Gini}$ *as in Thomas et al. (2001)* | | | | |
| Gini of past education ($Gini$) | 0.226*** | 0.434*** | 0.329*** | 0.102** |
| | (0.062) | (0.106) | (0.083) | (0.038) |
| R-squared | 0.690 | 0.698 | 0.711 | 0.758 |
| *B. Using sample of countries with two periods* | | | | |
| Gini of past education | 0.187** | 0.210** | 0.200** | |
| | (0.070) | (0.072) | (0.075) | |
| First period (about 2004) | 0.023*** | 0.044*** | 0.038*** | |
| | (0.006) | (0.011) | (0.009) | |
| R-squared | 0.729 | 0.724 | 0.756 | |
| *C. Effects of retaking the cognitive test* | | | | |
| Gini of past education | 0.235*** | 0.443*** | 0.338*** | 0.102** |
| | (0.062) | (0.102) | (0.081) | (0.043) |
| Share of persons retaking test | -0.007 | -0.052** | -0.032* | -0.022 |
| | (0.012) | (0.025) | (0.018) | (0.024) |
| R-squared | 0.697 | 0.705 | 0.719 | 0.760 |

Note: The unit of the analysis of the Ordinal Least Square (OLS) regressions is the synthetic unit formed by age group and country. There are 6 age groups and 29 countries, and therefore the sample consists of 174 observations. All regressions include dummy variables for countries, a constant and control for gender-related differences in survival rates. In panel B, the variable 'first period' takes value 1 for the groups observed about 2004 and zero for the groups observed about 2015. There is a total of 13 countries with observations in two distant periods: United States (2002, 2014), United Kingdom (2002, 2014), Austria (2004, 2015), Belgium (2005, 2015), Denmark (2004, 2015), France (2004, 2015), Spain (2004, 2015), Germany (2004, 2015), Sweden (2004, 2015), Netherlands (2004, 2013), Italy (2004, 2015), Switzerland (2004, 2015) and Israel (2006, 2015). Verbal fluency is not examined as this is not present in the US. Robust standard errors are clustered by country and are in parentheses. Significance levels are * p<0.10, ** p<0.05, *** p<0.01.

The third robustness check challenges the identification condition. In the baseline model we include country fixed effects, implying that identification arises from variability in inequality of past educational attainment across cohorts within the same country. This source of variability would ideally arise from effects of shocks (crises, school reforms) that are exogenous at the individual level but common to all people of the same cohort, and that vary across cohorts. In the baseline setting, however, it is not possible to distinguish cohorts from age groups, increasing the potential risk that inequality in cognitive functioning at old age and educational inequality systematically covariate across age groups. Controlling for age fixed effects would substantially reduce identification power to variations within the same country and cohort. We propose an alternative strategy that consists in pooling the country-cohort/age data with information on same age-range individuals from survey waves distanced by about 10 years from the baseline data. Thus, we expand country-cohort data with information on inequality in past education and in old age cognitive functioning from synthetic individuals that are of the same age-range as in the baseline panel, but born 10 years earlier. By doing so, we isolate cross-cohort variability within the same age group. We can exploit this 'longitudinal' feature of the data (where educational and cognitive inequalities are measured for same age-range synthetic individuals from two distinct cohorts) only for 13 countries. For each of these countries, information on cognitive functioning scores is reported for two sufficiently distanced periods: the first period is about 2002/2004 and the second period is about 2013/2015 (the baseline data).[6]

We test robustness of the baseline model by augmenting the model with fixed effects related to the age-range of the respondent. To increase estimation power, we rely on an indicator for survey year that is equal to one if a synthetic country-cohort observation is from about 2004 and zero if it is from about year 2015. Identification purely relies on average differences in cohort composition across same-age individuals within the same country. The magnitude and significance of the coefficients of inequality in education (Table 4, panel B) are comparable to baseline estimates. A one percent change in Gini of past education is associated with 0.187 percentage increase in Gini of immediate memory, with 0.21 percentage increase in Gini of delayed memory and with 0.2 percentage increase in Gini of average memory scores (verbal fluency is not available for the US in both waves).

The last robustness check is for potential bias arising for learning effects in cognitive functioning tests that are attributable to retake of the cognitive tests for those individuals participating to longitudinal surveys. For a substantial number of countries, retake of the test is not an issue.[7] We include in our baseline regressions a variable indicating the percentage of people (within each age-group country) who have taken the test during the wave of analysis and in the previous wave (see Table 4, panel C). We observe a statistically significant coefficient for this variable in the case of the regressions for delayed and average memory. Importantly, the results regarding the association between inequality of cognition and education do not invalidate baseline estimates.

[6] There is a total of 13 countries with observations in two distant periods: United States (2002, 2014), United Kingdom (2002, 2014), Austria (2004, 2015), Belgium (2005, 2015), Denmark (2004, 2015), France (2004, 2015), Spain (2004, 2015), Germany (2004, 2015), Sweden (2004, 2015), Netherlands (2004, 2013), Italy (2004, 2015), Switzerland (2004, 2015) and Israel (2006, 2015).

[7] There is no retake of the cognitive test in 11 out 29 countries (China, Croatia, Ghana, Greece, Hungary, India, Ireland, Poland, Portugal, Russia, South Africa).

## 5.3 Inequality of opportunity for educational attainment and its implications

Attainment of primary and secondary education contributes to the formation of one's human capital and lifelong well-being opportunities. Upper secondary and tertiary education attainment also bear important signaling components: the interplay of preferences, talents and effort determine investment in upper education, with larger attainment working as a signaling device of accumulation of specialized human capital and of own abilities. Inequality in educational attainment might hence be desirable for efficient allocation of talents, provided accessibility to primary, secondary and tertiary education is granted to everybody irrespectively of social origin and disposable resources, and skills acquisition only depends on one's choices and innate talents.

Recent literature and policy debate have brought about evidence that opportunities for access to, and for benefitting from, (good quality) education are unequally distributed across strata of the society. The quality of parental background is one of the major drivers of inequality of opportunities for human capital acquisition (see Cunha and Heckman, 2007, Roemer and Trannoy, 2015 and Ramos and Van de gaer, 2016). Parental investments during childhood (both in terms of disposable income and of quality time spent with children) generate unfair differences in abilities early in life that later capitalize into educational attainment inequalities (Cunha et al., 2006) and cognitive functioning inequalities in old age (Case and Paxson, 2008).

We isolate and measure the extent of *unequal opportunities for educational* attainment in a way consistent with the literature, and we quantify the contribution of this aspect of educational inequalities experienced early in life on the unequal distribution of old-age cognition scores.

Inequality of opportunity arises when individual *circumstances* (such as parental education or gender), that are normatively irrelevant in determining individual educational choices, produce non-negligible effects on inequalities of educational attainment. Let us define a type as a group of individuals sharing similar circumstances. For each type $t = 1, \dots, T$ we can construct age group and country specific measures of average educational attainment, denoted $\mu_t$.

In line with the literature (Ramos and Van de gaer, 2016), we propose to measure *inequality of opportunity* (IOP) by the contribution of between-types inequality in average educational attainment over population inequality in educational attainment, that is $IOP(F) = I(\mu_1, \dots, \mu_T)/I(F)$, where $F$ is the population distribution of educational attainment. Ferreira and Guignoux (2011) and Checchi and Peragine (2010) have developed on this approach and have demonstrated that the unique index of inequality that satisfies desirable properties and is consistent with normative fundamentals of inequality of opportunity measurement is the mean log deviation, that is $I(F) = \frac{1}{n}\sum_{i=1}^{N} ln\frac{\mu}{y_i}$ with $y_i$ indicating the exact educational attainment of individual $i$.

We retrieve information on educational attainment and parental education background for most of the countries considered in this study.[8] Parental education is the highest education level achieved by each of the parents of the interviewed person (no education, primary/secondary/tertiary education). We generate types by either looking at each possible match of both parents education (*Types A*), or by focusing on the highest educational achievement among parents (*Types B*). Additionally, we consider refinements to the type indicator by further partitioning the population according to the gender of the survey respondent (thus giving *Types AG* and *Types BG* respectively, where 'G' states for gender). This allows to explicitly account for gender-biased behavior towards participation to education in older cohorts, and for connections with parental background quality.

We follow Ferreira and Gignoux (2011) to produce parametric and non-parametric estimates of relative inequality of opportunity in educational attainment based on the mean log deviation index of inequality. We are able to estimate cohort-country specific level of inequality of opportunity that we later merge with information on inequality in old-age cognition. Cohort survival probabilities vary substantially across educational levels, implying that educational composition estimated from recent surveys (where responded belong to the 50+ age group) may differ from educational composition estimated at age 25. The computation of IOP estimates accounts for differences arising from survival probability that is specific to the country, sex, age and education level of the individual.[9]

We focus first on the baseline specification of the testing model, where inequality in past education is replaced by indices of inequality of opportunity. We consider four separate sets of

[8] Mexico, Ireland, the UK and the US are excluded for lack of comparability in the definition of parental education, as well as Hungary, India for which information on educational attainment is missing. Israel is also excluded from the analysis because of lack of education-survival data that is needed to compute the IOP indicator.

[9] We correct for differences in survival probabilities by multiplying the individual survey design weight by the probability of surviving from age 25 to the current observed age of the person. These probabilities are specific by country, sex, age, year, educational level and birth cohort group and are estimated with information extracted from the database of human capital of the Wittgenstein Centre for Demography and Global Human Capital (Lutz et al. 2014). The procedure consists in 'extract' the number of individuals of a specific cohort-sex-country-education across years and utilise Gompertz functions to find the parameters to construct life tables. Then, the computation of individual survival probabilities is performed with these life tables.

regressions for each inequality in old age cognitive functioning, each corresponding to a different definition of types in the population. Results of these regressions are in Table A2 in the appendix. We find that IOP of past education is only weakly associated with old age cognition for types A and B. In most of the cases, coefficients are not significant. Association is stronger when the IOP index accounts also for the implications of gender differences, as for types AG and BG. In the latter case, leading to most significant results, we find that a one percent increase in IOP goes along with a 0.07 percent increase in the Gini of immediate memory, with 0.22 percent increase in the Gini of delayed memory, with 0.15 percent increase in Gini of average memory and with 0.02 percent increase in the Gini of verbal fluency. Gender implications for unequal distribution of education attainment opportunities are shown to drive implications of IOP on inequalities in cognitive functioning at old age.

We test an extended version of the baseline model, where inequality in old age cognition is regressed on inequality in education ($Gini(F)$), on gender differences in survival probabilities, *and* additionally on IOP estimates. This model aims at verifying whether the IOP measures for Types A, B AG and BG are capturing the relevant channels through which inequality education affects inequality in cognition. Results reported in Table A3 in the appendix discard this hypothesis. There is no statistical support to conclude that IOP has explanatory power on inequality in cognitive functioning once educational inequality are taken into account (models (1)-(8)). Only IOP indices that account as well for implications of gender differences have statistically significant positive marginal effects on inequality in old age cognitive functioning. More interestingly, the effect of inequality of education survives after controlling for implications of inequality of educational opportunities. Effects in the preferred specification of the model (see models (9) to (16) in Table A3) are in the range of 0.2-0.35, consistent with baseline estimates in table 2. This evidence confirms that unequal opportunities for education stemming from differences in family background quality (captured by parental education) and gender have important effects on old age cognitions. Nonetheless, other channels may equally explain the tight partial effects of inequality in education on inequality in cognition, which persist even after controlling for IOP.[10]

[10] Education attainment is treated as a cardinal variable by the IOP measures we consider. As an additional robustness check, we obtain parametric IOP estimates based on the indices in Ferreira and Gignoux (2014), which are appropriate for variables that convey only ordinal information. Regression results (available upon request) are comparable in size and magnitude to those in Table A5 and Table 2.

## 6 Conclusions

Our results document significant long-term effects of past educational inequalities on inequalities in old age cognitive functioning observed in the present. Furthermore, we find that the relative higher life expectancy of women contributes to increased cognitive inequality. Given the lower educational attainment of older women, and the positive relationship between education and cognitive abilities, we can speculate that countries that experienced a large gender gap in education are showing higher old age cognitive inequalities. Thus, reducing the gender gap in education and improving the distribution of education among the young will reduce inequalities in cognitive functioning in the future.

Furthermore, we assess the role of inequality of opportunities experienced at young age and find evidence suggesting that unequal opportunities for education stemming from differences in parental education and gender have important effects on the distribution of old age cognition.

## References

Aaberge R., Peluso E. and Sigstad H. (2015) The dual approach for measuring multidimensional deprivation and poverty. Statistics Norway Discussion Paper 820/2015.

Atkinson, A. B. (1970) On the measurement of inequality. Journal of economic theory 2, 244-263.

Attewell, P., Newman, K. S. (2010) Growing gaps: Educational inequality around the world. Oxford University Press, Oxford, UK.

Banks, J., Mazzonna, F. (2012) The effect of education on old age cognitive abilities: evidence from a regression discontinuity design. The Economic Journal 122, 418-448.

Barro, R. J., Lee, J. W. (2013) A new data set of educational attainment in the world, 1950–2010. Journal of Development Economics 104, 184-198.

Benaabdelaali, W., Hanchane, S., Kamal, A. (2012) Educational Inequality in the World, 1950–2010: Estimates from a New Dataset, in: John A. Bishop, Rafael Salas (ed.) Inequality, Mobility and Segregation: Essays in Honor of Jacques Silber (Research on Economic Inequality, Volume 20) Emerald Group Publishing Limited, pp.337-366.

Blazer, D.G., Yaffe, K., Liverman, C. T. (2015) Cognitive aging: Progress in understanding and opportunities for action, Institute of Medicine of the National Academies. National Academies Press, Washington, DC.

Bonsang, E., Adam, S., Perelman, S. (2012), Does retirement affect cognitive functioning? Journal of health economics 31, 490-501.

Case, A., and Paxson, C. (2008) Height, health and cognitive function at older ages. *American Economic Review: Paper & Proceedings*, 98:463-467.

Castelló, A. Doménech, R. (2002) Human capital inequality and economic growth: some new evidence. The economic journal 112, C187-C200.

Checchi, D. (2004) Does educational achievement help to explain income inequality? chapter 4 in A. Cornia (ed), Inequality, Growth and Poverty in an Era of Liberalization and Globalization. Oxford University Press.

Checchi D. and Peragine V. (2010) Inequality of opportunity in Italy, The Journal of Economic Inequality, 8(4): 429-450.

Chen, W. Y. (2016) On the relationship between economic conditions around the time of birth and late life cognitive abilities: Evidence from Taiwan. Economics & Human Biology 22: 126-139.

Christelis, D., Jappelli, T., Padula, M. (2010) Cognitive abilities and portfolio choice. European Economic Review 54, 18-38.

Cohen, D., Soto, M. (2007) Growth and human capital: good data, good results. Journal of economic growth 12, 51-76.

Cunha, F. and Heckman, J. (2007) The Technology of Skill Formation. *American Economic Review*, 97: 31–47.

Cunha, F., Heckman, J.J., Lochner, L. and Masterov, D.V. (2006) Interpreting the evidence on life cycle skill formation. In E.A. Hanushek and F. Welch (Eds.) *Handbook of the Economics of Education* (pp. 697-812). Amsterdam: North-Holland.

de Grip, A., Dupuy, A., Jolles, J., van Boxtel (2015) Retirement and cognitive development in the Netherlands: Are the retired really inactive? *Economics and Human Biology*, 19: 157-169.

Ferreira F. and Gignoux J. (2011) The Measurement Of Inequality Of Opportunity: Theory And An Application To Latin America, Review of Income and Wealth, 57(4): 622-657.

Ferreira F. and Gignoux J. (2014) The Measurement of Educational Inequality: Achievement and Opportunity," World Bank Economic Review, 28(2):210-246.

Gastwirth, J. (1971). A General Definition of the Lorenz Curve. Econometrica, 39(6):1037-1039.

Glymour, M. M., Kawachi, I., Jencks, C. S., Berkman, L. S. (2008) Does childhood schooling affect old age memory or mental status? Using state schooling laws as natural experiments. Journal of Epidemiology and Community Health 62, 532-537 (2008).

Guven, C., Lee, W.S. (2015) Height, aging and cognitive abilities across Europe. Economics & Human Biology 16: 16-29.

Handels, R. L. H., Wolfs, C. A. G, Aalten, P., Verhey, F R. J., Severens, J. L. (2013) Determinants of care costs of patients with dementia or cognitive impairment. Alzheimer Disease & Associated Disorders 27, 30-36.

Harttgen, K., Klasen, S. (2012) A household-based human development index. World Development 40(5), 878-899.

Lambert, P.J. (2001) The Distribution and Redistribution of Income. 3rd Edition. Manchester: Manchester University Press.

Lee, S. Kawachi, I., Berkman, L. F., Grodstein, F. (2003) Education, other socioeconomic indicators, and cognitive function. American Journal of Epidemiology 157, 712-720.

Leist, A.K., Mackenbach, J.P. (2014) Social, behavioral, and contextual influences on cognitive function and decline over the life course. in: Health and cognition in old age. From biomedical and life course factors to policy and practice, A. K. Leist, J. Kulmala, F. Nyqvist, Eds. (Springer International Publishing, 2014), pp. 105-122.

Lusardi, A., Michaud, P.C., Mitchell, O. (2017) Optimal Financial Knowledge and Wealth Inequality. Journal of Political Economy 125 (2).

Lutz, W., Butz, B.P., KC, S. (2014) World Population and Human Capital in the 21st Century. Editors. Oxford, UK: Oxford University Press.

McFadden, D. (2008) Human capital accumulation and depreciation. Review of Agricultural Economics 30, 379-385.

Meng, X. D'Arcy, C. (2012) Education and dementia in the context of the cognitive reserve hypothesis: a systematic review with meta-analyses and qualitative analyses. PLoS One 7(6), e38268.

Prince, M. et al. (2015) World Alzheimer Report 2015. The global impact of dementia, an analysis of prevalence, incidence, cost and trends. Alzheimer's Disease International (ADI), London.

Rindermann, H. (2008) Relevance of education and intelligence at the national level for the economic welfare of people. Intelligence 36, 127-142.

Ramos X. and Van de gaer D. (2016) Approaches To Inequality Of Opportunity: Principles, Measures And Evidence, Journal of Economic Surveys 30(5), 855-883.

Roemer, J. (1998) Equality of opportunity. Harvard University Press, Cambridge.

Roemer J. and Trannoy A. (2015) Equality of Opportunity, Editor(s): Anthony B. Atkinson, François Bourguignon, In Handbook of Income Distribution (Volume 2, Ch. 4), Elsevier.

Rohwedder, S., Willis, R. (2010) Mental retirement. Journal of Economic Perspectives 24(1), 119-138.

Singh-Manoux, A. et al., Does cognitive reserve shape cognitive decline? Annals of Neurology 70, 296-304 (2011).

Skirbekk, V., Loichinger, E. Weber, D. (2012) Variation in cognitive functioning as a refined approach to comparing aging across countries. Proceedings of the National Academy of Sciences 109, 770-774.

Skirbekk, V., Stonawski, M., Bonsang, E., Staudinger, U.M. (2013) The Flynn effect and population aging. Intelligence 41, 169-177.

Smith, J.P., McArdle, J. J., Willis, R. (2010) Financial decision making and cognition in a family context. The Economic Journal 120, F363-F380.

Thomas, V., Wang , Y., Fan, X. (2001) Measuring Education Inequality: Gini Coefficients of Education. Policy Research Working Paper, N°. 2525, World Bank Institute.

United Nations (2015), World Population Prospects 1950-2100. 2015 Revision, United Nations.

Weber, D., Skirbekk, V., Freund, I., Herlitz, A. (2014) The changing face of cognitive gender differences in Europe. Proceedings of the National Academy of Sciences 111, 11673-11678.

Yitzhaki, S. (1998). More than a Dozen Alternative Ways of Spelling Gini. Economic Inequality 8, 13–30.

# Appendix

## Table A1. Descriptive statistics

| Country / Age group | Gini of inmediate memory | Gini of delayed memory | Gini of average memory | Gini of verbal fluency | Gini of past education | Survival rate | Differential survival rate per sex | IOP |
|---|---|---|---|---|---|---|---|---|
| Country: | | | | | | | | |
| Austria | 0.1390 | 0.2251 | 0.1888 | 0.1602 | 0.2390 | 0.7351 | 0.1293 | 0.1288 |
| Belgium | 0.1491 | 0.2534 | 0.2088 | 0.1701 | 0.2195 | 0.7376 | 0.1184 | 0.1514 |
| China | 0.2099 | 0.2537 | 0.2348 | 0.2032 | 0.4014 | 0.5145 | 0.0658 | 0.0843 |
| Croatia | 0.1730 | 0.3270 | 0.2622 | 0.2011 | 0.1555 | 0.6826 | 0.1600 | 0.2175 |
| Czech Republic | 0.1419 | 0.2494 | 0.2036 | 0.1737 | 0.1362 | 0.7133 | 0.1424 | 0.0996 |
| Denmark | 0.1446 | 0.2293 | 0.1923 | 0.1551 | 0.1918 | 0.7583 | 0.0852 | 0.1575 |
| Estonia | 0.1695 | 0.2874 | 0.2353 | 0.1870 | 0.1692 | 0.7143 | 0.1823 | 0.1214 |
| France | 0.1576 | 0.2609 | 0.2152 | 0.1686 | 0.3272 | 0.7440 | 0.1432 | 0.1596 |
| Germany | 0.1467 | 0.2481 | 0.2034 | 0.1688 | 0.2347 | 0.7410 | 0.1137 | 0.1128 |
| Ghana | 0.1717 | 0.2505 | 0.2119 | 0.2216 | 0.7423 | 0.5326 | 0.0409 | 0.1176 |
| Greece | 0.1615 | 0.2756 | 0.2324 | 0.1990 | 0.2489 | 0.7440 | 0.1010 | 0.1557 |
| Hungary | 0.1985 | 0.3292 | 0.2749 | 0.1919 | 0.1437 | 0.7143 | 0.1001 | . |
| India | 0.2232 | 0.3276 | 0.2851 | 0.2724 | 0.7324 | 0.5223 | 0.0136 | . |
| Ireland | 0.1634 | 0.2256 | 0.1965 | 0.1880 | 0.2381 | 0.7240 | 0.0790 | . |
| Israel | 0.1698 | 0.2614 | 0.2231 | 0.2066 | 0.2200 | 0.7592 | 0.0557 | 0.2466 |
| Italy | 0.1816 | 0.3156 | 0.2613 | 0.2196 | 0.2494 | 0.7593 | 0.1095 | 0.1903 |
| Luxembourg | 0.1630 | 0.2707 | 0.2198 | 0.1778 | 0.2622 | 0.7166 | 0.1273 | 0.2788 |
| Mexico | 0.1855 | 0.2630 | 0.2303 | 0.1775 | 0.5030 | 0.6771 | 0.0821 | . |
| Netherlands | 0.1562 | 0.2669 | 0.2178 | 0.1716 | 0.1712 | 0.7764 | 0.0851 | 0.2010 |
| Poland | 0.1837 | 0.3715 | 0.2908 | 0.1959 | 0.1353 | 0.7230 | 0.1388 | . |
| Portugal | 0.1881 | 0.3251 | 0.2673 | 0.1802 | 0.3293 | 0.7329 | 0.1203 | . |
| Russian Federation | 0.1516 | 0.2730 | 0.2164 | 0.3234 | 0.2516 | 0.6883 | 0.1832 | 0.2198 |
| Slovenia | 0.1691 | 0.3309 | 0.2607 | 0.1772 | 0.1550 | 0.6987 | 0.1540 | 0.1585 |
| South Africa | 0.1794 | 0.2158 | 0.2017 | 0.2119 | 0.5204 | 0.4530 | 0.0937 | 0.1735 |
| Spain | 0.1996 | 0.3269 | 0.2747 | 0.2017 | 0.3510 | 0.7666 | 0.1014 | 0.1216 |
| Sweden | 0.1530 | 0.2305 | 0.1968 | 0.1563 | 0.1856 | 0.7844 | 0.0852 | 0.1360 |
| Switzerland | 0.1390 | 0.2151 | 0.1818 | 0.1610 | 0.2021 | 0.7708 | 0.1054 | 0.0859 |
| USA | 0.1553 | 0.2229 | 0.1933 | 0.1735 | 0.1259 | 0.7170 | 0.1268 | . |
| United Kingdom | 0.1515 | 0.2399 | 0.2036 | 0.1780 | 0.2697 | 0.7328 | 0.1141 | . |
| Total | 0.1681 | 0.2715 | 0.2271 | 0.1922 | 0.2797 | 0.7012 | 0.1089 | 0.1580 |
| | | | | | | | | |
| Age group: | | | | | | | | |
| 50-54 | 0.1515 | 0.2255 | 0.1953 | 0.1802 | 0.2201 | 0.9204 | 0.0460 | 0.1713 |
| 55-59 | 0.1486 | 0.2274 | 0.1950 | 0.1829 | 0.2351 | 0.8696 | 0.0730 | 0.1263 |
| 60-64 | 0.1542 | 0.2472 | 0.2075 | 0.1876 | 0.2687 | 0.7957 | 0.1040 | 0.1453 |
| 65-69 | 0.1640 | 0.2661 | 0.2224 | 0.1916 | 0.2883 | 0.6870 | 0.1370 | 0.1588 |
| 70-74 | 0.1831 | 0.3045 | 0.2519 | 0.1996 | 0.3287 | 0.5479 | 0.1566 | 0.1571 |
| 75-79 | 0.2075 | 0.3580 | 0.2902 | 0.2110 | 0.3373 | 0.3865 | 0.1368 | 0.1893 |
| Average | 0.1681 | 0.2715 | 0.2271 | 0.1922 | 0.2797 | 0.7012 | 0.1089 | 0.1580 |

Note: in the first panel, each cell indicates the average of the relevant statistic among the age groups of the country. The age groups are 50-54, 55-59, 60-64, 65-69, 70-74 and 75-79. In the second panel, each cell indicates the average of the relevant statistic among countries for each age group. The survival rate of the age group is the probability that the individuals aged 25-29 in the past will survive until current age. The differential survival rate is the survival rate of females minus that of males. IOP is the indicator of inequality of opportunity (non-parametric and weighted by survival probabilities)

## Table A2. Effects of IOP on inequality of cognitive functioning in old age

| Variables | Gini of immediate memory | Gini of delayed memory | Gini of average memory | Gini of verbal fluency | Gini of immediate memory | Gini of delayed memory | Gini of average memory | Gini of verbal fluency | Gini of immediate memory | Gini of delayed memory | Gini of average memory | Gini of verbal fluency | Gini of immediate memory | Gini of delayed memory | Gini of average memory | Gini of verbal fluency |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) |
| Survival gender differential | 0.279*** | 0.689*** | 0.494*** | 0.108** | 0.278*** | 0.684*** | 0.491*** | 0.107** | 0.274*** | 0.673*** | 0.483*** | 0.106** | 0.276*** | 0.682*** | 0.488*** | 0.107** |
| | (0.028) | (0.052) | (0.037) | (0.045) | (0.028) | (0.048) | (0.035) | (0.046) | (0.033) | (0.063) | (0.046) | (0.047) | (0.033) | (0.061) | (0.045) | (0.047) |
| IOP (*Type A*) | 0.043 | 0.187** | 0.112* | 0.006 | | | | | | | | | | | | |
| | (0.040) | (0.087) | (0.062) | (0.045) | | | | | | | | | | | | |
| IOP (*Type B*) | | | | | 0.023 | 0.169* | 0.098 | 0.031 | | | | | | | | |
| | | | | | (0.041) | (0.097) | (0.066) | (0.059) | | | | | | | | |
| IOP (*Type AG*) | | | | | | | | | 0.068* | 0.224*** | 0.147** | 0.030 | | | | |
| | | | | | | | | | (0.036) | (0.078) | (0.055) | (0.044) | | | | |
| IOP (*Type BG*) | | | | | | | | | | | | | 0.077** | 0.223*** | 0.149*** | 0.026 |
| | | | | | | | | | | | | | (0.033) | (0.068) | (0.049) | (0.034) |
| Constant | 0.126*** | 0.164*** | 0.151*** | 0.178*** | 0.129*** | 0.168*** | 0.154*** | 0.175*** | 0.122*** | 0.156*** | 0.145*** | 0.175*** | 0.120*** | 0.153*** | 0.142*** | 0.175*** |
| | (0.004) | (0.012) | (0.008) | (0.006) | (0.004) | (0.013) | (0.008) | (0.007) | (0.004) | (0.011) | (0.007) | (0.006) | (0.004) | (0.010) | (0.007) | (0.006) |
| Observations | 126 | 126 | 126 | 126 | 126 | 126 | 126 | 126 | 126 | 126 | 126 | 126 | 126 | 126 | 126 | 126 |
| R-squared | 0.631 | 0.641 | 0.640 | 0.833 | 0.629 | 0.636 | 0.636 | 0.834 | 0.642 | 0.659 | 0.657 | 0.834 | 0.650 | 0.666 | 0.665 | 0.834 |

Note: The unit of the analysis is the synthetic unit formed by age group and country. See Section 5.3 for explanations on sample selection. The dependent variable is inequality in cognitive functioning at old age ($Gini(F)$ with $\alpha = 2$). IOP index is based on the mean log deviation of the distribution of type-specific average education attainment. IOP indices are non-parametric estimates with survival probabilities adjusted individual weights. *Type A* originated from all admissible pairs of maternal and paternal education (no education, primary, secondary or tertiary). *Type B* originated from maximum level of education in the family of origin, distinguishing same education parents. *Type AG* and *Type BG* obtained by refining types A and B by gender of the survey respondent. All regressions include dummy variables for countries. Robust standard errors are clustered by country and are in parentheses. Significance levels are * p<0.10, ** p<0.05, *** p<0.01.

## Table A3. Effects of IOP *and* inequality in past education ($\boldsymbol{Gini}(\boldsymbol{F})$) on inequality of cognitive functioning in old age

| Variables | Gini of immediate memory | Gini of delayed memory | Gini of average memory | Gini of verbal fluency | Gini of immediate memory | Gini of delayed memory | Gini of average memory | Gini of verbal fluency | Gini of immediate memory | Gini of delayed memory | Gini of average memory | Gini of verbal fluency | Gini of immediate memory | Gini of delayed memory | Gini of average memory | Gini of verbal fluency |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) |
| Gini of past education | 0.195*** | 0.356*** | 0.272*** | 0.151** | 0.197*** | 0.355*** | 0.273*** | 0.150** | 0.190*** | 0.333*** | 0.259*** | 0.151** | 0.186*** | 0.328*** | 0.254*** | 0.151** |
| | (0.060) | (0.088) | (0.073) | (0.059) | (0.061) | (0.089) | (0.074) | (0.058) | (0.062) | (0.099) | (0.080) | (0.059) | (0.062) | (0.099) | (0.080) | (0.059) |
| Survival gender differential | 0.148*** | 0.450*** | 0.311*** | 0.007 | 0.147*** | 0.448*** | 0.309*** | 0.007 | 0.149*** | 0.455*** | 0.314*** | 0.007 | 0.152*** | 0.464*** | 0.319*** | 0.007 |
| | (0.045) | (0.073) | (0.057) | (0.052) | (0.045) | (0.073) | (0.057) | (0.052) | (0.046) | (0.082) | (0.062) | (0.052) | (0.047) | (0.080) | (0.061) | (0.052) |
| IOP (*Type A*) | 0.024 | 0.152* | 0.085 | -0.009 | | | | | | | | | | | | |
| | (0.033) | (0.077) | (0.053) | (0.042) | | | | | | | | | | | | |
| IOP (*Type B*) | | | | | -0.006 | 0.117 | 0.058 | 0.009 | | | | | | | | |
| | | | | | (0.038) | (0.091) | (0.061) | (0.056) | | | | | | | | |
| IOP (*Type AG*) | | | | | | | | | 0.029 | 0.156** | 0.094* | -0.001 | | | | |
| | | | | | | | | | (0.030) | (0.073) | (0.050) | (0.039) | | | | |
| IOP (*Type BG*) | | | | | | | | | | | | | 0.042 | 0.162** | 0.102** | -0.002 |
| | | | | | | | | | | | | | (0.027) | (0.059) | (0.042) | (0.029) |
| Constant | 0.091*** | 0.100*** | 0.102*** | 0.151*** | 0.094*** | 0.106*** | 0.106*** | 0.149*** | 0.091*** | 0.101*** | 0.102*** | 0.150*** | 0.089*** | 0.099*** | 0.100*** | 0.150*** |
| | (0.011) | (0.021) | (0.016) | (0.013) | (0.011) | (0.020) | (0.015) | (0.013) | (0.012) | (0.022) | (0.017) | (0.012) | (0.012) | (0.022) | (0.017) | (0.012) |
| Observations | 126 | 126 | 126 | 126 | 126 | 126 | 126 | 126 | 126 | 126 | 126 | 126 | 126 | 126 | 126 | 126 |
| R-squared | 0.743 | 0.725 | 0.735 | 0.868 | 0.742 | 0.720 | 0.731 | 0.868 | 0.744 | 0.730 | 0.739 | 0.867 | 0.748 | 0.735 | 0.744 | 0.867 |

Note: The unit of the analysis is the synthetic unit formed by age group and country. See Section 5.3 for explanations on sample selection. The dependent variable is inequality in cognitive functioning at old age ($Gini(F)$ with $\alpha = 2$). Gini of past education is measured by the $Gini(F)$ in (3). IOP index is based on the mean log deviation of the distribution of type-specific average education attainment. IOP indices are non-parametric estimates with survival probabilities adjusted individual weights. *Type A* originated from all admissible pairs of maternal and paternal education (no education, primary, secondary or tertiary). *Type B* originated from maximum level of education in the family of origin, distinguishing same education parents. *Type AG* and *Type BG* obtained by refining types A and B by gender of the survey respondent. All regressions include dummy variables for countries. Robust standard errors are clustered by country and are in parentheses. Significance levels are * p<0.10, ** p<0.05, *** p<0.01.