The Cognitive and Economic Impact of Social Activities in Older Age: Evidence from 17 European Countries[#]

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Abstract

Using harmonized micro data from 17 European countries, we investigate the causal impact of being socially active on old age cognition. To this effect, we employ nonparametric bounds-based partial identification methods that require fairly weak assumptions. We find that social activities have a strong positive effect on cognition, as the narrowest identification regions of the treatment effect exclude zero. This result is more likely to hold for females than for males. We also provide evidence, again using bounds-based estimation, on the economic significance of social participation by examining the beneficial effect of higher cognition on households' economic well-being.

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1. **Introduction**

In recent years, numerous studies have documented a strong positive association between engaging in social activities and cognitive ability.[1] What is less clear is the causal interpretation of this association, i.e. whether an active social life actually preserves cognitive skills.

The answer to this question is especially important for older individuals, because the extent to which they maintain their cognitive skills has a significant impact on how well they age. For instance, enhanced cognitive skills are associated with better physical health (Der et al., 2009) and can influence behaviour in directions that are beneficial to health (Cutler and Lleras-Muney, 2010). Moreover, Plassman et al. (2010) and Deary et al. (2009) find that cognitive ageing is a good predictor of mental health (dementia)[2] and lifetime length.

The preservation of cognitive abilities in old age also has a beneficial economic effect along several dimensions. For example, higher cognition leads to higher productivity at work, thus helping older workers remain active, which in turn makes it easier to finance the cost of ageing (Engelhardt et al., 2010). Moreover, previous research has established a strong positive association of cognitive abilities with financial literacy (Delavande et al., 2008), wealth and risky portfolio holdings (Smith et al., 2010; Lee and Willis, 2001; McArdle et al., 2009), occupational rank, job performance and income (Murnane et al., 1995, 2000; Zagorsky, 2007; Judge et al., 2010), and consumption smoothing and life-satisfaction in retirement (Banks et al., 2010).

Existing literature has proposed four main channels through which social involvement may help preserve cognitive functions. First, the lack of a social network may cause loneliness,[3] which has been used to predict mental problems (Prince et al., 1997). Second, by

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[1] See e.g. Bassuk et al. (1999), Zunzunegui et al. (2003), Wang et al. (2002), Yeh and Liu (2003), Fratiglioni et al. (2004), Barnes et al. (2004), Lovden et al. (2005), Jopp and Hertzog (2007), Ertel et al. (2008).
[2] See also Fratiglioni et al. (2000), Verghese et al. (2003), Karp et al. (2005), Saczynski et al. (2006).
[3] See Andersson (1992), Cutrona, Russel and Rose (1986), Jones and Moore (1986), Weiss (1989).

providing meaningful social roles and a sense of purpose in old age (Berkman, 2000), social activities could have direct neurohormonal influences, including stress reduction (Fratiglioni et al., 2004). Third, social activities are likely to inhibit cognitive decline because they involve the challenge of effective communication and participation in complex interpersonal exchanges (Berkman, 2000). Finally, social activity might also require a degree of physical activity beyond regular exercise and walking, which could enhance physical health (Colcombe and Kramer, 2003; Fratiglioni et al., 2004). Moreover, an active social life may induce greater self-esteem and better self-care practices, i.e., regular exercise and smoking abstention (Hurst, 1997).

Two additional studies are more closely related to ours. Hu et al. (2012) use cross-sectional data from the China Health and Retirement Longitudinal Study and find a positive association between social activities and cognition (especially for short-term memory) for the Chinese elderly. They try to address the issue of the endogeneity of social activities by using IV methods, but their instruments are not related strongly enough to their measures of social activities. Engelhardt et al. (2010) use the first wave of the Survey of Health, Ageing and Retirement in Europe (SHARE) and a stochastic frontier approach, implemented through OLS regression, to highlight the positive association between social activities and cognition.

One issue arising in all these studies on the beneficial effects of social participation on cognition and well-being is that of the correlation of social activities with unobservables that affect also these outcomes. Such unobservables might be both time-invariant (e.g. personality traits) and time-varying (e.g. health and family problems), and their presence most likely biases the estimate of the effect of social activities on cognition. Unless this issue is addressed, it is difficult to interpret the strong association between cognition and social activities observed in the data as a causal relationship.

Our contribution consists of providing empirically robust estimates of the causal effect of participation in social activities on cognitive abilities of older Europeans. To this effect, we use (for the first time in the related literature) nonparametric estimation methods that bound the causal effect of interest. These methods have the advantage of directly addressing the issue of the endogeneity of social activities while making weak assumptions about the data. In addition, we provide this evidence for 17 different European countries, using survey data that are comparable across these countries.

More specifically, we use data from the first, second and fourth waves of SHARE to examine several indicators of cognition, namely immediate and delayed recall capacity, numeracy and fluency. In addition, we are able to retrieve from our micro data information on a number of social activities, including volunteering, participation in a political organization or a social club, and attendance of an educational course.

We calculate informative upper bounds for the causal effect of social activities on cognition, and, by using monotone instrumental variables, informative lower bounds as well. These bounds imply that being social active in older age has a sizeable positive effect on cognition. As expected, the lower bound estimates are smaller than the estimates derived under the assumption that social participation is exogenous to cognition. Furthermore, both upper and lower bound estimates are larger for women than for men, and the lower bound ones are positive across all European regions. We also provide evidence, again using bounds-based estimation, for the economic significance of social participation by investigating the beneficial effect of higher cognition on households' economic well-being.

The structure of the paper is as follows: Section 2 describes the data. Our estimation methodology and baseline results are presented in Section 3 and Section 4, respectively. Several robustness checks are performed in Section 5. Section 6 provides evidence of what our findings imply in terms of households' economic well-being, while Section 7 summarizes our findings.

2. Data

We use data from the first, second and fourth waves of SHARE, which took place in 2004-5, 2006-7 and 2010-11 in 17 European countries in total.[4] Sweden, Denmark, Germany, the Netherlands, Belgium, France, Switzerland, Austria, Italy, and Spain participated in all three waves, while the Czech Republic and Poland in the second and fourth waves. Greece took part in the first two waves but not in the fourth one, while Hungary, Portugal, Slovenia and Estonia became part of SHARE starting from the fourth wave.

SHARE surveys those aged 50 and above and collects data on demographics, physical and mental health (including the administration of tests like grip strength), cognition, social activities, housing, employment, income, housing, assets and expectations.[5] Its design and questionnaire are modeled after those of the US Health and Retirement Study. Importantly, the SHARE questionnaire is homogeneous, and thus comparable, across all participant countries.

There are two questions in SHARE that convey information on the social activities respondents engaged in during the month prior to the interview. The first one asks about the type of social activity and offers as alternatives: i) engaging in voluntary or charity work; ii) caring for sick or disabled adults; iii) helping family, friends or neighbours; iv) following an educational or training course; v) going to a sport, social or other kind of club; vi) participating in a religious organization (church, synagogue, mosque, etc.) or attending

[4] The third wave of SHARE, also known as SHARELIFE, is a retrospective lifetime survey that has a completely different questionnaire than the other three waves. In particular, the questions on cognition and social activities that we use in this paper were not asked in SHARELIFE.

[5] The sample includes also a few observations with age below 50 that correspond to partners of individuals who are 50 or more years old. More detailed information on SHARE can be found in Börsch-Supan *et al*. (2005), Börsch-Supan and Jürges (2005), Börsch-Supan *et al*. (2008).

religious services; vii) being involved in a political or community-related organization. The second question inquires about how often these activities are performed and allows for three possible answers: almost daily, almost every week and less often than almost weekly. In our analysis, we use a narrow definition of social activities that includes options i, iii, iv, and v above. The reason is twofold. First, caring for sick family members and friends or providing help to them could be due to the fulfilment of family duties rather than to socializing. Second, religious participation includes attendance of religious services; therefore, an affirmative answer could be an indicator of religious devotion rather than social engagement. As a result, we define our social activities variable as a binary indicator denoting whether the respondent participated - almost daily or weekly - in at least one of the aforementioned four social activities.

In order to obtain information on respondents' cognitive abilities we use questions that are meant to test their immediate and delayed recall capacities, and their numeracy and fluency skills.

As regards recall capacity, respondents were read a list of ten words. During the immediate memory test they were asked to recall aloud as many of the words as possible, immediately after the interviewer finished reading them the list. For the delayed memory test they were asked to recall the same words at a later time (after five other questions). Hence, the two recall scores are equal to the number of words correctly recalled.

For the fluency score, we use a variable showing the number of animals respondents named in one minute, excluding repetitions and proper nouns.

Finally, the following five questions provide information on numeracy: (1) how many people out of 1,000 would be expected to get sick if the chance of getting a disease is 10 percent;[6] (2) what is the sale cost of a sofa, given an initial price of 300 euro and a 50%

[6] The possible answers are 100, 10, 90, 900 and other answer.

discount;[7] (3) what is the initial price of a car if two-thirds of what it costs new is 6,000 euro;[8] (4) what is the final balance of a savings account that initially holds 2,000 euro, at 10 percent interest after 2 years.[9] The numeracy score is assigned as follows: if respondents answer (1) correctly they are then asked (3) and if they answer correctly again they are asked (4). Answering (1) correctly results in a score of 3, answering (3) correctly but not (4) results in a score of 4, while answering (4) correctly results in a score of 5. On the other hand, if they answer (1) incorrectly they are directed to (2). If they answer (2) correctly they score 2, otherwise they score 1. The score could thus be interpreted as the number of correctly answered questions plus one.

After combining waves 1, 2 and 4 of the SHARE data we ended up with a sample of 113,978 observations across the three waves. The numeracy questions were not asked to respondents in the panel subsamples in wave 4; as a result, there are about 30,000 observations fewer observations for this cognitive score. Table 1 provides information by country on both social activities and our measures of cognition. We note that Switzerland exhibits the highest average numeracy score (2.78 questions answered correctly out of 4), and Spain the lowest (1.52 correct answers). Spain represents the lowest extreme also for the case of immediate and delayed recall, with respondents managing to remember on average only 3.84 and 2.49 words out of 10, respectively. The opposite is true of Denmark, where respondents remembered 5.53 words immediately and 4.34 words after some time. As for fluency, Portugal had the lowest average score (13.31 words), while Sweden the highest (22.85 words). The same patterns hold when we differentiate our samples by sex, although in general there also seems to be slightly less variation across all four cognitive measures for women than for men.

[7] The possible answers are 150, 600 and other answer.
[8] The possible answers are 9,000, 4,000, 8,000, 12,000, 18,000, and other answer.
[9] The possible answers are 2,420, 2,020, 2,040, 2,100, 2,200, 2,400 and other answer.

With respect to social activities, we note that about 79% of respondents are not socially active. The countries with the highest prevalence of social participation are Denmark and the Netherlands (roughly 46% and 45%, respectively), while the lowest prevalence is found in Poland (3.5%). Fig. 1 plots the mean of each test score by whether one is socially active. In line with previous empirical findings, we note a strong positive association between social activities and all four cognitive test scores. In the remainder of the paper, we investigate the extent to which this strong association can be interpreted as a causal effect.

3. Empirical Methodology

When estimating the causal effect of social activities on cognition one must account for the likely endogeneity of social activities. Such endogeneity may be due to a number of factors. First, it is likely that time-invariant unobservable factors may affect both the propensity to be socially active and cognitive abilities. Examples of such factors can be a privileged family background, character traits (e.g. inquisitiveness, zest for life) or intellectual abilities that both make it easier to be socially active and are positively associated with cognition. Second, time-varying unobservable factors can also act as confounders. For example, a family crisis or an adverse professional development can reduce social activities and also cause psychological distress, which in turn can negatively impact cognition. In addition, social activity can be correlated to time-varying unobservables due to reverse causality (i.e., higher cognition makes it more likely that one is socially active).

All the aforementioned time-invariant and time-varying unobservable factors imply that people who are socially active are likely to be systematically different from those who are not, even after controlling for observable characteristics. As a result, ordinary least squares (OLS) estimation is likely to produce inconsistent estimates of the causal impact of social activity on cognition. Panel data methods represent an improvement on OLS estimation because they eliminate the confounding effect of time-invariant unobservables. They do not, however, resolve the problem of time-varying confounders between cognition and social activity. This problem could be addressed through IV estimation, but finding variables that are exogenous to the outcome while being associated with the treatment might be problematic.[10] Moreover, given that the effect of social activities on cognition is very likely heterogeneous across the population, IV estimation identifies only the local average treatment effect (LATE henceforth), i.e. the effect of social activity on cognition for those who become socially active due to a change in the value of the instrumental variable (Imbens and Angrist, 1994). This group of respondents cannot be identified in the data, and in any case we would prefer to estimate, if possible, the causal impact of social activity on cognition across the whole population.

In order to address these issues, we use an estimation method that can take into account all possible sources of endogeneity and partially identifies the causal effect of interest for the whole population. This method, introduced by Manski (1989, 1990, 1994), is nonparametric and produces bounds on the average treatment effect (ATE henceforth). In other words, it locates the ATE in an identification region instead of calculating a point estimate. Importantly, this method uses assumptions that are much weaker than those used in OLS, panel data and IV estimation methods.

As in Manski (1997), for each individual i there is a response function $y_i(\bullet): D \rightarrow Y$ that maps mutually exclusive and exhaustive treatments $d \in D$ into outcomes $y_i(d) \in Y$. Importantly, these response functions $y_i(\bullet)$ can differ across individuals in arbitrary ways, thus allowing for unlimited response heterogeneity. Let w_i denote the realized treatment received by i, and $y_i \equiv y_i(w_i)$ denote the associated observed outcome. On the other hand, $y_i(d)$ is a latent potential outcome when $d \neq w_i$. In our context, the cognitive test scores are

[10] In our context, such variables would influence social activities while being exogenous to cognition.

the outcomes, while the treatment variable denotes participation in social activities, and thus is equal to one if an individual is socially active, and zero otherwise. Consequently, $y_i(0)$ and $y_i(1)$ are the two possible values of the outcome for individual i. We would like to estimate the ATE of being socially active on individuals' test scores, i.e.

$$ATE = E[y(1)] - E[y(0)] \tag{1}$$

Equation (1) implies that in our context the ATE is equal to the difference in expected outcomes when the whole population is socially active as opposed to being inactive. By the law of iterated expectations, and given that $E[y(d)|w = d] = E[y|w = d]$, the expected outcome as a function of d is equal to

$$E[y(d)] = E[y|w = d]P(w = d) + E[y(d)|w \neq d]P(w \neq d) \tag{2}$$

where $P(w = d)$ denotes the probability that $w = d$. The term $E[y(d)|w \neq d]$ in the right hand side of (2) is a counterfactual one because it denotes the expectation of the outcome as a function of d when the treatment actually received is different from d. On the other hand, the remaining three terms in the right hand side of (2) have sample analogues that are observed in the data. Given that $E[y(d)|w \neq d]$ is unobserved, the unconditional expectation $E[y(d)]$ is also unobserved, i.e. it represents a potential outcome. Hence the ATE in (1) is equal to the difference between two average potential outcomes.

If one assumes that the counterfactual conditional expectation $E[y(d)|w \neq d]$ is equal to the observed one when the treatment actually received is equal to d, i.e. if

$$E[y(d)|w \neq d] = E[y|w = d] \tag{3}$$

then from (2) it follows that

$$E[y(d)] = E[y|w = d] \tag{4}$$

Equation (4) states that the unobserved potential outcome under d is equal to the mean outcome when the treatment actually received is equal to d. As the sample analogue of the latter is observed in the data, one can estimate the unobserved potential outcome $E[y(d)]$, and then in turn the ATE defined in equation (1), which is equal to

$$ATE = E[y|w = 1] - E[y|w = 0] \tag{5}$$

We refer to the estimate of the ATE in (5) as the one under exogenous treatment selection (ETS henceforth) because it is derived under the assumption that (3) holds, which in turn implies that respondents receiving different treatments are not systematically different from one another. In other words, (3) implies that selection into treatment is exogenous.

Equation (3) is likely to be true in the case of a randomized control trial, in which treatment assignment is indeed exogenous. In observational data, however, (3) is unlikely to hold because treatment assignment is not random, especially when the treatment variable reflects a decision taken by the respondents. In our context respondents decide whether to be socially active or not, and, as already mentioned, individuals that are socially active are likely to be systematically different from those that are not. Hence, the expected value of the outcome is likely to differ between these two groups for any value of the treatment. In other words, the fact that equation (3) is unlikely to hold in our data is due to the endogeneity of the decision to be socially active. Such endogeneity can have any source (e.g. time-invariant and time-varying unobservables, reverse causality, selectivity), as all sources eventually lead to non-random treatment assignment, i.e. to the violation of (3).

Once one rules out the application of (3), the problem of estimating the unobservable potential outcome $E[y(d)]$ arises. As a solution, Manski (1989) suggested bounding this outcome from above and below. Let us denote the lower and upper bounds on $E[y(d)]$, computed using a particular method M, as $LB^M[d]$ and $UB^M[d]$, respectively. Given that $LB^M[d] \leq E[y(d)] \leq UB^M[d]$, Manski (1990) points out that equation (1) in turn implies that one can bound the ATE using method M as follows:

$$LB^M[1] - UB^M[0] \leq ATE \leq UB^M[1] - LB^M[0] \tag{6}$$

The interval between the lower and the upper bound on the ATE is its identification region, and since it is an interval the ATE is partly identified.

It is important to note that one calculates the bounds of the potential outcome $E[y(d)]$ for each value d of the treatment independently from all other treatment values. This implies that one could calculate these bounds using methods that differ across treatment values. As we discuss below, we take advantage of this feature of the bounds calculation.

When calculating the upper and lower bounds on $E[y(d)]$, a natural starting point is to assume that, for any value d of the treatment, the outcome space Y is bounded below and above by finite values Y_{min} and Y_{max}, respectively. The assumption of the existence of these finite values is an appropriate one in our context, as all our cognition measures have a minimum of zero, while the numeracy score has a maximum equal to four and the two memory scores a maximum equal to 10. All these values are common to both levels of the treatment, i.e. both for those who are socially active and those who are not. As for the fluency score, the fact that there is a one-minute time limit for respondents to provide as many words as possible implies that the existence of a finite maximum score for this cognition measure is also a reasonable assumption. We put the fluency maximum equal to the observed maximum score across all countries in our data, which is 100 words.

As in Manski (1990), by using equation (2) and after replacing the unobserved term $E[y(d)|w \neq d]$ by Y_{min} and Y_{max}, one can bound $E[y(d)]$ from below and above as follows:

$$\begin{gathered} E[y|w=d]P(w=d) + Y_{min}\, P(w \neq d) \\ \leq E[y(d)] \leq \\ E[y|w=d]P(w=d) + Y_{max} P(w \neq d) \end{gathered} \tag{7}$$

The bounds in (7) are obtained without imposing any assumptions on the data, other than the existence of finite Y_{min} and Y_{max}. We thus denote them as the no assumptions (NA henceforth) bounds. Moreover, the NA bounds can be readily calculated using their sample analogues, as these are observed in the data. As Manski (1989) points out, taking sample averages leads to consistent estimates of $E[y|w = d]$, $P(w = d)$ and $P(w \neq d)$.

It follows from (7) that the distance between the NA upper and lower bound of $E[y(d)]$ (i.e. the length of its identification interval) is equal to $(Y_{max} - Y_{min})P(w \neq d)$. As a result, the identification region is narrower the smaller the distance between Y_{min} and Y_{max} and the smaller the probability of treatment values other than d. This is the case because all the uncertainty in the estimation of $E[y(d)]$ is due to the term $E[y(d)|w \neq d]P(w \neq d)$ in (2). Moreover, the distance between the upper and the lower bound of ATE computed using the NA method is equal to $Y_{max} - Y_{min}$ (Manski, 1990; see also Section A.1 in the Appendix).

The fact that the identification region of $E[y(d)]$ becomes narrower when $P(w \neq d)$ becomes smaller has important implications in our context. As mentioned in Section 2, the probability of not being socially active $P(w = 0)$ is equal to about 79% in our sample. Consequently, the identification region for $E[y(0)]$ is about four times narrower than that of $E[y(1)]$ because its length is equal to $(Y_{max} - Y_{min})P(w = 1)$ as opposed to $(Y_{max} - Y_{min})P(w = 0)$. This fact can be readily verified when examining the NA identification regions reported in Appendix Table A.1, both for the whole sample and for the subsamples defined by sex. Obviously, the narrower the identification region for a potential outcome is, the better, as this leads in turn to a narrower identification region for the ATE. As we discuss below, however, a very tight identification region can also constrain the use of particular estimation methods that attempt to further narrow it.

The NA identification region for the ATE is typically very wide, and always includes zero. Hence, one has to make additional assumptions in order to make it narrower. The first such assumption is that of monotone treatment response (MTR henceforth; see Manski, 1997). The MTR assumption states that for all sample units i, and for any two treatment values $d_1 \in D$ and $d_2 \in D$ such that $d_2 > d_1$,

$$y_i(d_2) \geq y_i(d_1) \tag{8}$$

In our context, the MTR assumption implies that being socially active has a weakly increasing effect on cognition for all individuals in the sample. Importantly, (8) holds irrespective of the treatment actually received. Given that at each point in time one observes only one outcome for each individual in the sample, one cannot test for the validity of (8) in isolation using the data at hand. As already discussed in the Introduction, however, there are various reasons, also supported by considerable evidence, why one would expect social activity to have a positive effect on cognition. On the other hand, it is difficult to think of a mechanism through which being socially active would reduce an individual's cognitive capacities. Moreover, and to the best of our knowledge, there is no empirical evidence for such a detrimental effect. Importantly, the MTR assumption fully allows for the possibility that there is no effect of social activity on cognition; therefore, we believe that the MTR assumption is a reasonable one to make.

In practice, we use a yet weaker, and thus more conservative, version of the MTR assumption than the one in (8). This weaker version states that for any treatment value $d \in D$, and any two values $d_1 \in D$ and $d_2 \in D$ such that $d_2 > d_1$,

$$E[y(d_2|w = d)] \geq E[y(d_1|w = d)] \tag{9}$$

Equation (9) implies that social activity has a weakly positive effect on cognition on average, but not necessarily for every individual in the sample. Furthermore, this average weak monotonicity holds irrespective of the treatment actually received. Clearly, (8) implies (9), but the converse is not necessarily true. As discussed below, we test the joint validity of (9) and of another hypothesis, and we are unable to refute this joint hypothesis.

As Manski (1997) shows (and we further discuss in Section A.2 in the Appendix), the MTR assumption implies that the bounds on $E[y(d)]$ can be expressed as follows:

$$\begin{gathered} E[y|w < d]P(w < d) + E[y|w = d]P(w = d) + Y_{min}\, P(w > d) \\ \leq E[y(d)] \leq \\ Y_{max}P(w < d) + E[y|w = d]P(w = d) + E[y|w > d]P(w > d) \end{gathered} \tag{10}$$

We note that the term $Y_{min}\, P(w < d)$ in the NA lower bound in (7) has now been replaced by $E[y|w < d]P(w < d)$, which can be estimated from the data. Correspondingly, the term $Y_{max}\, P(w > d)$ in the NA upper bound in (7) has been replaced by $E[y|w > d]P(w > d)$, which can also be estimated. These two operations tighten the identification region of $E[y(d)]$. As is the case with the NA bounds, and as shown in Appendix Table A.1, the identification region of $E[y(0)]$ is much narrower than that of $E[y(1)]$.

The narrower identification region of $E[y(d)]$ under MTR yields in turn a narrower identification region of ATE resulting from (10), which is now bounded below by zero (Manski, 1997).[11] This is to be expected, as the MTR assumption in (9) rules out the possibility that a higher level of the treatment induces a lower mean outcome, while allowing for the possibility of a zero effect. Furthermore, the upper bound on ATE derived using the MTR assumption is equal to the NA one.

One can further narrow down the identification regions of $E[y(d)]$ and by adding another assumption to the MTR one, namely that of monotone treatment selection (MTS henceforth), introduced by Manski and Pepper (2000, MP henceforth). The MTS assumption states that for any treatment value $d \in D$, and any two values $d_1 \in D$ and $d_2 \in D$ such that $d_2 > d_1$,

$$E[y(d)|w = d_2] \geq E[y(d)|w = d_1] \tag{11}$$

In our context, this assumption implies that those who are actually observed to be socially active in the data have, under any circumstances, higher cognitive capacities than those who

[11] As shown in Section A.2 in the Appendix, the upper bound on $E[y(0)]$ and the lower bound on $E[y(1)]$ are both equal to the observed overall sample mean.

are not socially active. This assumption could be justified, for example, if being socially active is due to personality traits such as higher intelligence, intellectual curiosity or zest for life. These characteristics could be associated with higher cognition, which would manifest itself even in the counterfactual situation in which those individuals would not be socially active.

Another way to think about the MTS assumption is as a particular form of non-random selection into treatment, i.e. a particular form of violation of (3). If (3) does not hold, then those who choose different levels of the treatment are also systematically different with respect to the outcome in general. The MTS assumption pins down the direction of this difference, as it states that higher treatment levels lead to weakly higher outcomes.

One can test the joint validity of the MTR and MTS hypotheses using a result from MP,[12] namely that these two hypotheses jointly imply that for any two treatment values $d_1 \in D$ and $d_2 \in D$ such that $d_2 > d_1$,

$$E[y|w = d_2] \geq E[y|w = d_1] \tag{12}$$

Equation (12) states that the MTR and MTS assumptions jointly imply that the observed mean outcomes (i.e. the levels of $E[y(d)]$ under ETS) are weakly increasing in the value of the treatment. Appendix Table A.1 shows that this is clearly the case in our data for all four cognitive test scores, as the mean test scores of the socially active are significantly larger than those of the socially inactive. Hence, we cannot refute the validity of the joint MTR+MTS assumption.

As shown by MP (and further discussed in Section A.3 in the Appendix), the MTR+MTS assumption implies that $E[y(d)]$ can now be bounded as follows:

[12] Their derivation can be found in p.1004 of MP, and we reproduce it in Section A.4 in the Appendix.

$$E[y|w < d]P(w < d) + E[y|w = d]P(w \geq d) \\ \leq E[y(d)] \leq \\ E[y|w = d]P(w \leq d) + E[y|w > d]P(w > d) \tag{13}$$

We note that the term $Y_{min}\, P(w > d)$ in the MTR lower bound in (10) has now been replaced by $E[y|w = d]P(w > d)$, which can be estimated from the data. Correspondingly, the term $Y_{max}\, P(w < d)$ in the MTR upper bound in (10) has been replaced by $E[y|w = d]P(w < d)$, which can also be estimated. As a result, the identification region of $E[y(d)]$ becomes again narrower. Moreover, the MTR+MTS identification region of $E[y(0)]$ is again much narrower than that of $E[y(1)]$, as can be seen in Appendix Table A.1.

As MP show, the identification region of the ATE under MTR+MTS, while narrower than the one under MTR, still has a lower bound equal to zero. On the other hand, González (2005) shows that its upper bound is now equal to the ATE under ETS (i.e. to the difference in mean outcomes between the two levels of the treatment).

One can further tighten the identification region of $E[y(d)]$ and the ATE by combining the MTR and MTS assumptions with the use of a variable Z that is exogenous to $E[y(d)]$, in the sense that for all values z of Z the following condition holds:

$$E[y(d)|Z = z] = E[y(d)] \tag{14}$$

While equation (14) requires that Z be exogenous to the outcome, MP point out that it still needs to be correlated with the treatment variable, as typically required in IV estimation. In addition, given that (14) is an assumption on the unobserved potential outcome $E[y(d)]$, the exogeneity of Z cannot be tested without using further assumptions. Obviously, this difficulty is not particular to bounds-based estimation, as it is present also in any conventional IV setup.

If an exogenous Z can be found, then one can choose various values in its domain, and (14) implies that each of these values can be used to obtain an estimate of $E[y(d)]$. Hence, after calculating the lower and upper bounds of $E[y(d)]$ under MTR+MTS for each value of Z, one can calculate the maximum of the lower bounds of $E[y(d)]$ across all these values, and use this maximum as an estimate of the lower bound of $E[y(d)]$. Correspondingly, one could compute the minimum across all the values of Z of all upper bounds of $E[y(d)]$ under MTR+MTS, and use this minimum as the estimate of the upper bound of $E[y(d)]$. As a result, the bounds on $E[y(d)]$ under the combination of MTR+MTS with an exogenous instrument can be computed as follows:

$$\max_{z} LB^{MTR+MTS}[d|Z = z] \leq E[y(d)] \leq \min_{z} UB^{MTR+MTS}[d|Z = z] \tag{15}$$

The optimization operations in (15) can produce a larger lower bound and a smaller upper bound on $E[y(d)]$ compared to their MTR+MTS counterparts in (13). Importantly, the larger the number of values of Z over which the optimization operations in (15) take place, the narrower the identification region of $E[y(d)]$ and the ATE can become. This happens because optimizing over more values of Z can lead to higher maxima and/or lower minima. On the other hand, if the MTR+MTS identification region is relatively tight to begin with, using exogenous instruments to further tighten it can result in a crossing of the bounds, i.e. in the lower bound becoming larger than the upper one.

In our context, an exogenous instrument would be a variable that is not correlated with cognition but is correlated with social activities. Finding such a variable is quite problematic, so we do not make use of one. A considerably weaker kind of instrumental variable is the monotone one (MIV henceforth), introduced by MP, which satisfies the following requirement for any pair of values z_1, z_2 of Z such that $z_2 > z_1$,

$$E[y(d)|Z = z_2] \geq E[y(d)|Z = z_1] \tag{16}$$

Equation (16) states that the MIV can influence the outcome in a given direction, while the possibility of no influence whatsoever is also allowed for. Hence, the assumption of a monotone instrumental variable is a much weaker than the assumption of an exogenous one. It is important to note that (16) captures only a positive association of Z with Y; a causal relationship is neither implied nor required.

Once one adds the MIV assumption to MTR+MTS, then for a given value z of Z one can calculate the maximum of the MTR+MTS lower bounds over all values of Z that are smaller or equal to z. By (16), this maximum lower bound cannot be larger than $E[y(d)|Z = z]$. Similarly, one can calculate the minimum MTR+MTS upper bound over all values of Z larger or equal to z, and (16) implies that this minimum cannot be smaller than $E[y(d)|Z = z]$. Hence the MTR+MTS+MIV assumption implies that

$$\max_{z_1 \le z} LB^{MTR+MTS}[d|Z = z_1] \le E(y(d)|Z = z) \le \min_{z \ge z_2} UB^{MTR+MTS}[d|Z = z_2] \qquad (17)$$

Once the bounds in (17) have been computed for all z, one can take their weighted average over all z and bound the potential outcome $E\big(Y(d)\big)$ as follows:

$$\begin{aligned} &\sum_z P(Z = z) \max_{z_1 \le z} LB^{MTR+MTS}[d|Z = z_1] \\ \le &\sum_z P(Z = z) E[y(d)|Z = z] = E[y(d)] \le \\ &\sum_z P(Z = z) \min_{z \ge z_2} UB^{MTR+MTS}[d|Z = z_2] \end{aligned} \qquad (18)$$

Hence, by integrating Z out of the conditional expectation in (17) one can obtain bounds on $E[y(d)]$. In contrast, this is not needed when using exogenous instruments because such instruments do not affect $E[y(d)]$ by assumption, as can be seen in (14).

We choose as our monotone instrument a variable denoting whether respondents smoke or not. In our context, the MIV assumption in (16) implies that smoking is negatively associated with cognition, or not associated at all with it. As is the case with exogenous instruments, this weak monotonicity assumption is imposed on the unobserved potential outcome $E[y(d)]$; hence, it cannot be tested using the observed data without imposing further assumptions.

There is, however, an extensive literature documenting a negative association of smoking with old age cognition. Researchers have suggested two main channels through which smoking affects cognition. First, as Meyer (1999) shows, cerebral atrophy, cortex/subcortex perfusional (i.e., oxygenation) declines with smoking, while white matter lesions appear severely accelerated by this habit. Second, smoking increases cardiovascular risks, which have been linked to increased risk of dementia (Frishman et al., 1998; Peters et al., 2008). Additionally, several studies have found smoking to be strongly associated with the risk of Alzheimer's disease among the elderly (Brenner et al., 1993; Almeida et al., 2002; Peters et al., 2008). Smoking has also been linked with cognitive decline and dementia among middle-aged and older people (Kalmijn et al., 2002; Sabia et al., 2012; Meyer et al., 1999; Ott et al., 2004; Reitz et al., 2005; Barnes et al., 2007). These finding were also confirmed in a meta-analysis by Anstey et al. (2007).

Importantly, there is evidence on the negative association between smoking and cognition that comes from data used in this paper, i.e. the SHARE survey. In particular, Engelhardt et al. (2010) document this negative association using the first wave of SHARE. In addition, Gibney and McGovern (2012), using the first two SHARE waves, find that not smoking is positively associated with the alleviation of mental distress. In addition, the negative association between smoking and lower performance scores in cognitive tests is also documented by Dregan et al. (2012) in the English counterpart of SHARE, namely the English Longitudinal Study of Ageing.

In our baseline results, we use a binary MIV that is going to be equal to one when respondents do not smoke, and to zero otherwise (the ordering of the values is chosen so as to respect the direction of the inequalities in (16)). We show results also from a three-valued version of our MIV, namely one that distinguishes between respondents currently smoking, currently not smoking but having been past smokers, and having never smoked. Despite the large consensus on the older smokers' increased risk of cognitive decline, there is still conflicting evidence on any differences in risk between ex-smokers and never smokers. For instance, Anstey et al. (2007) find that former smokers did not have an increased risk of dementia compared with never smokers, but did show an increased risk of yearly decline in cognition. Sabia et al. (2012), on the other hand, show that recent ex-smokers experience a significantly higher decline in cognitive functions than long-term ex-smokers, who appear similar to never smokers. Finally, Kalmijn et al. (2002) find that the cognitive test scores of ex-smokers were in-between those of smokers and never smokers.

Similar to exogenous IVs, the larger the number of values over which one applies the optimization operations in (18), the narrower the identification region of $E[y(d)]$ and the ATE can become. We also note that the weak inequality of the MIV condition in (16) accommodates the possibility that the effects on cognition of being an ex-smoker and of having never smoked are not different from each other.

As is the case with exogenous IVs, if the MTR+MTS identification region is relatively narrow to begin with, applying MIVs to the MTR+MTS bounds can make them cross. We indeed encountered this problem with the bounds on $E[y(0)]$, i.e. on the mean cognitive scores when one is not socially active. On the other hand, there is no crossing bounds problem with $E[y(1)]$. As can be seen in Appendix Table A.1 the MTR+MTS identification region of $E[y(0)]$ is very narrow for all four cognitive scores. In particular, its width is about four times narrower than that of $E[y(1)]$.

The reason for this crossing of the bounds on $E[y(0)]$ is the aforementioned imbalance in the prevalence of social activities, which makes even the NA identification region of $E[y(0)]$ quite narrow. After imposing MTR+MTS, it becomes even narrower (see Appendix Table A.1). Hence, there is little room to further narrow it down by adding the MIV assumption without making the bounds cross. In other words, we attribute the problem of the crossing of the bounds on $E[y(0)]$ to a particular feature of our data, rather than to a problem with the MIV assumption per se, especially because: i) the MTR+MTS+MIV bounds on $E[y(1)]$ do not cross; ii) there is no crossing of the bounds when we add only

MIV to MTR, as the identification region of $E[y(1)]$ is wider in this case;[13] ii) there is strong empirical evidence on the negative association between smoking and cognition.

As Manski (2003, p. 132) notes, if a joint hypothesis (MTR+MTS+MIV in our case) cannot be used for the entire domain of the joint distribution of a group of variables (Y, D, and Z in our case), then it can still be the case that it applies to parts of the domain. Accordingly, we apply the MTR+MTS+MIV assumption only when $D = 1$. As already discussed, bounds-based estimation allows the bounds calculation method to differ across treatment values.[14] As a result, we use MTR+MTS to calculate the bounds on $E[y(0)]$, and MTR+MTS+MIV for those on $E[y(1)]$.

In order to conduct inferences on $E[y(d)]$ and the ATE we compute confidence intervals (CIs henceforth) that cover these magnitudes with 95% probability by using 1,000 bootstrap replications, as described in Imbens and Manski (2004). Given that the MTR+MTS+MIV bounds in (18) involve optimization operations, the bootstrapped estimates of the bounds can be biased. Therefore, we apply the bias correction procedure suggested by Kreider and Pepper (2007).[15] We found, however, that this bias correction made essentially no difference to our results. As we have repeated observations for a large number of individuals in our sample, we draw the bootstrap samples after clustering by individuals and also stratifying by country.

The features of the bounds-based estimation method presented in this Section provide many reasons why one would prefer it to more commonly used methods, e.g. OLS-, IV- or panel data-based ones, when trying to estimate the causal effect of interest. First, bounds-based estimation is completely nonparametric, as it only involves taking simple sample averages of the outcome and the treatment. Hence, it is not affected by the problem of

[13] Results using the MTR+MIV method are available from the authors upon request.
[14] This is so because bounds calculations for each treatment value are independent from the calculations referring to the remaining treatment values.
[15] See also Manski and Pepper (2009) and de Haan (2012) for further discussions of this issue.

estimates resulting from local minima and maxima. Second, bounds-based estimation leads to estimates of the ATE across all sample units, and not of the LATE as is the case with IV estimation when the treatment is heterogeneous. Third, it allows for arbitrary forms heterogeneity of the treatment effect because the ATE is just an average magnitude across sample units. Hence, the treatment effect for each sample unit can depend on any other variable in a fully flexible way. Such unlimited heterogeneity of the treatment effect is not typically allowed for, as in most estimation methods one makes particular assumptions about how the treatment variable enters into the specification. Moreover, if while performing bounds-based estimation one is interested in studying the heterogeneity of the treatment effect in particular dimensions, then one can simply restrict estimation to subsamples defined by particular combinations of values of control variables. Fourth, given that one is bounding the unconditional expectation $E[y(d)]$, the effect on the outcome of any variables other than the treatment is integrated out. As a result, one does not need to worry about: i) which variables to add in the empirical specification; ii) the manner in which they appear; iii) whether they are endogenous or not. Fifth, bounds-based estimation accommodates any form of endogeneity (e.g. due to both time-varying and time-invariant unobservables or selectivity), as it allows for non-random selection into treatment in any form. This also implies that one does not need to assume particular properties of an error term, as is the case with regression methods. Sixth, it uses very few and quite mild assumptions to narrow the identification region of the estimates, and some of these assumptions can be tested (e.g. MTR+MTS). Importantly, it is completely transparent about how the addition of each assumption affects the identification region. In contrast, most commonly used estimation methods typically impose many assumptions on the empirical model at the same time, and thus it is typically not clear how each assumption affects estimates. Seventh, bounds-based estimation allows the use of exogenous IVs and MIVs, which can tighten identification regions. As is the case with standard IV estimation, the assumptions behind those variables cannot be tested without making further assumptions. However, MIVs, which cannot be used in standard IV estimation, have properties that are much less restrictive than those of exogenous IVs. Finally, in bounds-based estimation one uses the data as a cross-section, and thus panel data are not required. One can accommodate any dependencies among sample units (e.g. due to repeated observation or features of the sampling process) through the appropriate clustering and stratification when bootstrapping standard errors.

On the other hand, bounds-based estimation can sometimes lead to identification regions that are wide, and thus do not allow one to draw strong conclusions. This is the price that sometimes one has to pay for imposing very few and weak assumptions on the data. As Manski (1994) notes, the point identification obtained by more commonly used estimation methods may give one a false certainty about results, as the reduction in uncertainty is obtained through assumptions that are not testable, and that might not hold in the data. This discrepancy between point identification through strong assumptions and partial identification through mild assumptions shows up very clearly in our results.

4. Empirical Results

We first discuss the results (shown in Table 2, Panel A) for the ATE of being socially active on respondents' cognitive test scores, as obtained from the whole sample. Subsequently, we discuss results by sex.

The first method used is the ETS one, which assumes that social participation is completely exogenous. As discussed in Section 3, the ETS estimate of the ATE is equal to the mean difference in test scores between those who are socially active and those who are not. The same estimate can be obtained by running an OLS regression on a constant and a dummy variable denoting social participation. The ETS results imply that being socially active has a strong positive effect on cognition, with the point estimates for all four test scores being about 0.5 SDs in magnitude. In addition, the 95% CIs around the ETS estimates are very narrow, which implies that there is little uncertainty affecting these estimates.

As already discussed in Section 3, however, the ETS estimate is likely to be upwardly biased due to various unobservables that are positively correlated with both social participation and cognition. We thus address the endogeneity of social participation with the bounds-based estimation methods discussed in Section 3. For each of these methods we first show the upper and lower bound that define its identification region, and then the 95% confidence intervals using the bootstrap procedures described in Section 3.

We start with the NA method, which naturally produces the widest identification region, as it makes no assumptions other than the existence of finite extrema. As one can see, the lower bounds of the ATE are well below zero, while the upper bounds are well above. As discussed in Section 3 and in Section A.1 in the Appendix, the length of the identification region is equal to $Y_{max} - Y_{min}$.

Adding the MTR assumption implies that the lower bound of the ATE cannot be smaller than zero, while the upper bound remains unchanged. Adding the MTS assumption to the MTR one leaves the lower bound equal to zero, while the upper bound now becomes equal to the ETS one (i.e. to the difference in observed mean outcomes by the level of social activity). The 95% CI of the ATE covers all its identification region and extends a bit higher than the upper bound; hence, the uncertainty about the ATE under MTR+MTS is considerably higher than that under ETS.

Importantly, since the upper bound of the MTR+MTS identification range is equal to the ATE under ETS, one can view this estimate of the ATE as a feasible, if extreme, one. Hence, it can serve as an anchor for the impact of social participation on cognition. On the other hand, obtaining this estimate only through regression-based methods would leave one with serious doubts about its validity, thus making it an unreliable guide on how to think about the issue at hand.

When using a MIV together with the MTR and MTS assumptions, the identification region becomes narrower, and now the lower bound of the ATE becomes significantly larger than zero (as also evidenced by the lower bound of the 95% CI). This is true for all four cognitive test scores, and the lower bounds fall in the range of 0.12 (fluency) to 0.16 (recall) SDs of the respective test scores. Hence, even the lowest possible estimates of the ATE imply a significant positive effect of social participation on cognitive ability. As for the upper bounds of the ATE, they remain very close to their counterparts under ETS.

We then examine whether the estimates differ by sex, and the results are shown in Table 2, Panels B and C. Before discussing them, we note that performing bounds-based estimation using the whole sample in no way implies that the ATE is presumed the same for both sexes. As discussed in Section 3, bounds-based estimation allows for arbitrary heterogeneity in the treatment effect across sample units, and sex is just one dimension in which such heterogeneity can be present. As a result, splitting the sample by sex implies that one fixes the heterogeneity of the treatment effect in a particular dimension in each subsample, while again allowing for any other possible forms of heterogeneity.

Table 2 shows a significant asymmetry in the results between sexes, starting with the ETS ones. In particular, the estimates for females are larger than those for males in all four scores. As for the ATEs under MTR+MTS+MIV, the lower bounds of the results for females are larger than zero in all cases, while for males this is true only for the two memory scores. Even in this case, however, the lower bounds for females are five to six times larger than those for males. The differences in the upper bounds between the sexes are smaller, but it is still the case that those for females are larger by 15% (numeracy) to 70% (delayed recall).

All in all, our results imply that estimates that are obtained assuming exogeneity of social activities with respect to cognition are likely to be at the very extreme of the acceptable range of values. Moreover, the very low uncertainty with which they are estimated is misleading. On the other hand, our bounds-based estimation methods show that the ATEs that allow for the endogeneity of social activities can be much smaller than the ETS ones. However, the tightest identification regions (obtained via MTR+MTS+MIV), imply that, even at the lowest bound, social activities have a sizeable impact on cognition, albeit smaller than the one estimated under ETS. This result is more likely hold for females than for males, but the estimates of the ATEs on the upper end of the identification range are quite large for both sexes.

5. Robustness Checks

We first want to see whether there are differences in the ATEs across countries or regions of Europe.[16] We opt for showing results for four country groups, as performing estimation by country entails using subsamples that are defined by country, treatment and instrument values. This in turn implies that some of these subsamples contain very few observations. For the same reason we do not perform estimation by country group and sex. The four country groups that we use are as follows: i) Northern Europe, which includes Sweden, Denmark, Germany, the Netherlands and Belgium; ii) Middle Europe, which includes France, Switzerland and Austria; iii) Southern Europe, which includes Italy, Spain, Portugal and Greece; iv) Eastern Europe, which includes the Czech Republic, Poland, Hungary, Slovenia and Estonia.

The results by country groups are shown in Table 3, and we note that the ATEs under ETS are in general weaker in Northern Europe, and strongest in Eastern Europe. The

[16] We note again that pooling all countries together does not imply that the treatment effect in bounds-based estimation is homogeneous across the sample.

relatively smaller magnitude of the ATEs in Northern Europe shows up also under MTR+MTS+MIV, but only for the lower bounds. On the other hand, lower bounds are largest in Middle and Southern Europe. We also note that the largest upper bounds can be found in Eastern Europe, and they in turn lead to the widest identification regions. All in all, these patterns displayed in Table 3 imply that social activity has a strong positive effect on cognition in all four regions examined.

We next check whether the identification ranges change if we use the three-valued version of our MIV, namely the definition of smoking that distinguishes between those who never smoked and the ex-smokers. One would expect that the use of this MIV would tighten the bounds, as the optimization operations in (18) take place across more values. The results shown in Table 4 imply that the identification regions become indeed narrower, and this is almost exclusively due to smaller upper bounds, while the lower ones remain unaffected (with the exception of fluency for males).

We also check whether our results change if we measure the cognition results not by the raw scores, but rather by a binary variable denoting whether one is above the median score.[17] Consequently, the ATEs reflect the change in the probability of being above the median score induced by social participation. The results are shown in Table 5, and we note that the ATEs under ETS imply that social participation increases the probability of scoring above the median by 18 to 25 percentage points. Once more, the results are stronger for females than for males, and very precisely estimated. When we turn to the results under MTR+MTS+MIV we note that the lower bounds of the ATEs for the whole sample range from about 4 to 7 percentage points, while the upper bounds are about the same as the ETS estimates. Hence, taking into account the endogeneity of social participation leads again to a substantially larger uncertainty about the ATEs; even their lowest possible values, however,

[17] In the case of numeracy, the binary indicator is equal to 1 if the score is larger than two, which is the case for about 41% of our observations.

imply a considerable impact of social participation on cognition. As was the case with our baseline estimates, the lower bounds for males are smaller than those for females, and the same is true for the upper bounds.

6. Cognition and Economic Well-Being

While there is little doubt that the impact that social activities have on cognition is a significant issue, it would be also very useful to know whether social activities, by improving cognition, have also economic consequences. To this effect, we attempt to quantify the impact of cognition on measures of households' economic welfare. As already discussed in the Introduction, numerous studies document a positive association of old age cognition with economic well-being. We build on this literature by providing evidence for a causal relationship, using again bounds-based estimation methods.

We use two measures of economic well-being in our investigation, namely household net worth and household net financial assets. We transform both variables using the inverse hyperbolic sine transformation (Burbidge et al., 1988), which is asymptotic to the logarithmic one starting from very small values, while also being defined for negative ones. In order to measure cognition we use the binary indicators denoting test scores above the median, which we discussed in Section 5. We use these binary cognition indicators instead of the raw test scores because bounds-based estimation is performed separately in each subsample defined by a particular treatment value. Hence, using raw test scores would entail using many relatively small subsamples (this is especially true in the case of fluency). As a result of the above, the ATEs denote the semi-elasticities of the two measures of households' resources with respect to having a cognitive test score that is larger than the median one.

Our bounds-based estimation proceeds as in Section 4, i.e. we calculate ATEs under the ETS, MTR, MTR+MTS, and MTR+MTS+MIV assumptions. The bounds for the levels of

$E[y(d)]$ are shown in Appendix Table A.2. The data reveal a clear monotone relationship between the binary cognition indicators and the observed means of both measures of economic resources, which are equal to the levels of $E[y(d)]$ under ETS. Hence, the joint test of the MTR+MTS assumption discussed in Section 3 (and in Section A.4 in the Appendix) indicates that one cannot refute the validity of the joint hypothesis.

Given that net worth and net financial assets are measured at the household level, we use one observation per couple. We measure numeracy at the household level by taking the maximum score over the two partners in a couple, or the score of the household reference person when the latter does not have a partner.

We use as a monotone instrument the self-reported health status, which can take five values: excellent, very good, good, fair and bad. In order to use this variable as a monotone instrument we assume that, in accordance with (16), better health status does not have a detrimental effect on household wealth.[18] The positive association between health and economic resources can be due to a direct effect of the former on the latter (e.g. being healthy can lead to increased earning capacity and reduced medical expenses), or due to the influence of a third variable like education, which positively affects both health and economic resources. The literature providing empirical evidence for the positive association between health and wealth is by now voluminous, and there is also evidence related to SHARE countries (see Semyonov et al., 2013, and the references cited therein).

The results of our estimation are shown in Table 6. We note that the ETS estimates are quite large, as they imply that having an above average cognition score increases household net worth from 120% to 140% and net financial assets from 130% to 210%. Once we start imposing further assumptions the upper bounds of the semi-elasticities become smaller, and the narrowest identification ranges obtained through MTR+MTS+MIV imply that these

[18] In order to respect the direction of the weak inequalities in (16), larger values of the self-reported health variable denote better health.

upper bounds range from 60% to 100% for net worth, and from 74% to 180% for net financial assets. On the other hand, the lower bounds are equal to zero; hence, they are not informative about the impact of cognition on economic resources.

It is, however, very likely that cognition has a positive impact on economic well-being. First, there exists by now considerable empirical evidence for a strong positive association between them, as documented in the related literature discussed in the Introduction. Second, there are many reasons why higher cognition can have a positive impact on economic welfare: it can improve earnings, make it easier to spot profitable investment opportunities, reduce the likelihood and gravity of investment mistakes, and lead to better health (and thus to a better financial situation) through a superior grasp of the effects of certain lifestyle choices.

Therefore, and in order to illustrate the possible impact of social activity on economic welfare through improved cognition, we perform our calculations under the assumption that the semi-elasticity of net worth and net financial assets with respect to cognition is a small (compared to the upper bound estimates) positive number, namely 5%. If we then use the MTR+MTS+MIV lower bounds of the effect of social participation on cognition shown in Table 5, we calculate that being socially active increases both measures of economic resources by at least 0.195% (=0.039*0.05). The corresponding effects of fluency and immediate and delayed recall are equal to 0.26%, 0.34%, and 0.31%, respectively. These effects are non-negligible, both on their own and when added up, and they are obtained after making conservative assumptions about both the effect of social participation on cognition and the effect of the latter on economic resources. Hence, and taking into consideration the non-avoidable uncertainty associated with these calculations, being socially active very likely has positive implications for households' economic well-being.

7. Summary

In this paper we used survey data for individuals aged 50 and above from 17 European countries to investigate the impact of social activities on cognition later in life. We investigated this issue by addressing the problem of endogeneity of social activities through the use nonparametric partial identification methods. Our results imply that ignoring such endogeneity leads to severe underestimation of the uncertainty about the causal effect of interest. We show, however, that the most informative lower bounds of the ATE identification regions imply that social activities have an important positive causal effect on cognition. The upper bounds of these regions naturally imply larger effects, but are still smaller (although not considerably so) than the ATE point estimates under ETS.

We also investigate (again via nonparametric partial identification methods) whether being socially active has a positive economic impact in older age by preserving cognitive abilities. We find that this is indeed the case, even if one assumes a very small effect of cognition on economic welfare (as measured by household net worth and net financial assets).

From a policy perspective, our findings suggest that promoting active ageing should be a priority. For instance, access to transport and to technologies supporting self-sufficiency and independent life, opportunities for social, cultural and leisure activities, as well as educational courses targeted to older individuals, could be subsidized. Similarly, policies targeting the reduction of the employment gap between older women and men could be implemented to provide equal chances to longer and better working life (e.g., increasing delayed retirement provisions, flexible hours, part-time work). Finally, insurance companies could implement schemes that reward those who engage in activities that enhance cognitive fitness, and public campaigns could raise awareness about the benefits of active ageing. Such interventions may provide older individuals with higher quality of life, and also be cost-effective by keeping them in better health, mental and physical, deeper into their lives.

One potentially interesting issue to pursue in future work would be whether the positive impact of social activities extends to ages younger than 50. In a related vein, being socially active in older age could reflect long-life behavioural patterns or lifestyle changes that occurred late in life. It would therefore be worthwhile to examine, using panel data surveys that comprise many waves, the influence on cognition of the timing and duration of participation in social activities along the life course.

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Appendix

In this Appendix, we will restate results on the calculations of bounds originally discussed in Manski (1990, 1997), Manski and Pepper (2000) and González (2005).

A.1 No Assumptions Bounds

Equation (2) implies that the two potential mean outcomes are equal to

$$\begin{aligned} E[y(0)] &= E[y|w=0]P(w=0) + E[y(0)|w=1]P(w=1) \\ E[y(1)] &= E[y(1)|w=0]P(w=0) + E[y|w=1]P(w=1) \end{aligned} \tag{A.1}$$

Equation (7) implies in turn that by substituting Y_{min} and Y_{max} for the counterfactual terms in (A.1) on can construct the NA bounds on $E\big(y(0)\big)$ and $E\big(y(1)\big)$ as follows:

$$\begin{aligned} LB^{NA}[0] &= E[y|w=0]P(w=0) + Y_{min}P(w=1) \\ UB^{NA}[0] &= E[y|w=0]P(w=0) + Y_{max}P(w=1) \\ LB^{NA}[1] &= Y_{min}P(w=0) + E[y|w=1]P(w=1) \\ UB^{NA}[1] &= Y_{max}P(w=0) + E[y|w=1]P(w=1) \end{aligned} \tag{A.2}$$

The values of the NA bounds for all outcomes can be found in Appendix Table A.1. The bounds in (A.2) produce the following NA bounds on the ATE:

$$\begin{gathered} LB^{NA}[1] - UB^{NA}[0] \leq ATE \leq UB^{NA}[1] - LB^{NA}[0] \\ \Longrightarrow \\ \big[Y_{min} - E[y|w=0]\big]P(w=0) + [E[y|w=1] - Y_{max}]P(w=1) \\ \leq ATE \leq \\ \big[Y_{max} - E[y|w=0]\big]P(w=0) + [E[y|w=1] - Y_{min}]P(w=1) \end{gathered} \tag{A.3}$$

Given that $Y_{min} \leq E[y|w=0]$ and $E[y|w=1] \leq Y_{max}$, the NA lower bound on the ATE is less or equal to zero. Moreover, by inspecting (A.3) one notes that the width of the identification region of the ATE under NA is equal to $Y_{max} - Y_{min}$.

A.2 MTR Bounds

The MTR assumption in (9) implies that $E[y|w<d] \leq E[y(d)|w<d]$. Hence, the counterfactual term $E[y(1)|w=0]$ in the equation for $E[y(1)]$ is larger or equal to the observed term $E[y|w=0]$. This in turn implies that, by substituting in (A.1) the latter term

for the former, one can form a lower bound on $E[y(1)]$. Similarly, MTR implies that $E[y|w > d] \geq E[y(d)|w > d]$. As a result, the counterfactual term $E[y(0)|w = 1]$ in the equation for $E[y(0)]$ is smaller or equal to the observed term $E[y|w = 1]$. This in turn implies that one can form an upper bound on $E[y(0)]$ by substituting in (A.1) the latter term for the former. On the other hand, given that $P(w < 0) = P(w > 1) = 0$, (7) implies that the lower bound on $E[y(0)]$ and the upper bound on $E[y(1)]$ do not change after imposing the MTR assumption. Hence, the MTR bounds on $E[y(0)]$ and $E[y(1)]$ are equal to

$$\begin{aligned} LB^{MTR}[0] &= E[y|w = 0]P(w = 0) + Y_{min}P(w = 1) \\ UB^{MTR}[0] &= E[y|w = 0]P(w = 0) + E[y|w = 1]P(w = 1) = E(y) \\ LB^{MTR}[1] &= E[y|w = 0]P(w = 0) + E[y|w = 1]P(w = 1) = E(y) \\ UB^{MTR}[1] &= Y_{max}P(w = 0) + E[y|w = 1]P(w = 1) \end{aligned} \tag{A.4}$$

Equation (A.4) implies that the narrower, relative to NA, identification region of $E[y(0)]$ under MTR is due to the smaller $UB^{MTR}[0]$ (given that $E[y|w = 1] \leq Y_{max}$). Moreover, the narrower identification region of $E[y(1)]$ is due to the larger $LB^{MTR}[1]$ (given that $E[y|w = 0] \geq Y_{min}$). In addition, both $UB^{MTR}[0]$ and $LB^{MTR}[1]$ are equal to the overall sample mean. The values of the MTR bounds on all outcomes are shown in Appendix Table A.1.

The above imply that the ATE under MTR can be bounded as follows:

$$\begin{gathered} LB^{MTR}[1] - UB^{MTR}[0] \leq ATE \leq UB^{MTR}[1] - LB^{MTR}[0] \\ \Longrightarrow \\ 0 \leq ATE \leq \\ \left[Y_{max} - E[y|w = 0]\right]P(w = 0) + [E[y|w = 1] - Y_{min}]P(w = 1) \end{gathered} \tag{A.5}$$

As a result, under MTR the ATE is bounded below by zero, while its upper bound is equal to the one under NA.

A.3 MTR+MTS Bounds

The MTS assumption in (11) implies that $E[y|w = d] \leq E[y(d)|w < d]$. Hence, the counterfactual term $E[y(0)|w = 1]$ in the equation for $E[y(0)]$ is larger or equal than the observed term $E[y|w = 0]$. This in turn implies that one can form a lower bound on $E[y(0)]$ by substituting in (A.1) the latter term for the former. Similarly, MTS implies that $E[y|w = d] \geq E[y(d)|w < d]$. Hence, the counterfactual term $E[y(1)|w = 0]$ in the equation for $E[y(1)]$ is smaller or equal than the observed term $E[y|w = 1]$. As a result, one can form an upper bound on $E[y(1)]$ by substituting in (A.1) the latter term for the former. On the other hand, given that $P(w < 0) = P(w > 1) = 0$, (10) implies that the upper bound of $E[y(0)]$ and the lower bound of $E[y(1)]$ do not change after adding the MTS assumption to the MTR one.

The above imply that the MTR+MTS bounds on $E[y(0)]$ and $E[y(1)]$ are equal to

$$\begin{aligned} LB^{MTR+MTS}[0] &= E[y|w = 0]P(w = 0) + E[y|w = 0]P(w = 1) = E[y|w = 0] \\ UB^{MTR+MTS}[0] &= E[y|w = 0]P(w = 0) + E[y|w = 1]P(w = 1) = E[y] \\ LB^{MTR+MTS}[1] &= E[y|w = 0]P(w = 0) + E[y|w = 1]P(w = 1) = E[y] \\ UB^{MTR+MTS}[1] &= E[y|w = 1]P(w = 0) + E[y|w = 1]P(w = 1) = E[y|w = 1] \end{aligned} \tag{A.6}$$

As implied by (A.6), the narrower (relative to MTR) identification region of $E[y(0)]$ under MTR+MTS is due to a larger $LB[0]$ (given that $E[y|w = 0] \geq Y_{min}$. Moreover, the narrower identification region of $E[y(1)]$ is due to a smaller $UB[1]$ (given that $E[y|w = 1] \leq Y_{max}$). These two bounds are now equal to the observed mean outcomes evaluated at the respective treatment values. Once more, the values of the MTR+MTS bounds on all outcomes are shown in Appendix Table A.1.

Equation (A.6) implies that the bounds on the ATE under MTR+MTS are equal to

$$\begin{gathered} LB^{MTR+MTS}[1] - UB^{MTR+MTS}[0] \\ \leq ATE \leq \\ UB^{MTR+MTS}[1] - LB^{MTR+MTS}[0] \\ \Longrightarrow \\ 0 \leq ATE \leq E[y|w = 1] - E[y|w = 0] \end{gathered} \tag{A.7}$$

Hence, the ATE under MTR+MTS is bounded below by zero and bounded above by the difference in observed mean outcomes, i.e. by the ATE under ETS.

A.4 Testing the MTR+MTS Assumption

While both the MTR assumption shown in (9) and the MTS assumption shown in (11) refer to the unobserved potential outcome $E[y(0)]$, MP (p. 1004) show that the combination of these two assumptions results in weak inequalities between observables quantities, namely the observed mean outcomes for given values of the treatment. In particular, they show that MTR+MTS implies that for any pair of treatment values $d_1 \in D$ and $d_2 \in D$ such that $d_2 > d_1$,

$$\begin{aligned} E[y|w = d_2] = E[y(d_2)|w = d_2] \geq E[y(d_2)|w = d_1] \\ \geq E[y(d_1)|w = d_1] = E[y|w = d_1] \end{aligned} \tag{A.8}$$

The first inequality in (A.8) is due to the MTS assumption, while the second one to the MTR assumption. (A.8) implies that one can test the joint MTR+MTS assumption by testing whether the observed mean outcomes are weakly increasing in the values of the treatment.

Table 1. Descriptive Statistics

Variable	Sweden	Denmark	Germany	Netherlands	Belgium	France
Number of correctly answered numeracy questions (max=4)	2.63	2.55	2.62	2.64	2.35	2.18
Number of words in fluency test	22.85	22.25	20.64	20.04	19.95	19.32
Number of words recalled immediately (max=10)	5.30	5.53	5.39	5.31	5.09	4.80
Number of words recalled with a delay (max=10)	4.13	4.34	3.86	4.03	3.57	3.43
Participation in at least one social activity	0.335	0.460	0.255	0.454	0.317	0.272
Number of observations	7,465	6,187	6,883	8,012	11,569	10,983

Variable	Switzerland	Austria	Italy	Spain	Greece	Czech Rep.
Number of correctly answered numeracy questions (max=4)	2.78	2.72	1.89	1.52	2.35	2.56
Number of words in fluency test	20.26	21.72	14.17	14.47	14.43	21.64
Number of words recalled immediately (max=10)	5.45	5.30	4.42	3.84	4.73	5.33
Number of words recalled with a delay (max=10)	4.17	3.89	2.94	2.49	3.23	3.70
Participation in at least one social activity	0.345	0.192	0.128	0.111	0.079	0.163
Number of observations	5,907	8,109	8,844	7,808	5,581	8,415

Variable	Poland	Hungary	Portugal	Slovenia	Estonia	Total
Number of correctly answered numeracy questions (max=4)	1.87	2.33	1.88	2.13	2.36	2.19
Number of words in fluency test	16.20	17.38	13.31	20.72	21.53	18.13
Number of words recalled immediately (max=10)	4.44	5.10	4.21	4.82	5.18	4.84
Number of words recalled with a delay (max=10)	2.85	3.57	3.07	3.24	3.62	3.39
Participation in at least one social activity	0.035	0.093	0.060	0.221	0.146	0.211
Number of observations	4,054	2,923	1,950	2,668	6,620	113,978

Notes: All figures denote weighted averages. Social activities are considered to be performed only if respondents answer that they engage in them at least once a week.

Table 2. Average Treatment Effect of Social Activity on Cognitive Test Scores

Method	Numeracy				Fluency				Immediate Recall				Delayed recall			
	Lower Bound	Upper Bound	Low 95% CI	High 95% CI	Lower Bound	Upper Bound	Low 95% CI	High 95% CI	Lower Bound	Upper Bound	Low 95% CI	High 95% CI	Lower Bound	Upper Bound	Low 95% CI	High 95% CI
Panel A. Whole Sample																
Exogenous Treatment Selection	0.564		0.533	0.595	4.191		3.990	4.393	0.924		0.878	0.970	0.986		0.931	1.040
No Assumptions	-1.939	2.061	-1.952	2.073	-30.325	69.675	-30.629	69.978	-4.596	5.404	-4.616	5.424	-3.747	6.253	-3.774	6.280
MTR	0.000	2.061	0.000	2.073	0.000	69.675	0.000	69.978	0.000	5.404	0.000	5.424	0.000	6.253	0.000	6.280
MTR + MTS	0.000	0.564	0.000	0.593	0.000	4.191	0.000	4.375	0.000	0.924	0.000	0.968	0.000	0.986	0.000	1.035
MTR + MTS + MIV	0.164	0.566	0.140	0.596	0.898	4.200	0.717	4.386	0.294	0.898	0.256	0.945	0.325	0.950	0.279	1.002
Number of observations	92,582				112,164				112,696				112,678			
Panel B. Females																
Exogenous Treatment Selection	0.580		0.538	0.622	4.844		4.566	5.123	1.121		1.057	1.186	1.241		1.163	1.318
No Assumptions	-1.817	2.183	-1.833	2.199	-29.021	70.979	-29.390	71.348	-4.537	5.463	-4.564	5.491	-3.659	6.341	-3.690	6.373
MTR	0.000	2.183	0.000	2.199	0.000	70.979	0.000	71.348	0.000	5.463	0.000	5.491	0.000	6.341	0.000	6.373
MTR + MTS	0.000	0.580	0.000	0.617	0.000	4.844	0.000	5.097	0.000	1.121	0.000	1.181	0.000	1.241	0.000	1.313
MTR + MTS + MIV	0.272	0.563	0.233	0.602	1.716	4.764	1.482	5.035	0.579	1.071	0.520	1.134	0.624	1.178	0.557	1.253
Number of observations	50,854				61,943				62,190				62,176			
Panel C. Males																
Exogenous Treatment Selection	0.494		0.448	0.540	3.368		3.077	3.660	0.705		0.641	0.770	0.712		0.637	0.788
No Assumptions	-2.089	1.911	-2.107	1.929	-31.931	68.069	-32.368	68.505	-4.669	5.331	-4.697	5.358	-3.856	6.144	-3.891	6.180
MTR	0.000	1.911	0.000	1.929	0.000	68.069	0.000	68.505	0.000	5.331	0.000	5.358	0.000	6.144	0.000	6.180
MTR + MTS	0.000	0.494	0.000	0.534	0.000	3.368	0.000	3.633	0.000	0.705	0.000	0.763	0.000	0.712	0.000	0.780
MTR + MTS + MIV	0.000	0.487	0.000	0.527	0.002	3.338	0.000	3.604	0.086	0.697	0.037	0.756	0.129	0.691	0.073	0.762
Number of observations	41,728				50,221				50,506				50,502			

Table 3. Average Treatment Effect of Social Activity on Cognitive Test Scores, by Country Group

Method	Numeracy				Fluency				Immediate Recall				Delayed recall			
	Lower Bound	Upper Bound	Low 95% CI	High 95% CI	Lower Bound	Upper Bound	Low 95% CI	High 95% CI	Lower Bound	Upper Bound	Low 95% CI	High 95% CI	Lower Bound	Upper Bound	Low 95% CI	High 95% CI
Panel A. Northern Europe																
Exogenous Treatment Selection	0.373		0.327	0.418	2.749		2.434	3.064	0.589		0.520	0.657	0.731		0.645	0.817
No Assumptions	-2.126	1.874	-2.151	1.899	-37.143	62.857	-37.726	63.440	-4.896	5.104	-4.931	5.139	-4.252	5.748	-4.296	5.792
MTR	0.000	1.874	0.000	1.899	0.000	62.857	0.000	63.440	0.000	5.104	0.000	5.139	0.000	5.748	0.000	5.792
MTR + MTS	0.000	0.373	0.000	0.415	0.000	2.749	0.000	3.035	0.000	0.589	0.000	0.653	0.000	0.731	0.000	0.809
MTR + MTS + MIV	0.030	0.373	0.000	0.415	0.441	2.736	0.132	3.022	0.145	0.584	0.079	0.650	0.202	0.709	0.119	0.791
Number of observations	30,779				39,703				39,794				39,794			
Panel B. Middle Europe																
Exogenous Treatment Selection	0.399		0.346	0.452	3.026		2.708	3.344	0.703		0.617	0.788	0.770		0.672	0.868
No Assumptions	-1.996	2.004	-2.019	2.027	-35.043	64.957	-35.677	65.590	-4.684	5.316	-4.718	5.351	-4.033	5.967	-4.083	6.018
MTR	0.000	2.004	0.000	2.027	0.000	64.957	0.000	65.590	0.000	5.316	0.000	5.351	0.000	5.967	0.000	6.018
MTR + MTS	0.000	0.399	0.000	0.446	0.000	3.026	0.000	3.342	0.000	0.703	0.000	0.780	0.000	0.770	0.000	0.861
MTR + MTS + MIV	0.155	0.398	0.110	0.447	1.016	2.876	0.685	3.197	0.331	0.661	0.254	0.743	0.406	0.710	0.306	0.803
Number of observations	20,778				24,538				24,731				24,725			
Panel C. Southern Europe																
Exogenous Treatment Selection	0.508		0.434	0.582	2.967		2.577	3.356	1.034		0.922	1.147	0.843		0.722	0.964
No Assumptions	-1.735	2.265	-1.756	2.286	-22.072	77.928	-22.522	78.378	-4.191	5.809	-4.229	5.847	-3.140	6.860	-3.186	6.905
MTR	0.000	2.265	0.000	2.286	0.000	77.928	0.000	78.378	0.000	5.809	0.000	5.847	0.000	6.860	0.000	6.905
MTR + MTS	0.000	0.508	0.000	0.574	0.000	2.967	0.000	3.302	0.000	1.034	0.000	1.134	0.000	0.843	0.000	0.950
MTR + MTS + MIV	0.320	0.471	0.275	0.542	1.475	2.879	1.245	3.244	0.490	0.944	0.418	1.047	0.469	0.780	0.394	0.893
Number of observations	20,023				23,744				23,884				23,880			
Panel D. Eastern Europe																
Exogenous Treatment Selection	0.713		0.625	0.801	5.322		4.592	6.052	1.061		0.862	1.260	1.214		0.972	1.455
No Assumptions	-2.019	1.981	-2.049	2.011	-21.575	78.425	-21.982	78.832	-4.606	5.394	-4.657	5.445	-3.224	6.776	-3.281	6.832
MTR	0.000	1.981	0.000	2.011	0.000	78.425	0.000	78.832	0.000	5.394	0.000	5.445	0.000	6.776	0.000	6.832
MTR + MTS	0.000	0.713	0.000	0.798	0.000	5.322	0.000	6.002	0.000	1.061	0.000	1.247	0.000	1.214	0.000	1.450
MTR + MTS + MIV	0.045	0.707	0.000	0.793	0.751	5.290	0.461	5.967	0.205	1.082	0.129	1.256	0.261	1.197	0.179	1.402
Number of observations	21,002				24,179				24,287				24,279			

Notes: Northern Europe consists of Sweden, Denmark, Germany, the Netherlands and Belgium. Middle Europe consists of France, Switzerland and Austria. Southern Europe consists of Italy, Spain, Portugal and Greece. Eastern Europe consists of the Czech Republic, Poland, Hungary, Slovenia and Estonia.

Table 4. Average Treatment Effect of Social Activity on Cognitive Test Scores, 3-valued MIV

Method	Numeracy				Fluency				Immediate Recall				Delayed recall			
	Lower Bound	**Upper Bound**	**Low 95% CI**	**High 95% CI**	**Lower Bound**	**Upper Bound**	**Low 95% CI**	**High 95% CI**	**Lower Bound**	**Upper Bound**	**Low 95% CI**	**High 95% CI**	**Lower Bound**	**Upper Bound**	**Low 95% CI**	**High 95% CI**
								A1. Whole Sample								
MTR + MTS + MIV	0.164	0.485	0.140	0.528	0.894	3.305	0.724	3.591	0.294	0.759	0.256	0.828	0.325	0.776	0.279	0.849
								A2. Females								
MTR + MTS + MIV	0.272	0.503	0.233	0.555	1.716	3.650	1.482	4.000	0.586	0.810	0.527	0.893	0.611	0.858	0.543	0.945
								A3. Males								
MTR + MTS + MIV	0.004	0.492	0.000	0.533	0.257	2.971	0.193	3.347	0.086	0.687	0.037	0.775	0.129	0.681	0.073	0.779

Table 5. Average Treatment Effect of Social Activity on the Probability of Scoring above the Median in the Cognitive Tests

Method	Numeracy				Fluency				Immediate Recall				Delayed recall			
	Lower Bound	Upper Bound	Low 95% CI	High 95% CI	Lower Bound	Upper Bound	Low 95% CI	High 95% CI	Lower Bound	Upper Bound	Low 95% CI	High 95% CI	Lower Bound	Upper Bound	Low 95% CI	High 95% CI
Panel A. Whole Sample																
Exogenous Treatment Selection	0.208		0.194	0.222	0.254		0.241	0.267	0.212		0.200	0.224	0.175		0.164	0.187
No Assumptions	-0.383	0.617	-0.388	0.622	-0.447	0.553	-0.453	0.559	-0.485	0.515	-0.490	0.521	-0.538	0.462	-0.543	0.467
MTR	0.000	0.617	0.000	0.622	0.000	0.553	0.000	0.559	0.000	0.515	0.000	0.521	0.000	0.462	0.000	0.467
MTR + MTS	0.000	0.208	0.000	0.221	0.000	0.254	0.000	0.266	0.000	0.212	0.000	0.223	0.000	0.175	0.000	0.186
MTR + MTS + MIV	0.039	0.208	0.028	0.220	0.051	0.255	0.040	0.267	0.067	0.209	0.057	0.220	0.062	0.172	0.053	0.183
Number of observations	92,582				112,164				112,696				112,678			
Panel B. Females																
Exogenous Treatment Selection	0.206		0.187	0.225	0.296		0.279	0.312	0.248		0.232	0.264	0.210		0.196	0.224
No Assumptions	-0.338	0.662	-0.344	0.669	-0.421	0.579	-0.428	0.585	-0.476	0.524	-0.483	0.531	-0.534	0.466	-0.541	0.473
MTR	0.000	0.662	0.000	0.669	0.000	0.579	0.000	0.585	0.000	0.524	0.000	0.531	0.000	0.466	0.000	0.473
MTR + MTS	0.000	0.206	0.000	0.223	0.000	0.296	0.000	0.310	0.000	0.248	0.000	0.263	0.000	0.210	0.000	0.222
MTR + MTS + MIV	0.069	0.201	0.053	0.219	0.105	0.290	0.089	0.305	0.135	0.239	0.121	0.255	0.119	0.206	0.105	0.219
Number of observations	50,854				61,943				62,190				62,176			
Panel C. Males																
Exogenous Treatment Selection	0.192		0.171	0.213	0.202		0.183	0.222	0.171		0.153	0.189	0.137		0.119	0.155
No Assumptions	-0.438	0.562	-0.445	0.569	-0.478	0.522	-0.486	0.529	-0.495	0.505	-0.503	0.512	-0.543	0.457	-0.551	0.464
MTR	0.000	0.562	0.000	0.569	0.000	0.522	0.000	0.529	0.000	0.505	0.000	0.512	0.000	0.457	0.000	0.464
MTR + MTS	0.000	0.192	0.000	0.210	0.000	0.202	0.000	0.219	0.000	0.171	0.000	0.187	0.000	0.137	0.000	0.153
MTR + MTS + MIV	0.000	0.187	0.000	0.206	0.000	0.201	0.000	0.218	0.016	0.172	0.003	0.189	0.021	0.133	0.008	0.150
Number of observations	41,728				50,221				50,506				50,502			

Table 6. Average Treatment Effect of Cognition on Household Net Worth and Net Financial Assets

Method	Net Worth				Net Financial Assets			
	Lower Bound	Upper Bound	Low 95% CI	High 95% CI	Lower Bound	Upper Bound	Low 95% CI	High 95% CI
	Panel A. Numeracy							
Exogenous Treatment Selection	1.402		1.281	1.524	2.144		1.965	2.322
No Assumptions	-17.087	17.655	-17.232	17.800	-15.538	17.159	-15.651	17.272
MTR	0.000	17.655	0.000	17.800	0.000	17.159	0.000	17.272
MTR + MTS	0.000	1.402	0.000	1.508	0.000	2.144	0.000	2.298
MTR + MTS + MIV	0.000	0.970	0.000	1.080	0.002	1.827	0.000	2.005
Number of observations	61,275				61,275			
	Panel B. Fluency							
Exogenous Treatment Selection	1.188		1.057	1.319	1.882		1.707	2.058
No Assumptions	-14.613	20.129	-14.748	20.264	-14.065	18.632	-14.176	18.744
MTR	0.000	20.129	0.000	20.264	0.000	18.632	0.000	18.744
MTR + MTS	0.000	1.188	0.000	1.305	0.000	1.882	0.000	2.035
MTR + MTS + MIV	0.000	0.654	0.000	0.763	0.000	1.461	0.000	1.624
Number of observations	73,652				73,652			
	Panel C. Immediate Recall							
Exogenous Treatment Selection	1.236		1.103	1.368	1.473		1.300	1.647
No Assumptions	-13.689	21.054	-13.825	21.190	-13.707	18.990	-13.815	19.098
MTR	0.000	21.054	0.000	21.190	0.000	18.990	0.000	19.098
MTR + MTS	0.000	1.236	0.000	1.360	0.000	1.473	0.000	1.632
MTR + MTS + MIV	0.000	0.697	0.000	0.823	0.000	0.955	0.000	1.123
Number of observations	73,876				73,876			
	Panel D. Delayed Recall							
Exogenous Treatment Selection	1.191		1.043	1.338	1.323		1.138	1.509
No Assumptions	-12.333	22.409	-12.458	22.534	-12.935	19.762	-13.043	19.869
MTR	0.000	22.409	0.000	22.534	0.000	19.762	0.000	19.869
MTR + MTS	0.000	1.191	0.000	1.323	0.000	1.323	0.000	1.489
MTR + MTS + MIV	0.000	0.598	0.000	0.718	0.000	0.749	0.000	0.917
Number of observations	73,876				73,876			

Notes: Both net worth and net financial assets are transformed using the inverse hyperbolic sine transformation.

Appendix Table A.1. Bounds on $E[y(d)]$ of cognitive scores

Method	Numeracy				Fluency				Immediate Recall				Delayed recall			
	Lower Bound	Upper Bound	Low 95% CI	High 95% CI	Lower Bound	Upper Bound	Low 95% CI	High 95% CI	Lower Bound	Upper Bound	Low 95% CI	High 95% CI	Lower Bound	Upper Bound	Low 95% CI	High 95% CI
Panel A. Whole Sample																
ETS																
E[y(0)]	2.079		2.064	2.094	17.230		17.136	17.325	4.639		4.616	4.663	3.184		3.158	3.209
E[y(1)]	2.643		2.616	2.670	21.422		21.246	21.598	5.564		5.524	5.603	4.169		4.121	4.217
NA																
E[y(0)]	1.677	2.451	1.663	2.465	13.553	34.898	13.444	35.303	3.652	5.780	3.624	5.813	2.506	4.634	2.481	4.674
E[y(1)]	0.511	3.738	0.500	3.745	4.573	83.227	4.461	83.599	1.184	9.056	1.155	9.078	0.887	8.759	0.865	8.787
MTR																
E[y(0)]	1.677	2.188	1.663	2.201	13.553	18.125	13.444	18.216	3.652	4.836	3.624	4.858	2.506	3.393	2.481	3.418
E[y(1)]	2.188	3.738	2.175	3.745	18.125	83.227	18.034	83.599	4.836	9.056	4.814	9.078	3.393	8.759	3.369	8.787
MTR + MTS																
E[y(0)]	2.079	2.188	2.065	2.201	17.230	18.125	17.133	18.216	4.639	4.836	4.615	4.858	3.184	3.393	3.156	3.418
E[y(1)]	2.188	2.643	2.175	2.668	18.125	21.422	18.034	21.588	4.836	5.564	4.814	5.602	3.393	4.169	3.369	4.211
MTR + MTS + MIV																
E[y(0)]	2.079	2.188	2.065	2.201	17.230	18.125	17.133	18.216	4.639	4.836	4.615	4.858	3.184	3.393	3.156	3.418
E[y(1)]	2.352	2.645	2.325	2.671	19.023	21.431	18.828	21.600	5.130	5.538	5.088	5.579	3.718	4.133	3.668	4.179
Panel B. Females																
ETS																
E[y(0)]	1.876		1.856	1.896	16.635		16.512	16.758	4.601		4.569	4.634	3.182		3.147	3.217
E[y(1)]	2.456		2.419	2.493	21.479		21.232	21.726	5.723		5.667	5.778	4.423		4.354	4.492
NA																
E[y(0)]	1.543	2.252	1.525	2.271	13.306	33.320	13.179	33.807	3.685	5.676	3.648	5.715	2.548	4.540	2.515	4.587
E[y(1)]	0.435	3.726	0.422	3.736	4.299	84.285	4.166	84.726	1.140	9.148	1.106	9.174	0.881	8.889	0.850	8.922
MTR																
E[y(0)]	1.543	1.979	1.525	1.995	13.306	17.605	13.179	17.716	3.685	4.825	3.648	4.852	2.548	3.429	2.515	3.461
E[y(1)]	1.979	3.726	1.962	3.736	17.605	84.285	17.493	84.726	4.825	9.148	4.797	9.174	3.429	8.889	3.397	8.922
MTR + MTS																
E[y(0)]	1.876	1.979	1.857	1.995	16.635	17.605	16.517	17.716	4.601	4.825	4.570	4.852	3.182	3.429	3.148	3.461
E[y(1)]	1.979	2.456	1.962	2.488	17.605	21.479	17.493	21.704	4.825	5.723	4.797	5.772	3.429	4.423	3.397	4.488
MTR + MTS + MIV																
E[y(0)]	1.876	1.979	1.857	1.995	16.635	17.605	16.517	17.716	4.601	4.825	4.570	4.852	3.182	3.429	3.148	3.461
E[y(1)]	2.251	2.439	2.210	2.474	19.320	21.399	19.076	21.645	5.404	5.673	5.342	5.726	4.053	4.359	3.981	4.429
Panel C. Males																
ETS																
E[y(0)]	2.339		2.318	2.361	17.992		17.848	18.135	4.688		4.655	4.722	3.186		3.149	3.224
E[y(1)]	2.834		2.794	2.874	21.360		21.110	21.610	5.393		5.339	5.448	3.898		3.833	3.964
NA																
E[y(0)]	1.841	2.693	1.820	2.711	13.856	36.841	13.692	37.423	3.612	5.907	3.571	5.952	2.454	4.751	2.420	4.804
E[y(1)]	0.604	3.751	0.586	3.762	4.910	81.925	4.749	82.475	1.238	8.943	1.199	8.977	0.895	8.599	0.865	8.642
MTR																
E[y(0)]	1.841	2.445	1.820	2.462	13.856	18.766	13.692	18.888	3.612	4.850	3.571	4.879	2.454	3.350	2.420	3.381
E[y(1)]	2.445	3.751	2.428	3.762	18.766	81.925	18.644	82.475	4.850	8.943	4.821	8.977	3.350	8.599	3.319	8.642
MTR + MTS																
E[y(0)]	2.339	2.445	2.320	2.462	17.992	18.766	17.855	18.888	4.688	4.850	4.655	4.879	3.186	3.350	3.151	3.381
E[y(1)]	2.445	2.834	2.428	2.868	18.766	21.360	18.644	21.591	4.850	5.393	4.821	5.442	3.350	3.898	3.319	3.958
MTR + MTS + MIV																
E[y(0)]	2.339	2.445	2.320	2.462	17.992	18.766	17.855	18.888	4.688	4.850	4.655	4.879	3.186	3.350	3.151	3.381
E[y(1)]	2.445	2.827	2.427	2.861	18.768	21.330	18.573	21.563	4.936	5.385	4.880	5.435	3.479	3.877	3.415	3.941

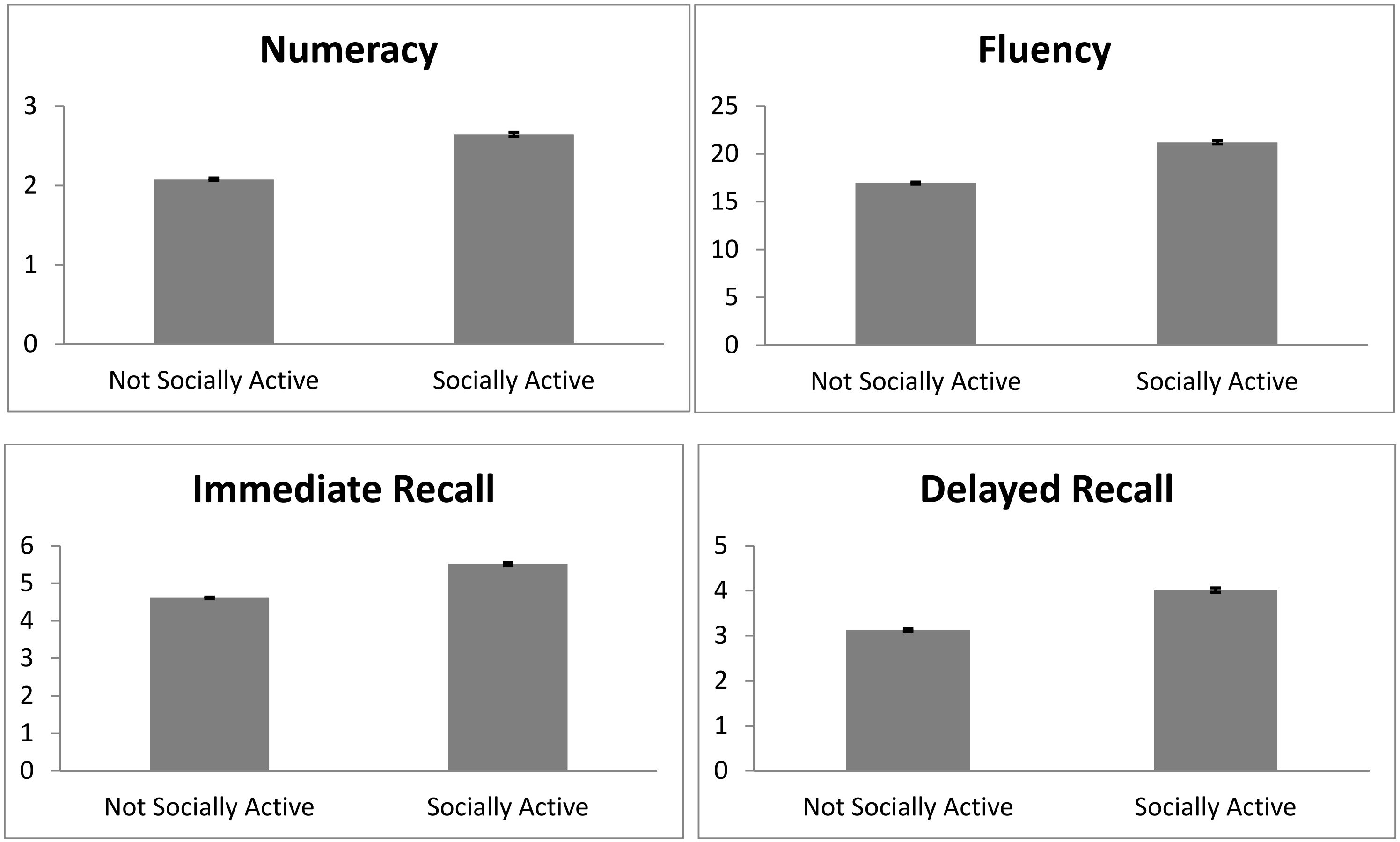
Notes: The ETS values are the observed mean scores. The MTR+MTS+MIV bounds on $E[y(0)]$ are equal to the MTR+MTS ones. The treatment variable is social participation.

Appendix Table A.2. Bounds on $E[y(d)]$ of net worth and net financial assets

Method	Net Worth				Net Financial Assets			
	Lower Bound	Upper Bound	Low 95% CI	High 95% CI	Lower Bound	Upper Bound	Low 95% CI	High 95% CI
Panel A. Numeracy								
ETS								
E[y(0)]	10.523		10.423	10.622	5.881		5.755	6.007
E[y(1)]	11.925		11.856	11.994	8.024		7.899	8.149
NA								
E[y(0)]	-2.508	14.171	-2.686	14.238	-4.600	11.097	-4.750	11.189
E[y(1)]	-2.916	15.147	-3.103	15.195	-4.441	12.559	-4.604	12.636
MTR								
E[y(0)]	-2.508	11.196	-2.686	11.251	-4.600	6.910	-4.750	6.990
E[y(1)]	11.196	15.147	11.141	15.195	6.910	12.559	6.830	12.636
MTR + MTS								
E[y(0)]	10.523	11.196	10.435	11.251	5.881	6.910	5.770	6.990
E[y(1)]	11.196	11.925	11.141	11.985	6.910	8.024	6.830	8.133
MTR + MTS + MIV								
E[y(0)]	10.752	11.198	10.668	11.253	6.052	6.910	5.932	7.000
E[y(1)]	11.197	11.723	11.142	11.795	6.913	7.879	6.829	8.013
Panel B. Fluency								
ETS								
E[y(0)]	10.463		10.353	10.573	5.851		5.721	5.981
E[y(1)]	11.651		11.581	11.722	7.733		7.617	7.850
NA								
E[y(0)]	-5.922	15.097	-6.088	15.163	-7.338	12.442	-7.482	12.524
E[y(1)]	0.484	14.208	0.303	14.263	-1.622	11.294	-1.785	11.379
MTR								
E[y(0)]	-5.922	11.182	-6.088	11.242	-7.338	6.990	-7.482	7.070
E[y(1)]	11.182	14.208	11.122	14.263	6.990	11.294	6.909	11.379
MTR + MTS								
E[y(0)]	10.463	11.182	10.362	11.242	5.851	6.990	5.738	7.070
E[y(1)]	11.182	11.651	11.122	11.717	6.990	7.733	6.909	7.840
MTR + MTS + MIV								
E[y(0)]	10.782	11.181	10.694	11.241	6.068	7.002	5.950	7.089
E[y(1)]	11.181	11.436	11.121	11.513	6.986	7.530	6.904	7.650
Panel C. Immediate Recall								
ETS								
E[y(0)]	10.370		10.259	10.481	6.024		5.895	6.154
E[y(1)]	11.605		11.533	11.677	7.498		7.384	7.612
NA								
E[y(0)]	-7.165	15.406	-7.331	15.469	-8.252	12.990	-8.388	13.067
E[y(1)]	1.718	13.888	1.538	13.948	-0.716	10.738	-0.870	10.826
MTR								
E[y(0)]	-7.165	11.172	-7.331	11.233	-8.252	6.982	-8.388	7.060
E[y(1)]	11.172	13.888	11.112	13.948	6.982	10.738	6.904	10.826
MTR + MTS								
E[y(0)]	10.370	11.172	10.265	11.233	6.024	6.982	5.908	7.060
E[y(1)]	11.172	11.605	11.112	11.675	6.982	7.498	6.904	7.602
MTR + MTS + MIV								
E[y(0)]	10.690	11.174	10.593	11.234	6.338	6.988	6.214	7.068
E[y(1)]	11.174	11.387	11.114	11.473	6.975	7.293	6.893	7.405
Panel D. Delayed Recall								
ETS								
E[y(0)]	10.316		10.185	10.446	6.029		5.878	6.180
E[y(1)]	11.506		11.439	11.574	7.353		7.247	7.458
NA								
E[y(0)]	-9.041	15.926	-9.200	15.983	-9.766	13.731	-9.900	13.803
E[y(1)]	3.593	13.368	3.427	13.429	0.796	9.996	0.644	10.085
MTR								
E[y(0)]	-9.041	11.171	-9.200	11.231	-9.766	6.980	-9.900	7.062
E[y(1)]	11.171	13.368	11.111	13.429	6.980	9.996	6.899	10.085
MTR + MTS								
E[y(0)]	10.316	11.171	10.193	11.231	6.029	6.980	5.892	7.062
E[y(1)]	11.171	11.506	11.111	11.570	6.980	7.353	6.899	7.451
MTR + MTS + MIV								
E[y(0)]	10.734	11.171	10.630	11.231	6.428	6.989	6.292	7.075
E[y(1)]	11.171	11.333	11.111	11.404	6.973	7.177	6.889	7.281

Notes: Both net worth and net financial assets are transformed using the inverse hyperbolic sine transformation. The ETS values are the observed mean scores. The treatment variables are the binary indicators of the cognition scores.

Fig. 1. Means of the four cognitive test scores, by the level of social activity



Notes: The height of the histogram bars corresponds to the weighted average of the cognition score within the group of individuals who exhibit the particular level of social activities. The vertical lines in the middle of the bars denote 95% confidence intervals.