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ISSN: 2365-9793

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ABSTRACT

Too Healthy to Fall Sick? Longevity Expectations and Protective Health Behaviours during the First Wave of COVID-19

Longevity expectations (LE) are subjective assessments of future health status that can influence a number of individual health protective decisions. This is especially true during a pandemic such as COVID-19, as the risk of ill health depends more than ever on such protective decisions. This paper exploits differences in LE to examine the causal effect of LE on protective health behaviours and a number of decisions around access to health care, using data from the Survey of Health Ageing and Retirement in Europe. We draw on an instrumental variable strategy exploiting individual level information on parental age at death. Consistent with the too healthy to be sick hypothesis, we find that individuals with higher expected longevity are more likely to engage in protective behaviours, and are less likely to forgo medical treatment. We estimate that a one standard deviation increase in expected longevity increases the probability to comply always with social distancing by 0.6%, to meet people less often by 0.4% and decreases the probability to forgo any medical treatment by 0.6%. Our estimates vary depending on the availability of health care, as well as individuals' gender and pre-existing health conditions.

JEL Classification: I12, I18

Keywords: longevity expectations, private information, health behaviours, forgone medical treatment, health capital, SHARE, Europe, instrumental variables, COVID-19

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1 Introduction

Longevity expectations (LE) are subjective assessments that amalgamate specific information such as an individual's genetics background and previous health investments (Perozek 2008, Hakes & Viscusi 1997). LE predict the time of one's death (e.g. Smith et al. 2001) and, the literature has shown that they are consistent with life tables (Hurd & McGarry 2002), even though they do exhibit some bias (Arni et al. 2021), expecially when they are compared with end-of-life data (Costa-Font & Vilaplana 2022).

LE influence the subjective time horizon of a utility—maximizer consumer, which ultimately affects her individual behaviours such as the decision of how much to save, to insure against old age risks, or when to retire (Hamermesh 1985). So far, the economics literature has documented that LE shape investment decisions, wealth accumulation as well as health and consumption decisions (Khan et al. 2014, Salm 2010, Costa-Font & Vilaplana 2022). To date, it is unclear how LE influence similar protective health behaviours during a pandemic where the risk of ill health due to the virus is more salient, and dependent on such behaviours. It is theoretically unclear how individuals react in the face of ill health.

This paper studies the effect of individual longevity expectations on protective health and other behaviours, which are of paramount importance in the context of a pandemic, as they influence their own health, and that of others they interact with.

Protective behaviours such as frequent hand washing, physical distancing or staying-at-home recommendations have been at the for front of public interventions focused limiting the spread of the virus across the population. Understanding people's behaviour, compliance and their determinants is therefore critical to designing current and future policy actions (Papageorge et al. 2021). So far, the evidence suggests cumulative effects in the uptake of key protective behaviours such as mask wearing though there are differences across behaviours; for instance, the uptake of physical distancing exhibits a non-linear effect and is influenced by social trust (Petherick et al. 2021). Explanations for such behaviours are typically linked to *pandemic fatigue*, and the opportunity costs of each one of such behaviours. In this paper, we offer an alternative explanation. We examine whether private information influences how individuals uniquely perceive the costs of limited protective behaviours to themselves and others. Furthermore, we study how LE affected decisions around avoiding necessary health care. During the COVID-19 pandemic, LE might have led to rescheduling medical visits or treatments, even though it might lead to a disinvestment in health. Consistently, Anderson et al. (2021) and Park & Stimpson (2021) show that the COVID-19 pandemic may have reduced or delayed access to medical care among Medicare beneficiaries for instance. However, to date, we do not know the underpinning behavioural mechanisms.

To reduce the risk of infection, LE may influence the decision to cancel or postpone scheduled medical appointments. However, it is unclear whether individuals are fully capable to evaluate the negative long-term health effects of delaying medical care. To provide some light into this questions, this paper contributes to the literature by identifying a specific mechanism driving such effect, which plays an important role in the formation of some protective behaviours, namely LE.

LE are formed on an individual's current knowledge, which typically comes from public and, especially, private information sources, and cannot be externally observed. Consistently, Smith et al. (2001) show that LE are able to predict actual deaths and are updated when a new health shock occurs accordingly. Among the different sources of private information, relatives' longevity, especially parents' longevity, plays a central role, as stressed in the literature (e.g. Hamermesh 1985, Bonsang & Costa-Font 2020, Costa-Font & Vilaplana 2022). Given that LE might be affected by attitudes and beliefs as well such as optimism and overconfidence biases (Arni et al. 2021), assessing empirically the effect of LE on health behaviours is therefore far from trivial. That is, are individuals expecting to live longer more likely to engage in protective behaviours insofar as they perceive a higher opportunity costs of early death? Or alternatively, does higher subjective longevity breed a sense of overconfidence, and provide a feeling of optimism, that encourage less protective behaviours? This paper follows the economics literature (e.g. Bloom et al. 2006, Fang et al. 2007) and exploits differences in parental age at death to provide local average treatment effects (LATE) estimates of the effect of longevity expectations on both protective behaviours and the decision to forgo medical treatments. We use data from the Survey of Health Ageing and Retirement in Europe (SHARE) both from retrospective and regular waves as well as a special wave designed to understand how older Europeans coped with the pandemic.

The effect of LE is a priori ambiguous because it may induce individuals with better health status, who can avoid being sick, to be imprudent in the presence of overconfidence and optimism biases (Arni et al. 2021, Costa-Font et al. 2009). However, we might expect healthier individuals to value more their health status, and perceiving a larger-than-the-average opportunity cost of engaging in limited protective behaviours. We call the latter the *too healthy to be sick* hypothesis. This paper adds further evidence on the plausibility of each hypothesis in a pandemic. In examining the determinants of protective behaviours, we find that LE proxies the individual specific awareness of its future health status, hence reflecting the potential opportunity costs of not conforming to protective practices. However, such effects are likely to differ according to other characteristics, above and beyond LE such as age. On this regard, this paper documents also heterogeneous effects related to supply-side effects, self-perceived health and gender.

The structure of the paper is as follows. Next, we report the related literature. Section three describes the data. Section four presents the empirical strategy, and section five contains the results and robustness analysis. A final section concludes.

2 Related Literature

2.1 Longevity Expectations and Household Behaviour

LE or subjective assessments of expected longevity play an important role in explaining individual decisions including their health investments, labour supply, insurance purchase, education, occupation and mobility (Ben-Porath 1972, Becker 1994, Jayachandran & Lleras-Muney 2009, among others). Assuming a fixed yearly return, health investments are more valuable in the long term. Accordingly, individuals expecting to live longer should, other things equal, invest more in health. This behaviour can be labelled as the 'too healthy to be sick' hypothesis.

Using the Health and Retirement Study (HRS) data for the United States, Bloom et al. (2006) draw on an instrumental variable framework to document that an increase in the subjective survival exerts a positive effect on household wealth accumulation, but no effect on the length of the working life. Similarly, Bíró (2013) shows that an increased perceived longevity leads to lower consumption levels, slowing down wealth decumulation.

2.2 Longevity Expectations and Health Behaviours

LE play a central role in influencing health related behaviours. Individuals, holding higher longevity expectations, are expected to invest more in healthy behaviours to enjoy better quality of life in those extra years an individual expects to live. This is because they face a higher opportunity cost of unhealthy behaviours. However, LE might also provide a disincentive to invest in health as long as individuals face a lower marginal value of additional years of life (Fang et al. 2007). Hence, it is an empirical question whether one effects prevails over the other.

Consistently, Bertoni et al. (2019) document that an increase in LE decreases the probability of being overweight or obese, and smoking, and increases the likelihood of daily fruit and vegetable consumption and physical activity. Hence, suggesting that the opportunity cost effect dominates the lower marginal value of life effect. However, one can argue that it is at times where individuals have to make critical health related decisions when such differences in expectations formation make a marginal difference.

2.3 Our contribution

This paper complements prior literature by estimating the effect of longevity expectations on investments in health amidst a pandemic (the first wave of the COVID-19 pandemic). We concentrate on identifying the effect among the most vulnerable group of the population, e.g., older individuals, that are exposed to a greater risk of suffering complications from the disease.

We draw on rich European data collected through the first round of a special SHARE COVID-19 survey and the regular waves. The available information allows us to investigate not only the most important protective behaviours authorities have officially promoted to limit the virus proliferation, but also relevant decisions about forgoing medical treatment, to confront the fear of contracting COVID-19 and its potential long-term detrimental effects both to individuals and health care systems. Unlike studies relying on COVID-19 specific surveys, SHARE data contain a rich set of records that can help identifying the effect of longevity expectations and dealing with some challenges such as the effect of individual specific longevity optimism (Costa-Font & Vilaplana 2022).

Preliminary evidence from SHARE COVID-19 data shows that, during the first wave, multimorbidity significantly correlated with protective behaviours after controlling for age, gender, education and financial distress (Delerue Matos et al. 2021). Older Europeans responded strongly to official guidelines, especially, Sand & Bristle (2021) highlight a correlation between threat perceptions and optimistic attitude with protective behaviours. Examining retirement decisions, Bertoni et al. (2021) document that those who retired earlier responded to the pandemic by limiting their mobility more, and by adopting stricter preventive behaviours in public. One potential explanation for such an effect is the one offered in this paper, namely that some individuals might perceive a high opportunity costs of not engaging in protective behaviours in a pandemic, namely being *too healthy to fall sick*. To test this, we examine some of the protective behaviours analysed in Bertoni et al. (2021) and show the role of longevity expectations in shaping them.

COVID-19 has exerted an impact on the access to health care in Europe. Studies using SHARE data show an association between fragile economic conditions and unmet healthcare needs - defined as voluntary forgoing care, having pre-scheduled treatments postponed and being unable to obtain medical appointments when needed (Arnault et al. 2021). This association varies depending on the health conditions of individuals before the outbreak and differs with respect to the cross-country differences in access to healthcare before the pandemic. Smolic et al. (2021) investigate the associations between unmet healthcare needs and micro-level characteristics together with macro-level factors. This study adds to this literature by examining how LE might mediate some of such effects.

3 Data

3.1 The COVID-19 SHARE sample

We use SHARE data, a rich longitudinal database, collecting information on different aspects of health, well being, retirement, socio-economic status and social networks of individuals aged 50 or over in Europe (Börsch-Supan 2019, 2020*a*,*b*).

The first SHARE regular wave was conducted in 2004 and included samples of eleven European countries participating in the study in addition to Israel; the last available wave refers to 2020 and covers entirely the EU-28. In waves 3 (2008/2009) and 7 (2017), the survey additionally collected individuals' retrospective information such as early-childhood conditions and labour market history to allow empirical analysis with a longer term perspective. The COVID-19 outbreak took place during the fieldwork of the eighth wave, and SHARE suspended the data collection process in March 2020 in all countries and in June 2020 collected the first wave of a special COVID-19 survey, which contains very specific questions about life during the first wave of the COVID-19 pandemic. More specifically, a sub-sample of SHARE longitudinal respondents was interviewed via a Computer Assisted Telephone Interview (CATI)[1] covering different domains, including lifestyle changes as well as health, behaviours and healthcare use.

[1] For methodological details see Scherpenzeel et al. (2020).

3.2 Measurement of Longevity Expectations

A central variable of interest in our analysis is longevity expectations. In regular SHARE waves, individuals are asked about *what are the chances they will live to be a specific age or more.* The age threshold, T, used in the question depends on respondent's age: if it is lower or equal then 65, T is 75; if it is in between 66 and 70, T is 80; if it is in between 71 and 75, T is 85; if it is in between 76 and 80, T is 90. The question is asked also to individuals older than 80 years of age, but we do not consider individuals aged 81 or more because they are very selected. Respondents can elicit their longevity expectations question using a scale that goes from zero to one hundred percent. This is a standard question used in a series of previous studies (Hurd & McGarry 2002).

Given that LE do not vary in short periods of time, in our analysis we use the most recent subjective longevity expectation assessment in SHARE. As we can report in Table B.1 in Appendix, for the majority of individuals, such assessment took place in waves 8 or 6. On average, the value of answers is 62 with a standard deviation of 29, and no significant differences are identified between men and women. We observe rounding and heaping which are already acknowledged in the literature (see Manski & Molinari 2010, among many others), as well as focal points (Hurd & McGarry 2002).

3.3 Sample Selection

The data release we are using counts 52,310 respondents and it is described in terms of fieldwork monitoring and participation details in Sand (2021).

From the SHARE COVID-19 survey sample of 52,310 individuals, we consider individuals living in Germany, Sweden, Spain, Italy, France, Denmark, Greece, Switzerland, Belgium, Israel, Czech Republic, Poland, Luxemburg, Slovenia, Estonia, Croatia, Lithuania, Bulgaria, Cyprus, Finland, Latvia, Malta, Romania and Slovakia.[2] Therefore, we do not include in our analysis the Netherlands, Hungary and Portugal for the following reasons. The Netherlands did not participated to the regular SHARE wave in waves 6 and 7, but implemented a mixed mode survey different from all the other countries. Hungary was not in the SHARE sample in wave 6, and for this reason, we are able to define parental birth cohort for very few observations. We do not consider also Portugal because very few individuals have information about parental education; the country did not participated to the waves where the information was collected for the majority of individuals. After dropping the three countries mentioned, the sample counts 48,656 units of observation. We further select individuals whose age is in-between 50 and 80 years. The lower age bound is related to eligibility criteria of SHARE[3], whereas the upper bound is to avoid considering in our analysis a selected sample of very healthy individuals. Age constraints lead to 48,403 respondents. Our empirical strategy exploits the access to information about parental age at death and birth cohort

[2]Austrian data, not considered in our analysis, are provided separately from other countries in the official release because the fieldwork started and finished later.

[3]SHARE targets all sampled individuals aged 50 years and over regularly living in one of the countries participating to the survey. We drop from the initial sample few individuals whose age is lower than 50 years of age, who are typically interviewed as young spouse of the sampled person.

of parents (the latter computed using the available information on the current age if the parent is alive in previous waves, or the year of death asked from wave 7 on-wards). We are not able to obtain this information for 6,693 individuals; therefore, we are left with 41,710 units.

To satisfy the exclusion restrictions, we select individuals having dead parents: 31,599 individuals. As shown in the Appendix (Table A.1), the excluded individuals are younger than those included in our sample at this stage (on average, about 5 years younger). The longevity expectations question, by construction, depends on respondents' age and this can partly explain the significant difference in longevity expectations between excluded and included individuals: excluded - younger - individuals report higher longevity expectations. Looking at differences in protective behaviours between the two groups during the first wave of the pandemic, we can notice from Table A.1 panel (a) that, among the excluded, there is a lower fraction of individuals reporting *Shopping less often*, *Walking less often*, *Meeting People less often*, *Keeping Always Distance*. However, we can also observe that there is no significant difference between the two groups for *Hands Washing & Sanitizer Usage* and *Forgone Treatment SP*. Finally, among the excluded, there is also a lower fraction of individuals forgoing visits (to the general practitioner). We do not observe a clear behavioural pattern for the excluded pointing to a clear general direction in terms of potential bias. For this group we need to consider also that some behavioural responses might be driven through having alive parents.

We further select respondents with valid answers to all the relevant variables included in our model Table A.2 shows the percentage of item-non-response in each variable used. We provide additional evidence in the Appendix about differences in age, longevity expectations and protective behaviours between individuals included in our final sample and those excluded because of missing information on the relevant variables (we label them *Excluded due to item-non-response*). Table A.1 panel (b) shows that the differences in terms of age and longevity expectations, even if statistically significant, are smaller compared to panel (a); *Excluded due to item-non-response* individuals are slightly older, reporting lower longevity expectations. There are no significant differences between the two groups when looking at *Shopping less often* and all *Forgone Treatment* variables. The fraction of individuals reporting *Walking less often* is larger among the excluded but lower for *Meeting People less often*, *Keeping Always Distance* and *Hands Washing Sanitizer Usage*. Also in this case, we do not observe a clear behavioural pattern for the *Excluded due to item-non-response*.

In Appendix A we provide also Table A.3 reporting weighted estimates based on inverse probability weighting which are in line with Table 2 baseline results.

3.4 Protective Behaviours

In this study, we are especially interested in individuals self reported protective health behaviours and forgone medical treatment during the pandemic, which proxy investments in health. We focus on questions eliciting the extent to which respondents undertook different kinds of protective behaviours, including whether they ever left home since the outbreak and how often they did specific activities such as going out

Table 1: Summary statistics - Health Behaviours and Forgone Medical Treatment (%).

	ALL (1)	N (2)	Men (3)	Women (4)	t-tests (p-value) (5)
Going Shopping Less Often	74.34	22,405	67.23	79.64	0.00
Walking Less Often	52.58	22,242	48.41	55.70	0.00
Meeting People Less Often	90.88	22,061	89.24	92.12	0.00
Always Distance	82.36	22,531	79.34	84.62	0.00
Hands Washing & Sanitizer Usage	95.05	22,424	94.19	95.70	0.00
Forgone Treatment	12.86	22,474	10.21	14.86	0.00
Forgone Treatment: GP	5.53	20,664	4.36	6.44	0.00
Forgone Treatment: SP	8.83	21,450	6.79	10.39	0.00
Forgone Treatment: PH	1.59	18,701	1.34	1.61	0.11
Forgone Treatment: OT	1.48	19,287	0.80	1.94	0.00

for a walk as compared to before the outbreak. However, this study includes other protective behaviour that differ in how cognitively and economically costly they are, such as social distancing and washing hands or sanitizer/disinfection fluids usage too. Individuals are asked also about whether they voluntarily stopped or delayed any planned medical treatment, and even measures some detail about the specific type of treatment (general practitioner visit, specialist visit or other types of treatments) forgone.

Our final sample includes 22,602 individuals participating to the COVID-19 survey that have made a LE assessment in one of the previous recent waves, and report valid information in all the relevant variables included in the model, especially parental age at death and birth cohort.[4]

Our outcome variables are defined as binary indicators. Individuals are first asked if they ever left home since the outbreak, and, for those having left home, the survey includes a follow-up question about the type of activity they went out for. We consider shopping, walking and meeting more than five people outside the household.[5] Possible answer options to the follow-up question are *not any more*, *less often*, *about the same* or *more often*. Following the literature (Bertoni et al. 2021), we combine the first and the follow-up question, so that those who *never left home* are recorded as *not any more* (and do not consider question 1). For instance, *Going shopping less often* takes value one if the individual reports he or she has never left home since the outbreak or if he or she reports having left home in the first question but went out shopping not any more or less often.

As depicted in Table 1, we find that 74% of respondents went out shopping less often since the outbreak, 53% went out walking less often and 91% met more than five people outside the household less often. Hence, our interest lies in examining whether LE do indeed mediate on the behavioural sequence influencing such protective health related behaviours during the pandemic.

Those individuals who have left home since the outbreak responded two additional questions, one referring to social distancing and, another one referring to masks wearing. We exploit the responses to the first question to define a binary indicator taking value one if the individual never went out or kept always

[4]When excluding recent deaths, the number of individuals is 22,582.

[5]The follow-up question includes among activities also *Visiting other family members* but we do not consider it because exclusion restrictions are likely to be not satisfied, see discussion in the empirical strategy section.

distance to other people when he or she went outside home (*Always distance*). We do not consider masks wearing not only because it can be mediated by individual altruistic behaviour, as it captures how much respondents care about other individuals' health, but also because, in almost all the countries, masks wearing was compulsory, determined by the law, with no room for an individual choice.[6]

We additionally define a dummy that takes value one if the respondent reports having washed their hands or used a special hand sanitizer or disinfection fluids more frequently than usual (*Hands Washing & Sanitizer Usage*). 82% of respondents did keep always social distance; and a high share of respondents, 95%, reports having washed their hands or used special hand sanitizer or disinfection fluids more frequently than usual.

Next, to examine *forgone medical treatments*, we use a binary indicator that takes value one if individuals answer positively to the following question: *since the outbreak of Corona, did you forgo medical treatment because you were afraid to become infected by the corona virus?* This indicator identifies individuals who voluntary choose to give up medical treatments. The 13% of our sample forwent treatments. Table 1 reports a breakdown by type of forgone medical treatment: in the whole sample 6% forgo visits to the general practitioner, 9% visits to the specialist, 1.5% treatments of physiotherapy, psychotherapy or rehabilitation and 1% other medical treatments. In the empirical analysis we consider the general forgone treatment question and forgone medical treatments regarding visits to the general practitioner or specialist. We do not examine other types of treatments due to low case numbers for those outcomes. There are two additional questions related to the health care supply side,[7] we do not consider them since they do not involve any choice made by the individual but we will use this information in the heterogeneity analysis.

Table 1 reports evidence of differences by gender, which appear to be always statistically significant as shown in column 4. Among women, there is a higher percentage of individuals going shopping less often, walking less often, meeting people less often, keeping always social distance and washing hands or using a disinfection fluid more frequently. Regarding the forgone treatment variables, comparing men and women, we can see that, among the latter, there is a lower percentage of people forgoing all types of medical treatment. We will come back to such gender differences in considering the heterogeneity of our findings later in the paper. Country differences are reported graphically in the Appendix (Figure B.1) for all the outcomes of interest.

4 Empirical strategy

Our identification strategy lies in estimating the effect of LE on protective health behaviours during COVID-19 alongside forgone medical treatment, controlling for current health and other covariates that

[6]One might argue that the individual can decide whether to comply with regulations or not, but this is not the focus of our paper.

[7]The questions are: (1) *Did you have a medical appointment scheduled, which the doctor or medical facility decided to postpone due to Corona?*; (2) *Did you ask for an appointment for a medical treatment since the outbreak of Corona and did not get one?*

could exert a mediating influence. More specifically, we estimate the following linear probability model (LPM):

$$Y_i = \alpha + \beta LongExp_i + \mathbf{X}_i'\gamma + e_i. \tag{1}$$

where Y_i is the outcome - behaviours or forgone medical treatment - for individual i interviewed within the SHARE COVID-19 survey. $LongExp_i$ is standardized longevity expectations measured through the subjective survival probability question contained in one of the previous SHARE regular waves and therefore pre-determined[8]; β is the parameter of interest.

Nonetheless, though ordinary-Least-Squares (OLS) estimates of equation (1) might be biased in our framework due to measurement error in the longevity expectations and/or omitted variables (e.g. Bloom et al. 2006, Fang et al. 2007).

The advantage of the LPM specification is that we can easily account for the potential endogeneity of longevity expectations but, for completeness, in the Appendix, we report equivalent probit estimates when treating or not expected longevity as endogenous.

To account for endogeneity concerns, we use one instrument that is both relevant, i.e. correlated with $LongExp_i$, and exogenous, i.e. affecting health investments only through their effect on $LongExp_i$. The literature suggests to exploit parental age at death (see for instance Bloom et al. 2006, Fang et al. 2007). Parental age at death captures individual specific private information of an individuals genetic/hereditary health endowment affecting health investments only through subjective LE. In other words, the key assumption in this framework, to identify the parameter of interest, is that health investments are conditionally mean independent of the genetic health endowment, given the controls included in the model (e.g. parental birth cohort).

Based on the parental age at death information, we exploit individual level data on the variation in the number of parents whose age at death is larger than T - the threshold in the survival probability question. Yet, as a robustness check, we propose in the Appendix a set of estimates where we define differently our instrument, taking into account for instance the potential different impact of the mother as compared to the father.[9]

We focus on individuals with dead parents[10] to exclude a direct effect of parental age on the outcomes: individuals might adjust their health behaviours to protect their parents if alive.[11] We further drop individuals whose parents died recently - in 2018 or later -, for them there could be a direct strong effect on the adoption of specific health behaviours due to parental bereavement.

In the next section we will show that our instrument is relevant based on the F-statistics for the excluded instruments that are well above the critical values for weak identification (Staiger & Stock 1997, Lee

[8]We exploit the longitudinal component of the SHARE data using, for each individual, the most recent answer to the longevity expectations question.

[9]It would be very interesting to exploit the information regarding causes of death, but unfortunately, although very rich, SHARE data do not include those details.

[10]The information about the death of parents is collected in regular waves, it is therefore pre-determined. We do not consider here parental deaths due to COVID or happening after the longevity expectations assessment.

[11]Our sample selection is driven by internal validity issues; this choice might affect the external validity of our results.

et al. 2020). We further provide endogeneity test results based on Baum et al. (2003, 2007) to understand whether expected longevity can be treated as exogenous. We then explore plausible exogeneity of our instrument, and discuss inference about our parameter of interest, β, when relaxing the exclusion assumptions along the lines proposed by Conley et al. (2012).

Our baseline two-stage least squares (TSLS) specification includes one endogeneous variable and one instrument, the model is therefore just-identified. In the robustness analysis, we propose over-identified models and this allows us to run over-identification tests that we report and comment in the results section. In our model, in addition to standard socio-demographic variables,[12] we include among controls self-perceived health - current and referring to the wave in which individuals assess their survival probability -, a dummy *covid* taking value one if the respondent or anyone close to him/her experienced symptoms attributable to the COVID illness, a binary indicator for those who were diagnosed with a major illness or health condition since the last interview and a dummy *ever hospitalized* that identifies individuals being hospitalised before their survival probability assessment.

To account for potential cognitive biases, we include among covariates two indicators capturing individual COVID related optimism attitude as suggested by Sand & Bristle (2021). The two indicators refer to binary variables taking the value of one whether a respondent named any uplifting experience since the outbreak of COVID-19 (Optimistic attitude index 1) or named something to look forward to, once Corona abates (Optimistic attitude index 2), respectively. Regarding optimism, it might be argued that we are observing a selected sample: the most pessimistic individuals with lower subjective longevity expectations (and health capital) are those who have died and did not complete the SHARE COVID interview. Unfortunately, at the moment, there is not any published methodological document or analysis helping understanding specific selection issues regarding the first SHARE COVID wave. But if we assume that this is the case, we are likely to estimate a lower bound of the effect of longevity expectations on behaviours.

Another potential bias of our estimates might result from the effect of early life health. Hence, in our specification we control for poor childhood health, health related risk attitudes through a dummy for ever smokers, parents' birth cohort, parents' education and an indicator for having received any vaccinations during childhood to capture parental prevention behaviour. Table B.1 reports all the related summary statistics.

[12] In each specification, we control for gender, education level, home ownership, marital and employment status, having children, having grandchildren. We include also indicators for the wave in which the longevity expectation assessment is done, threshold dummies interacted also with the distance in years with respect to the respondent's age when the assessment is done. We further include country by month fixed effects.

5 Results

5.1 Baseline estimates

Table 2 reports our baseline results. In our framework, OLS estimates identify a partial association between subjective expected longevity and the outcome of interest, conditional on a number of controls described in the previous section, especially health indicators, parental education/prevention behaviour and birth cohort.

The estimated LE coefficients are statistically significant and report a positive effect. That is, we find a positive association between longevity expectations and *Meeting People Less Often*, *Always Distance*, *Hands Washing & Sanitizer Usage*, suggesting that the longer an individual life span, the more likely individuals are to invest in health protective behaviours during a pandemic such as COVID-19. Consistently, we find a negative association between longevity expectations and *Forgone Medical Treatment* in Column (6) in line with the opportunity costs explanation, namely individuals expecting to live longer are less likely to forgo medical treatment, and this holds specifically for visits to the specialist (Column 8). In contrast, we find no significant associations between LE and the *Shopping Less Often*, the *Walking Less Often* and the *Forgone Treatment GP* outcomes. The latter are basic daily decisions which can be done safely, either online or in safe environments.

Nonetheless, OLS estimates are potentially biased. This is due to measurement error in longevity expectations or omitted variable bias. Therefore, the identification of LE effect requires taking advantage of an exogenous source of variation. In this paper we exploit information on parental age at death and provide TSLS estimates to retrieve the effect of LE on the protective behaviours of interest. Table 2 includes estimates of selected first-stage coefficients showing the effect of the instrument (*NpassedTage*) on the endogenous variable. *NpassedTage* is highly significant (at the 1% level) with the expected positive sign.[13] The F-statistics on the excluded instruments reported in the table are well above the cut-off threshold, and the critical values for weak identification testing discussed in Lee et al. (2020). Hence, LE estimates are likely to be reasonably well identified.

Table 2 reports also endogeneity test results. The p-value is larger than the conventional 10% level for all outcomes with the exception of columns (1), (2) and (5), meaning that, in those cases, we reject the null that longevity expectations may be treated as exogenous. We therefore rely on OLS estimates to assess the role of LE on the protective behaviours reported in columns (3), (4), and (6) to (8). More precisely, based on OLS estimates, we find that a one standard deviation increase in LE decreases the probability to forgo any medical treatment by 0.6% (column 6) and by 0.5% for specialist visits (column 8). Relative to the mean, the estimated effect for the forgo medical treatment outcome is 5% and 6% when focusing on specialist visits.

Consistently, a one standard deviation increase in LE increases the probability to comply always with

[13] The related literature has found that greater parental longevity is associated with higher subjective probability of survival (see Hurd & McGarry 1995, Hurd et al. 1998, among others).

Table 2: The effect of expected longevity on health behaviours and forgone medical treatment.

Dep. Var.	(1) Shopping Less Often	(2) Walking Less Often	(3) Meeting People Less Often	(4) Always Distance	(5) Hands Washing & Sanitizer Usage	(6) Forgone Treatment	(7) Forgone Treatment GP	(8) Forgone Treatment SP
				OLS estimates				
LongExp	0.001	0.001	0.004*	0.006**	0.003*	-0.006**	-0.002	-0.005**
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
Obs	21,548	21,394	21,218	21,671	21,567	21,615	19,878	20,626
R^2	0.131	0.278	0.076	0.056	0.027	0.044	0.032	0.040
				TSLS estimates				
LongExp	0.071*	-0.075*	-0.021	-0.008	0.062***	-0.001	-0.001	-0.031
	(0.041)	(0.043)	(0.028)	(0.037)	(0.022)	(0.033)	(0.023)	(0.028)
Endogeneity test (p-value)	0.088	0.078	0.379	0.709	0.007	0.850	0.949	0.351
F-stat (First-stage)	125.452	126.817	120.605	126.322	125.456	123.590	121.679	122.639
				First-stage estimates				
NpassedTage	0.080***	0.081***	0.079***	0.080***	0.080***	0.079***	0.082***	0.081***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
				Reduced-form estimates				
NpassedTage	0.006*	-0.006*	-0.002	-0.001	0.005***	-0.000	-0.000	-0.003
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
R^2	0.131	0.278	0.075	0.056	0.027	0.044	0.032	0.040

Notes: Standard errors in round brackets. Significance levels: p-value *** ≤ 0.01, ** ≤ 0.05, * ≤ 0.1.

social distancing by 0.6% and to meet people less often by 0.4%.

Next we examine the effect of LE on *Shopping Less Often*, *Hands Washing & Sanitizer Usage* and *Walking Less Often*, where the endogeneity tests suggest to rely on TSLS estimates. Based on TSLS results, we estimate that a one standard deviation increase in LE increases the probability to shop less often by 7.1% and to wash hands or use a sanitizer/disinfection fluids more often by 6.2%. According to column (2) a one standard deviation increase in LE decreases also the probability of walking less often by 7.5%.

The full set of estimates, including all covariates, is reported in Appendix C.

Most of the outcomes considered are undoubtedly important protective behaviours against the proliferation of COVID-19 infections (e.g. hands washing) and the related results are in line with the idea of investments in health, except the estimated effect on *Walking Less Often*. Going out for a walk less often can, one hand, lower the risk of becoming infected (and have severe consequences on health) but, on the other hand, exercising less often can have negative effects on health too, especially in the long-term. Considering that the vast majority, 87%, of individuals walking less often declared they practiced always social distancing, the activity *going outside for a walk* (following social distancing guidelines) could be considered a way of investing in (physical and mental) health during the pandemic.

5.2 Robustness Checks

In this subsection we report the robustness analysis of the results presented in the previous section. We first examine the effect if including recent parental deaths in our sample, results are reported in Table B.2 and confirm Table 2 estimates. The only exception is column (1) where, based on endogeneity test results and OLS estimates, we do not find significant effect of longevity expectations on the probability to go out shopping less often.

We then show in Tables B.3 and B.4 how estimates change when we rely on different definitions of our instrument. In Table B.3 we use as instrumental variables two binary indicators: one dummy variable that takes the value one if both parents' age at death is larger than T, and a second binary variable equal to one if only one of the two parents died after T years of age. This provides us with one endogenous variable and two instruments and allows us to run over-identification tests which show that in all cases we do not reject the null of the J-test. In Table B.4 we use as instruments two dummies, one for the mother and one for the father having passed the age threshold T respectively, to investigate potential heterogeneous effects related to the mother's as compared to the father's death based on J-test results as suggested in Angrist & Pischke (2009). Table B.4 does not highlight systematic heterogeneous effects along these lines (we fail to accept the null only in column 2).

For completeness, in Table B.5 we report probit estimates taking into account the binary nature of our outcomes. The estimated marginal effects (also when accounting for endogeneity issues) are in line with our LPM baseline results.[14]

[14]Compared to probit estimates, TSLS estimates provide directly the effect we are interested in, without intermediate steps involving the calculation of marginal effects.

We further check the robustness of our estimates when dropping observations from one country at a time, to verify that no single country is driving our results. Estimates available upon request are in line with what reported in Table 2.

5.3 Plausible Exogeneity

Next, we provide an analysis of the plausible exogeneity for the outcomes where test results point to endogeneity problems: *Shopping Less Often*, *Walking less often* and *Hands Washing & Sanitizer Usage*. In those cases, our TSLS estimates rely on the assumption that genetic factors do not affect directly health investments, once we control for all the covariates included in the model. To understand how relaxing exclusion restrictions can affect our estimates, we follow Conley et al. (2012). Conley et al. (2012) propose a procedure to show how the parameter of interest changes when relaxing strict exogeneity, allowing the instrument to have a direct - near zero - effect on the outcome.

Figures B.2, B.3 and B.4 report the 90% confidence intervals of β in equation (1), according to the *union of Symmetric CI* and the *local-to-zero* methods. The two methods differ with respect to the prior information about the parameter capturing the direct effect of the instrument on the outcome - γ, according to Conley et al. (2012)'s notation. The *union of Symmetric CI* method, through δ, allows to change the support of γ which is [-2δ, 2δ]. According to the *local-to-zero* method, we assume $\gamma \sim \mathcal{N}(0, \delta^2)$ instead.

Figures B.2, B.3 and B.4 show that the effect of longevity expectations on the probability of *Shopping Less Often*, *Walking less often* and *Hands Washing & Sanitizer Usage* more frequently than usual becomes insignificant when δ is about 0.002, i.e. the magnitude of the standard error estimated for the parameter of *NpassedTage* in the reduced-form specification.

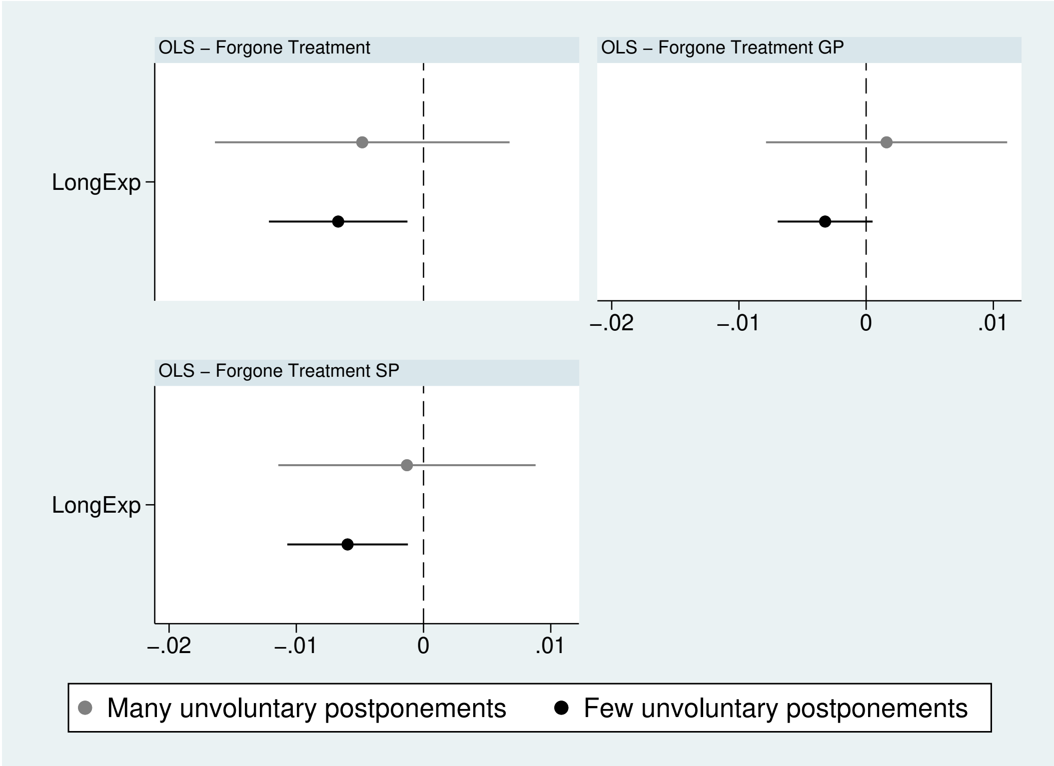
5.4 Heterogeneity Analysis

Next, in this subsection we describe the heterogeneity analysis we have conducted. We first exploit the two questions about involuntary postponements of visits/treatments and unmet needs (i.e. impossibility to have an appointment for a medical treatment since the outbreak) to stratify our sample according to living in a country with a health care system which might be under pressure due to the pandemic.

We first rank countries according to the percentage of individuals reporting involuntary postponements or unmet needs and consider, as one group, countries in the highest tertile (Sweden, Greece, Germany, Bulgaria, Cyprus, Latvia, Romania and Slovakia), against all the other ones.

Figure 1 shows how estimates differ between the two groups of countries when looking at the *Forgone treatment* outcomes. Significant results are estimated only for countries belonging to the second and third tertile. This result is consistent with idea that, in the former group, where health care systems have to postpone treatments or cannot accept treatment requests, individuals do not have an actual choice in terms of forgoing visits.

Figure 1: Heterogeneous effect of expected longevity on forgone medical treatment by group of countries

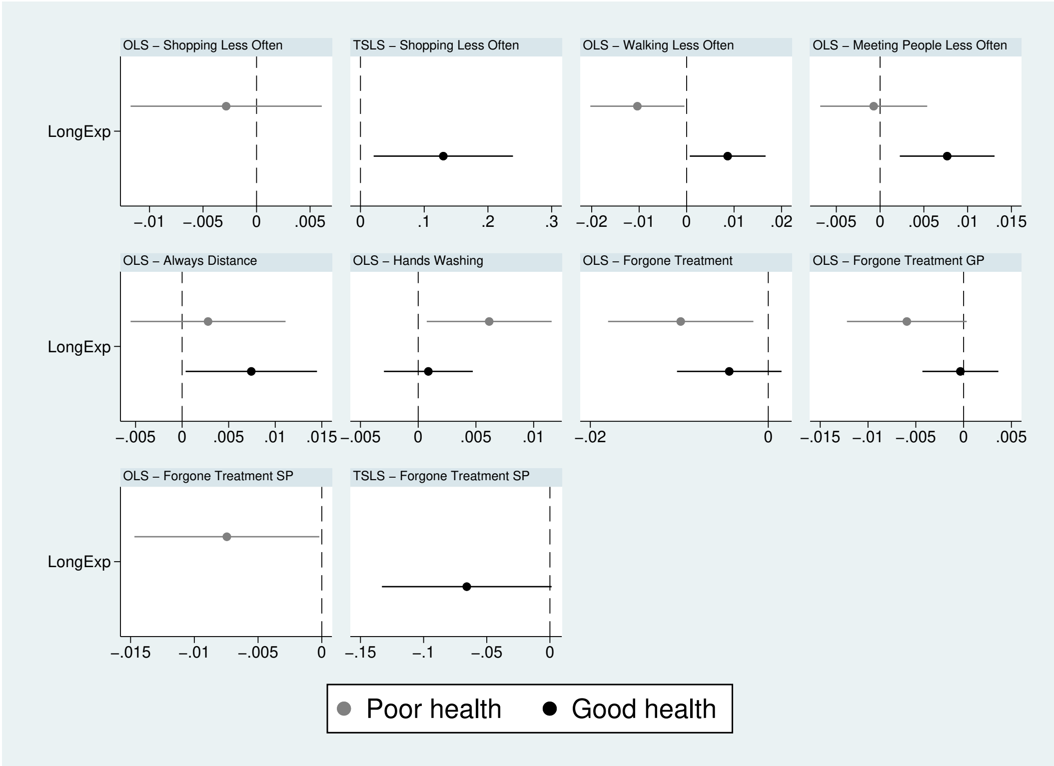


Note: 95% confidence intervals displayed.

Figure 2 reports stratified estimates distinguishing between individuals that reported Fair/Poor health (labelled *Poor Health* in the Figure) versus Good/Very good/Excellent (labelled *Good Health* in the Figure), when the survival probability assessment is done; poor health is therefore predetermined. For each outcome, we report, OLS or TSLS estimates depending on endogeneity test results. Consistently with this papers hypothesis, we find significant positive effects of LE on health behaviours especially for individuals in good health. It is worth noting that, the effect of LE on the probability to go out walking less often changes sign depending on individuals self-reported health: it is negative for individuals reporting being in poor health and positive for those in good health.

The previous literature has highlighted heterogeneous behavioural responses to the pandemic by gender (e.g. Galasso et al. 2020). Hence, next we investigate whether this is the case also when looking at the effect of longevity expectations on behaviours. Figure 3 depicts how our baseline results change for men and women. They suggest gender heterogeneity, and more specifically show that LE exhibit a negative and significant effect on the probability to forgo medical treatments among women, but no significant effects among men. Furthermore, we do not observe any striking and systematic differences in other behavioural responses. First-stage estimates and statistics suggest that women tend to react more in terms of expectations to parental deaths as compared to men. Point estimates of the $NpassedTage$ coefficient range from 0.097 to 0.102 (significant at the 1% level) for women, from 0.055 to 0.058 (significant at the

Figure 2: Heterogeneous effect of expected longevity on health behaviours and forgone medical treatment by self-reported health



Note: 95% confidence intervals displayed.

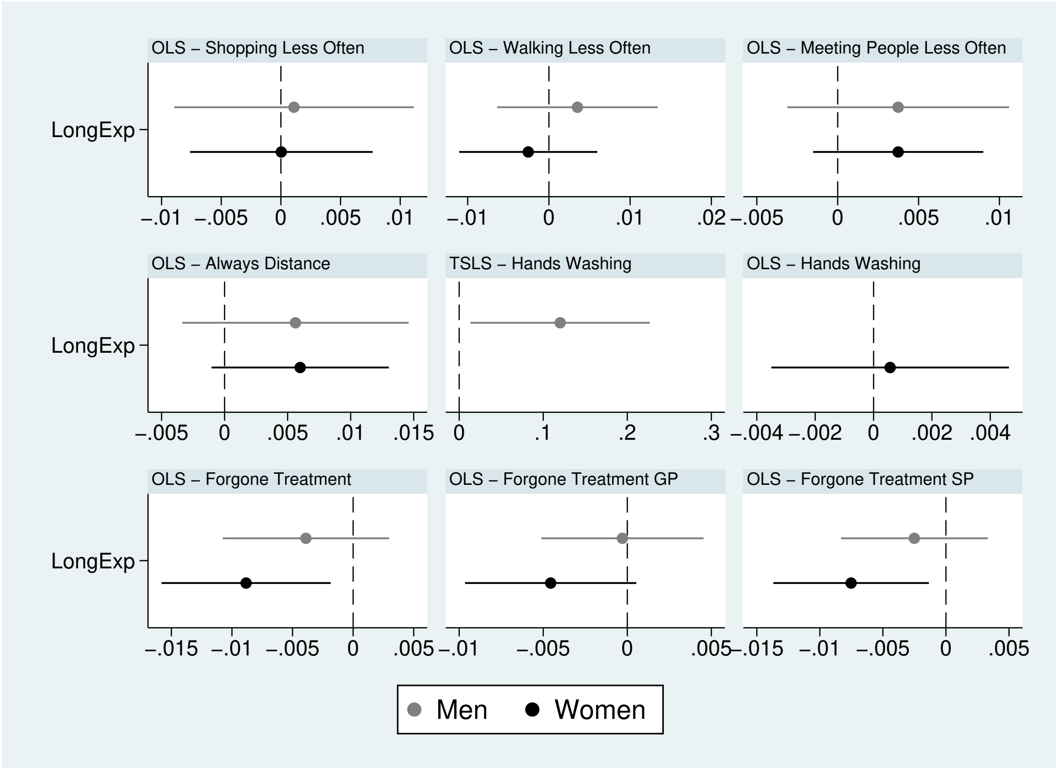
1% level) for men. The F-statistics on the excluded instruments range from 107 to 111 for women and from 25 to 27 for men.

6 Conclusions

We have studied how individuals' subjective longevity influences their protective behaviours in the context of a pandemic. This paper has empirically tested the *too healthy to be sick* hypothesis and documents that longevity expectations, namely subjective assessments of future longevity, are a proxy of individuals' future health capital, which influences decisions about protective health behaviours and health care use. Exploiting evidence from SHARE, this paper estimates the causal effect of LE on protective behaviours. We exploit an instrumental variable strategy were individual's parental age at death becomes a critical private information that can provide exogenous variation in LE. More specifically, LE contain private information that explains heterogeneous behavioural reactions to pandemic restrictions across the population as well as the decision to forgo medical treatments during the COVID-19 pandemic. We have further tested whether they contain *private information* or instead reflective of some cognitive biases such as health related optimism (Costa-Font and Vilaplana, 2022).

Our results are consistent with the idea that individuals holding higher LE continue to invest more in

Figure 3: Heterogeneous effect of expected longevity on health behaviours and forgone medical treatment by gender



Note: 95% confidence intervals displayed.

their health, in line with the *too healthy to be sick* hypothesis. We find robust evidence suggesting that a rise in LE increases the probability of individuals' engagement in several protective health behaviours during the first wave of COVID-19 epidemic, and we document that it reduces the probability of forgoing medical treatment. We estimate that a one standard deviation increase in expected longevity increases the probability to comply always with social distancing by 0.6%, to meet people less often by 0.4% and decreases the probability to forgo any medical treatment by 0.6%. These estimates help explaining the different behavioural reactions to a common health threat such as COVID-19 and suggest that incentives to increase compliance with restrictions should target specifically individuals who do not expect such restrictions to influence their health, who do not perceive the health effects of COVID-19 as weakening their health status, and hence face a lower perceived opportunity cost. Interventions, aimed at increasing the salience of the health-related opportunity costs of not complying with pandemic restrictions, might include the use of reminders of an individual's *healthiness* so they understand what is at stake.

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Appendix A. Sample selection.

Table A.1: Analysis on the excluded individuals

(1)	(2)	(3)	(4)	(5)
		Panel (a)		
	Included	Excluded due to sample selection	t-statistic	p-value
Age	70.68	64.73	63.99	0.00
Longevity Expectations	0.62	0.71	-28.08	0.00
Shopping less often	0.75	0.71	7.2	0.00
Walking less often	0.55	0.52	5.66	0.00
Meeting People less often	0.91	0.88	7.07	0.00
Always Distance	0.81	0.78	5.5	0.00
Hands Washing & Sanitizer Usage	0.95	0.95	-1.56	0.12
Forgone Treatment	0.13	0.12	2.4	0.02
Forgone Treatment GP	0.06	0.05	2.89	0.00
Forgone Treatment SP	0.09	0.08	0.95	0.34
		Panel (b)		
	Included	Excluded due to item-non response	t-statistic	p-value
Age	70.58	70.92	3.66	0.00
Longevity Expectations	0.62	0.60	-4.69	0.00
Shopping less often	0.74	0.75	1.74	0.08
Walking less often	0.53	0.61	13.82	0.00
Meeting People less often	0.91	0.90	-2.17	0.03
Always Distance	0.82	0.77	-11.11	0.00
Hands Washing & Sanitizer Usage	0.95	0.93	-5.87	0.00
Forgone Treatment	0.13	0.13	-0.56	0.58
Forgone Treatment GP	0.06	0.06	1.93	0.05
Forgone Treatment SP	0.09	0.09	-0.5	0.61

Table A.2: Item non response (N=31,599)

(1)	(2) %
Longevity expectations	0.0
Wave of LE Assessment	0.0
Age threshold in LE question (T)	0.0
Distance (in years) from T	0.2
Optimistic attitude index 1	1.9
Optimistic attitude index 2	1.4
Female	0.0
Couple	0.0
Working	0.5
ISCED	1.2
Having children	0.1
Having grandchildren	0.2
Ever homeowner	0.3
Ever smoked	0.2
Country	0.0
Month of Interview COVID survey	0.0
Self-perceived health COVID survey	0.4
Covid	0.7
New disease dignosed	0.4
Poor health during childhood	8.6
Vaccinated during childhood	9.2
Self-perceived health - wave of LE assessment	0.0
Ever hospitalized	0.0
Mother's or Father's age at death	2.5
Mother's year of birth	6.3
Father's year of birth	8.3
Mother's education	10.7
Father's education	12.7
Shopping less often	1.1
Walking less often	1.8
Meeting people less often	2.1
Always Distance	0.6
Hands Washing & Sanitizer Usage	0.4
Forgone Treatment	0.4
Forgone Treatment GP	7.9
Forgone Treatment SP	4.8

Table A.3: The effect of expected longevity on health behaviours and forgone medical treatment. Weighted Estimates.

Dep. Var.	(1) Shopping Less Often	(2) Walking Less Often	(3) Meeting People Less Often	(4) Always Distance	(5) Hands Washing & Sanitizer Usage	(6) Forgone Treatment	(7) Forgone Treatment GP	(8) Forgone Treatment SP
				OLS estimates				
LongExp	0.002	0.000	0.004**	0.006**	0.003*	-0.007***	-0.002	-0.005**
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
Obs	21,548	21,394	21,218	21,671	21,567	21,615	19,878	20,626
R^2	0.132	0.282	0.076	0.056	0.027	0.044	0.032	0.040
				TSLS estimates				
LongExp	0.071*	-0.075*	-0.021	-0.008	0.062***	-0.000	-0.001	-0.031
	(0.041)	(0.043)	(0.028)	(0.037)	(0.022)	(0.033)	(0.023)	(0.028)
Endogeneity test (p-value)	0.081	0.087	0.612	0.705	0.006	0.949	0.996	0.258
F-stat (First-stage)	125.042	126.249	119.362	126.210	125.657	123.494	122.213	122.084
				First-stage estimates				
NpassedTage	0.079***	0.080***	0.078***	0.079***	0.079***	0.079***	0.081***	0.080***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
				Reduced-form estimates				
NpassedTage	0.006*	-0.006*	-0.001	-0.001	0.005***	-0.001	-0.000	-0.003
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
R^2	0.131	0.278	0.075	0.056	0.027	0.044	0.032	0.040

Notes: Standard errors in round brackets. Significance levels: p-value *** ≤ 0.01, ** ≤ 0.05, * ≤ 0.1.

Appendix B. Tables and Figures.

Table B.1: Summary statistics

	(1)	(2)	(3)	(4)	(5)	(6)
	All		Men		Women	
	Mean or %	SD	Mean or %	SD	Mean or %	SD
Longevity Expectations	62.03	29.14	62.01	29.15	62.04	29.13
Socio-demographic characteristics:						
Female	57.1					
Age	70.58	7.55	70.73	7.4	70.46	7.66
Distance from T (years)	13.3	2.45	13.22	2.31	13.35	2.55
Having children	92		91		93	
Having grandchildren	77		74		79	
Living in a couple	69.45		81.64		60.29	
Working	15.81		17.56		14.5	
ISCED 0_2	33.67		30.79		35.83	
ISCED 3_4	41.8		43.21		40.74	
ISCED 5_6	24.53		26		23.43	
Ever homeowner	89.47		90.46		88.73	
Country:						
DE	7.37		8.19		6.76	
SE	3.56		3.73		3.43	
ES	4.29		4.27		4.3	
IT	8.37		8.94		7.94	
FR	4.88		4.69		5.01	
DK	5.57		5.87		5.35	
GR	1.8		1.89		1.73	
CH	5.16		5.74		4.73	
BE	8.78		9.12		8.52	
IL	2.11		1.94		2.25	
CZ	6.88		6.04		7.51	
PL	2.62		2.84		2.46	
LU	1.98		2.11		1.88	
SL	7.22		6.92		7.45	
EE	9.26		7.38		10.66	
HU	4.84		5.13		4.63	
LT	2.52		2.13		2.81	
BG	1.72		1.74		1.7	
CY	0.64		0.54		0.71	
FI	2.47		2.62		2.36	
LV	1.26		1.08		1.39	
MT	1.56		1.61		1.53	
RO	2.89		3.08		2.75	
SK	2.26		2.39		2.15	
Health-related indicators:						
Ever smoked	46.54		61.44		35.35	
Covid	12.33		12.18		12.44	
New Disease Diagnosed	9.88		10.34		9.52	
Poor health during childhood	62.76		65.38		60.79	
Vaccinated during childhood	97.65		97.8		97.54	

Ever hospitalized	37.07	39.12	35.53
Self-perceived health COVID survey:			
Excellent	6.93	7.46	6.53
Very Good	16.59	17.26	16.09
Good	45.31	45.22	45.39
Fair	25.59	24.56	26.36
Poor	5.57	5.5	5.63
Self-perceived health - wave of LE assessment:			
Excellent	5.44	6.16	4.9
Very Good	16.45	17.16	15.92
Good	39.78	40.85	38.97
Fair	30.02	28.26	31.34
Poor	8.32	7.58	8.87
Parental information:			
Mother passed T	45.45	46.02	45.02
Father passed T	29.77	30.32	29.35
Mother's education: ISCED 0_2	79.45	80.3	78.81
Mother's education: ISCED 3_4	16.84	16.24	17.3
Mother's education: ISCED 5_6	3.7	3.45	3.89
Father's education: ISCED 0_2	64.92	64.32	65.38
Father's education: ISCED 3_4	26.61	27.11	26.23
Father's education: ISCED 5_6	8.47	8.57	8.39
Mother's birth cohort:			
1919less	46.34	47.47	45.49
1920	20.96	20.46	21.33
1925	16.49	16.11	16.78
1930	10.15	10.03	10.23
1935more	6.07	5.93	6.18
Father's birth cohort			
1919less	60.17	60.44	59.96
1920	16.7	16.65	16.73
1925	12.57	12.83	12.38
1930	6.99	6.59	7.29
1935more	3.57	3.49	3.64
Other controls:			
Optimistic attitude index 1 (uplifting experience)	54.65	52.01	56.64
Optimistic attitude index 2 (something to look forward)	73.78	71.91	75.18
Wave of LE assessment:			
4	0.4	0.4	0.4
5	3.51	3.59	3.45
6	22.1	21.83	22.3
7	6.08	6.2	6
8	67.91	67.98	67.85
Age threshold in LE question (T):			
75	31.88	30.92	32.6
80	18.43	18.79	18.16
85	22.52	23.06	22.12
90	27.17	27.24	27.11
Month of COVID interview:			
June	58.64	57.52	59.47

July	40.25	41.19	39.54
August	1.11	1.29	0.98

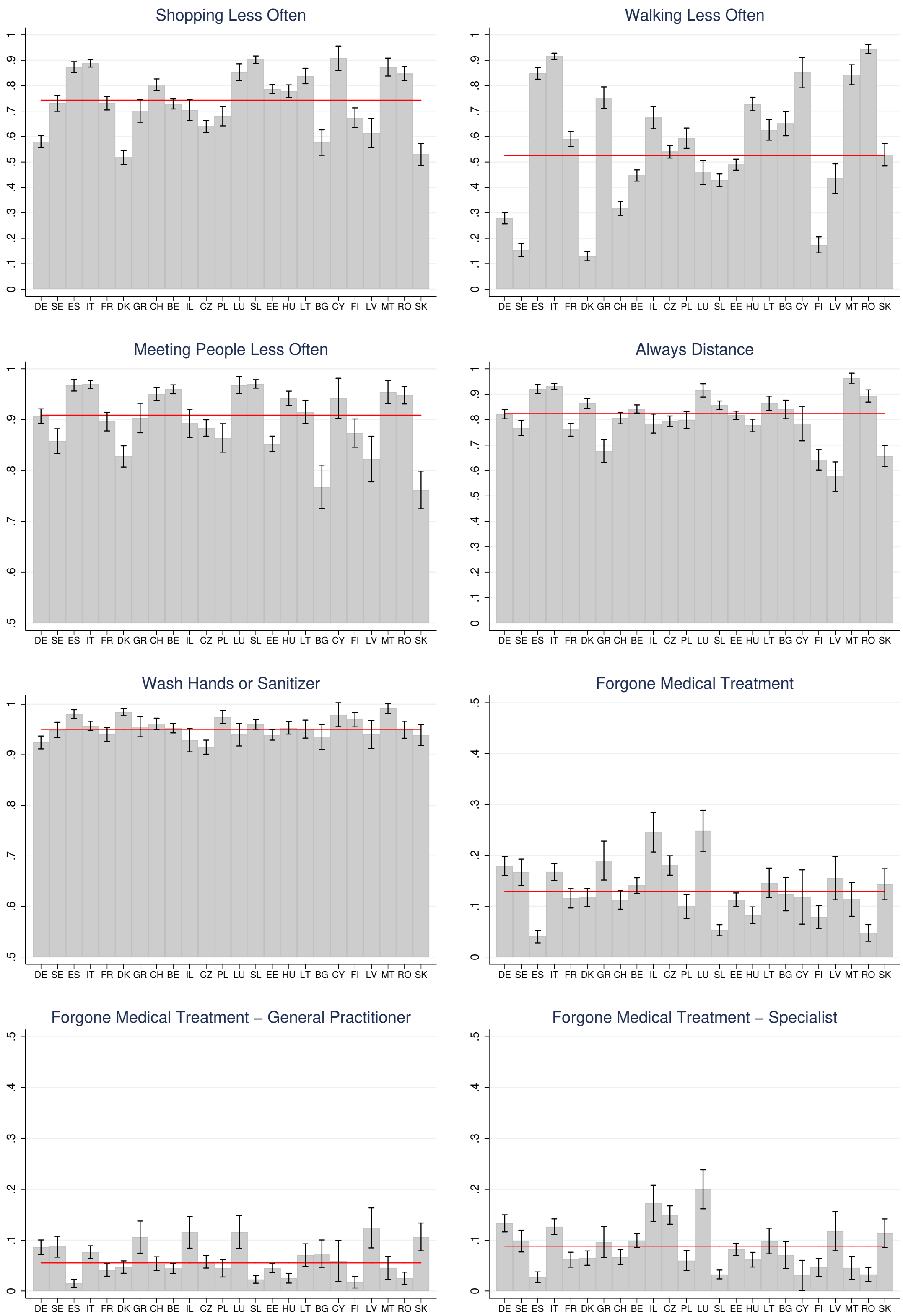

Figure B.1: Country heterogeneity.

Table B.2: The effect of expected longevity on health behaviours and forgone medical treatment. Including recent deaths

Dep. Var.	(1) Shopping Less Often	(2) Walking Less Often	(3) Meeting People Less Often	(4) Always Distance	(5) Hands Washing & Sanitizer Usage	(6) Forgone Treatment	(7) Forgone Treatment GP	(8) Forgone Treatment SP
				OLS estimates				
LongExp	0.002	0.001	0.004**	0.005*	0.002	-0.006**	-0.002	-0.005**
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Obs	22,405	22,242	22,061	22,531	22,424	22,474	20,664	21,450
R^2	0.131	0.277	0.076	0.058	0.027	0.043	0.031	0.039
				TSLS estimates				
LongExp	0.061	-0.075*	-0.025	-0.018	0.058***	-0.012	-0.004	-0.036
	(0.041)	(0.042)	(0.028)	(0.036)	(0.022)	(0.033)	(0.023)	(0.028)
Endogeneity test (p-value)	0.142	0.069	0.300	0.512	0.008	0.868	0.937	0.269
F-stat (First-stage)	130.086	131.799	126.498	131.591	131.095	128.750	126.408	127.760
				First-stage estimates				
NpassedTage	0.080***	0.081***	0.079***	0.080***	0.080***	0.079***	0.082***	0.081***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
				Reduced-form estimates				
NpassedTage	0.005	-0.006*	-0.002	-0.001	0.005***	-0.001	-0.000	-0.003
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
R^2	0.131	0.277	0.076	0.058	0.027	0.043	0.031	0.039

Notes: Standard errors in round brackets. Significance levels: p-value *** $\leq$ 0.01, ** $\leq$ 0.05, * $\leq$ 0.1.

Figure B.2: Plausible exogeneity - Shopping Less Often

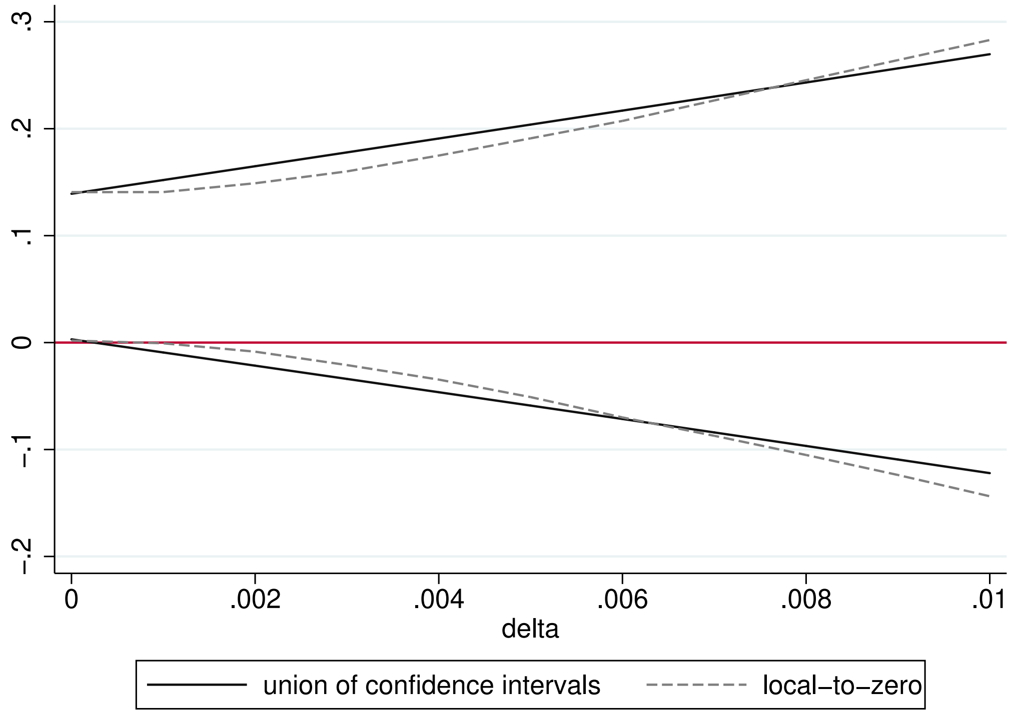

Figure B.3: Plausible exogeneity - Walking Less Often

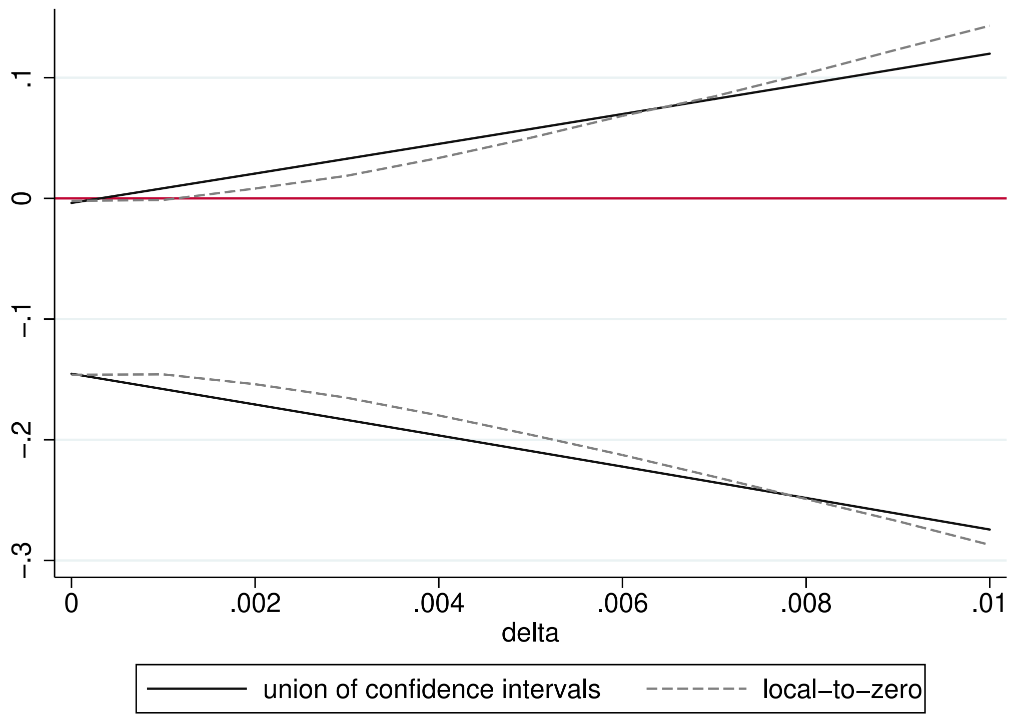

Figure B.4: Plausible exogeneity - Hands Washing & Sanitizer Usage

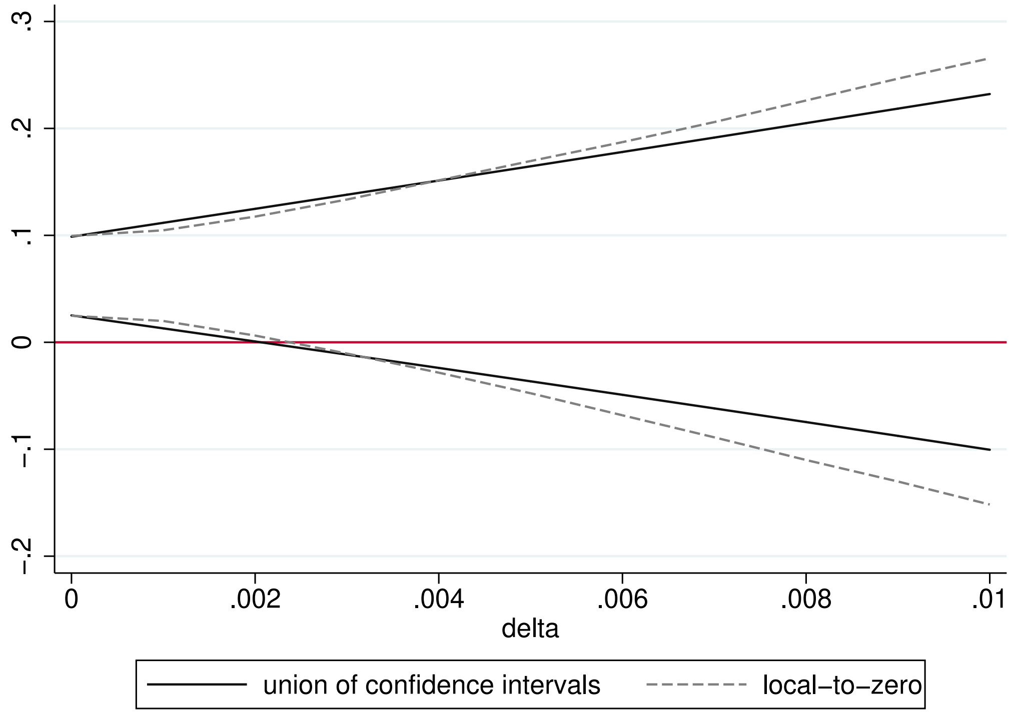

Table B.3: The effect of expected longevity on health behaviours and forgone medical treatment. Over-identified model: two instruments based on the number of parents who passed T.

Dep. Var.	(1) Shopping Less Often	(2) Walking Less Often	(3) Meeting People Less Often	(4) Always Distance	(5) Hands Washing & Sanitizer Usage	(6) Forgone Treatment	(7) Forgone Treatment GP	(8) Forgone Treatment SP
				OLS estimates				
LongExp	0.001	0.001	0.004*	0.006**	0.003*	-0.006**	-0.002	-0.005**
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
Obs	21,548	21,394	21,218	21,671	21,567	21,615	19,878	20,626
R^2	0.131	0.278	0.076	0.056	0.027	0.044	0.032	0.040
				TSLS estimates				
LongExp	0.046	-0.080**	-0.007	0.009	0.042**	-0.009	0.002	-0.021
	(0.032)	(0.033)	(0.022)	(0.029)	(0.017)	(0.026)	(0.018)	(0.022)
Endogeneity test (p-value)	0.156	0.015	0.621	0.915	0.022	0.921	0.814	0.460
F-stat (First-stage)	105.028	105.430	99.697	104.563	104.371	104.295	100.498	99.444
J-test (p-value)	0.339	0.850	0.431	0.470	0.144	0.678	0.850	0.568
				First-stage estimates				
Both parents	0.246***	0.247***	0.241***	0.244***	0.245***	0.246***	0.249***	0.242***
passed T	(0.019)	(0.020)	(0.020)	(0.019)	(0.019)	(0.019)	(0.020)	(0.020)
One parent	0.173***	0.175***	0.171***	0.173***	0.173***	0.172***	0.177***	0.174***
passed T	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)
				Reduced-form estimates				
Both parents	0.007	-0.021**	0.001	0.005	0.007	-0.004	0.001	-0.003
passed T	(0.009)	(0.009)	(0.006)	(0.008)	(0.005)	(0.007)	(0.005)	(0.006)
One parent	0.011*	-0.013*	-0.003	-0.001	0.010***	-0.000	-0.000	-0.005
passed T	(0.007)	(0.007)	(0.005)	(0.006)	(0.003)	(0.005)	(0.004)	(0.005)
R^2	0.131	0.278	0.075	0.056	0.027	0.044	0.032	0.040

Notes: Standard errors in round brackets. Significance levels: p-value *** ≤ 0.01, ** ≤ 0.05, * ≤ 0.1.

Table B.4: The effect of expected longevity on health behaviours and forgone medical treatment. Over-identified model: different instruments for mother and father.

Dep. Var.	(1) Shopping Less Often	(2) Walking Less Often	(3) Meeting People Less Often	(4) Always Distance	(5) Hands Washing & Sanitizer Usage	(6) Forgone Treatment	(7) Forgone Treatment GP	(8) Forgone Treatment SP
				OLS estimates				
LongExp	0.001	0.001	0.004*	0.006**	0.003*	-0.006**	-0.002	-0.005**
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
Obs	21,548	21,394	21,218	21,671	21,567	21,615	19,878	20,626
R^2	0.131	0.278	0.076	0.056	0.027	0.044	0.032	0.040
				TSLS estimates				
LongExp	0.035	-0.071**	-0.001	0.012	0.037**	-0.010	0.002	-0.017
	(0.033)	(0.034)	(0.023)	(0.030)	(0.017)	(0.026)	(0.019)	(0.023)
Endogeneity test (p-value)	0.301	0.035	0.833	0.845	0.050	0.881	0.813	0.586
F-stat (First-stage)	99.797	99.671	95.224	99.079	99.045	99.207	94.730	93.510
J-test (p-value)	0.533	0.031	0.761	0.482	0.394	0.688	0.747	0.959
				First-stage estimates				
MpassedTage	0.151***	0.151***	0.152***	0.151***	0.151***	0.150***	0.152***	0.150***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)
FpassedTage	0.109***	0.111***	0.103***	0.108***	0.108***	0.110***	0.113***	0.108***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
				Reduced-form estimates				
MpassedTage	0.003	-0.002	0.001	-0.001	0.007**	-0.000	-0.000	-0.002
	(0.006)	(0.006)	(0.004)	(0.006)	(0.003)	(0.005)	(0.004)	(0.004)
FpassedTage	0.007	-0.021***	-0.001	0.005	0.001	-0.003	0.001	-0.002
	(0.007)	(0.007)	(0.005)	(0.006)	(0.004)	(0.005)	(0.004)	(0.005)
R^2	0.131	0.278	0.075	0.056	0.027	0.044	0.032	0.040

Notes: Standard errors in round brackets. Significance levels: p-value *** ≤ 0.01, ** ≤ 0.05, * ≤ 0.1.

Table B.5: The effect of expected longevity on health behaviours and forgone medical treatment. Probit and IV-Probit estimates.

Dep. Var.	(1) Shopping Less Often	(2) Walking Less Often	(3) Meeting People Less Often	(4) Always Distance	(5) Hands Washing & Sanitizer Usage	(6) Forgone Treatment	(7) Forgone Treatment GP	(8) Forgone Treatment SP
	Probit estimates (Marginal effects)							
LongExp	0.001	0.001	0.004*	0.006**	0.003*	-0.006**	-0.002	-0.005**
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Obs	21,548	21,394	21,218	21,671	21,567	21,615	19,878	20,626
Log likelihood	-10727.607	-11330.023	-5685.9863	-9418.9431	-4015.6449	-7811.57	-3958.5457	-5747.1742
	IV-Probit estimates (Marginal effects)							
LongExp	0.07*	-0.069*	-0.02	-0.01	0.075**	-0.002	0.002	-0.034
	(0.039)	(0.04)	(0.029)	(0.037)	(0.036)	(0.033)	(0.023)	(0.03)
Endogeneity test (p-value)	0.084	0.094	0.400	0.677	0.006	0.907	0.846	0.315
Log likelihood	-38635.634	-39042.812	-33156.135	-37499.096	-31969.504	-35826.737	-29715.561	-32447.612

Notes: Standard errors in round brackets. Significance levels: p-value *** ≤ 0.01, ** ≤ 0.05, * ≤ 0.1.

Appendix C. Complete Baseline Estimates.

Table C.1: The effect of expected longevity on health behaviours and forgone medical treatment. OLS estimates.

Dep. Var.	(1) Shopping Less Often	(2) Walking Less Often	(3) Meeting People Less Often	(4) Always Distance	(5) Hands Washing & Sanitizer Usage	(6) Forgone Treatment	(7) Forgone Treatment GP	(8) Forgone Treatment SP
LongExp	0.001	0.001	0.004*	0.006**	0.003*	-0.006**	-0.002	-0.005**
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
Wave of LE assessment (ref category: 4)								
wave 5	-0.031	-0.059	-0.021	-0.088**	0.047*	0.025	0.020	0.034
	(0.045)	(0.048)	(0.031)	(0.042)	(0.024)	(0.037)	(0.026)	(0.032)
wave 6	-0.054	-0.087*	-0.024	-0.068*	0.063***	0.034	0.018	0.041
	(0.044)	(0.046)	(0.030)	(0.040)	(0.023)	(0.035)	(0.025)	(0.031)
wave 7	-0.087*	-0.105**	-0.021	-0.073*	0.076***	0.031	0.016	0.037
	(0.045)	(0.047)	(0.031)	(0.041)	(0.024)	(0.036)	(0.026)	(0.031)
wave 8	-0.071	-0.129***	-0.020	-0.072*	0.078***	0.038	0.016	0.049
	(0.044)	(0.046)	(0.030)	(0.040)	(0.023)	(0.035)	(0.025)	(0.031)
Age threshold in LE question (T) (ref category: 75)								
80	0.174**	0.238***	-0.000	0.114*	0.067*	0.088	0.087**	0.087*
	(0.075)	(0.079)	(0.051)	(0.068)	(0.040)	(0.061)	(0.044)	(0.053)
85	-0.030	0.026	0.016	0.072	0.034	-0.048	-0.062*	-0.021
	(0.059)	(0.062)	(0.040)	(0.053)	(0.031)	(0.048)	(0.034)	(0.041)
90	0.180***	0.200***	0.041	0.124**	-0.031	-0.020	-0.028	0.000
	(0.054)	(0.057)	(0.037)	(0.049)	(0.029)	(0.044)	(0.031)	(0.038)
Distance from T	-0.003**	-0.003**	-0.002	-0.001	0.001	-0.001	-0.001	0.000
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Female	0.119***	0.066***	0.029***	0.056***	0.017***	0.046***	0.019***	0.037***
	(0.006)	(0.006)	(0.004)	(0.006)	(0.003)	(0.005)	(0.004)	(0.004)
Optimistic1	0.012**	-0.025***	-0.003	0.020***	0.012***	0.004	-0.007**	0.005
	(0.006)	(0.006)	(0.004)	(0.005)	(0.003)	(0.005)	(0.004)	(0.004)
Optimistic2	0.031***	0.009	0.027***	0.024***	0.025***	0.016***	0.009**	0.012**
	(0.007)	(0.007)	(0.005)	(0.006)	(0.004)	(0.006)	(0.004)	(0.005)
Couple	0.051***	0.002	0.023***	0.018***	0.018***	0.002	-0.004	0.003
	(0.007)	(0.007)	(0.005)	(0.006)	(0.003)	(0.005)	(0.004)	(0.005)
Working	-0.078***	-0.033***	-0.102***	-0.040***	-0.002	-0.009	-0.005	-0.005
	(0.009)	(0.010)	(0.006)	(0.009)	(0.005)	(0.008)	(0.005)	(0.007)

Respondent's education (ISCED) (ref category: isced0_2)								
isced3_4	-0.005	-0.025***	-0.005	-0.001	0.006	0.019***	0.011**	0.011**
	(0.007)	(0.008)	(0.005)	(0.007)	(0.004)	(0.006)	(0.004)	(0.005)
isced5_6	0.007	-0.059***	0.014**	0.006	0.012**	0.045***	0.015***	0.036***
	(0.009)	(0.009)	(0.006)	(0.008)	(0.005)	(0.007)	(0.005)	(0.006)
children	0.027**	0.010	0.010	-0.001	0.020***	0.005	0.005	0.012
	(0.012)	(0.013)	(0.009)	(0.011)	(0.007)	(0.010)	(0.007)	(0.009)
grandchildren	0.020**	-0.003	-0.011*	0.002	0.006	-0.000	0.008*	-0.007
	(0.008)	(0.009)	(0.006)	(0.008)	(0.004)	(0.007)	(0.005)	(0.006)
everhomeowner	0.031***	-0.035***	-0.001	-0.011	-0.000	0.004	-0.001	0.001
	(0.009)	(0.010)	(0.006)	(0.009)	(0.005)	(0.008)	(0.005)	(0.007)
eversmoked	-0.030***	-0.007	-0.011***	0.005	-0.002	0.000	-0.002	0.003
	(0.006)	(0.006)	(0.004)	(0.005)	(0.003)	(0.005)	(0.003)	(0.004)
Mother's birth cohort (ref category: 1919less)								
1920-1924	-0.000	0.006	0.002	0.020***	-0.005	-0.017**	-0.008*	-0.015**
	(0.008)	(0.009)	(0.006)	(0.008)	(0.004)	(0.007)	(0.005)	(0.006)
1925-1929	0.022**	0.029***	-0.005	0.011	-0.008	-0.005	-0.000	-0.007
	(0.011)	(0.011)	(0.007)	(0.010)	(0.006)	(0.009)	(0.006)	(0.007)
1930-1934	0.000	0.020	-0.001	0.010	-0.015**	-0.016	-0.013	-0.014
	(0.014)	(0.014)	(0.009)	(0.012)	(0.007)	(0.011)	(0.008)	(0.010)
1935more	-0.011	0.039**	-0.022*	-0.001	-0.011	-0.008	0.003	-0.015
Father's birth cohort(ref category: 1919less)								
	(0.018)	(0.018)	(0.012)	(0.016)	(0.009)	(0.014)	(0.010)	(0.012)
1920-1924	0.004	0.005	0.004	-0.005	0.003	0.003	0.003	0.006
	(0.009)	(0.010)	(0.006)	(0.008)	(0.005)	(0.007)	(0.005)	(0.006)
1925-1929	-0.006	0.008	-0.002	0.005	0.005	-0.001	0.001	0.003
	(0.011)	(0.012)	(0.008)	(0.010)	(0.006)	(0.009)	(0.007)	(0.008)
1930-1934	0.005	0.009	-0.001	0.007	0.019**	0.003	-0.000	0.005
	(0.015)	(0.016)	(0.010)	(0.014)	(0.008)	(0.012)	(0.009)	(0.010)
1935more	-0.024	0.006	0.002	-0.018	-0.002	0.003	0.001	0.005
	(0.020)	(0.021)	(0.014)	(0.018)	(0.011)	(0.016)	(0.012)	(0.014)
Self-perceived health - COVID SURVEY (ref. category: Excellent)								
Very good	0.040***	0.058***	0.021**	0.004	0.014**	0.032***	0.019**	0.015
	(0.013)	(0.014)	(0.009)	(0.012)	(0.007)	(0.011)	(0.008)	(0.009)
Good	0.069***	0.088***	0.026***	-0.008	0.008	0.045***	0.033***	0.022**
	(0.013)	(0.013)	(0.009)	(0.011)	(0.007)	(0.010)	(0.007)	(0.009)

Fair	0.123***	0.161***	0.053***	0.002	0.007	0.077***	0.054***	0.051***
	(0.014)	(0.015)	(0.009)	(0.013)	(0.007)	(0.011)	(0.008)	(0.010)
Poor	0.181***	0.245***	0.077***	0.040**	-0.015	0.084***	0.051***	0.060***
	(0.018)	(0.019)	(0.012)	(0.016)	(0.010)	(0.015)	(0.010)	(0.013)
Covid	0.023***	-0.009	0.013**	-0.013	0.009*	0.038***	0.019***	0.029***
	(0.009)	(0.009)	(0.006)	(0.008)	(0.005)	(0.007)	(0.005)	(0.006)
New disease dignosed	0.021**	0.043***	0.001	0.023***	0.006	0.014*	0.003	0.013*
	(0.010)	(0.010)	(0.007)	(0.009)	(0.005)	(0.008)	(0.006)	(0.007)
Poor health during childhood	0.003	-0.009	0.002	0.012**	0.004	-0.002	-0.004	-0.003
	(0.006)	(0.006)	(0.004)	(0.006)	(0.003)	(0.005)	(0.004)	(0.004)
Self-perceived health - wave of LE assessment (ref. category: Excellent)								
Very good	0.023	-0.025*	-0.001	-0.019	0.001	0.011	0.006	0.006
	(0.014)	(0.015)	(0.010)	(0.013)	(0.008)	(0.012)	(0.008)	(0.010)
Good	0.046***	0.014	-0.000	-0.015	0.002	0.022*	0.009	0.016
	(0.014)	(0.015)	(0.010)	(0.013)	(0.007)	(0.011)	(0.008)	(0.010)
Fair	0.044***	0.036**	0.000	-0.010	0.005	0.042***	0.025***	0.030***
	(0.015)	(0.016)	(0.010)	(0.013)	(0.008)	(0.012)	(0.009)	(0.010)
Poor	0.075***	0.109***	0.017	0.027*	-0.011	0.054***	0.041***	0.037***
	(0.018)	(0.019)	(0.012)	(0.016)	(0.009)	(0.014)	(0.010)	(0.012)
Vaccinated during childhood	-0.024	-0.025	-0.006	0.018	0.016*	-0.013	-0.004	-0.006
	(0.019)	(0.019)	(0.013)	(0.017)	(0.010)	(0.015)	(0.011)	(0.013)
Ever hospitalised	0.027***	0.013**	-0.002	0.013**	0.003	0.012**	0.001	0.011**
	(0.006)	(0.006)	(0.004)	(0.006)	(0.003)	(0.005)	(0.004)	(0.004)
Mother's education (ref. category: isced 0_2)								
isced3_4_m	0.012	0.001	-0.007	-0.008	-0.001	0.012*	0.006	0.006
	(0.009)	(0.009)	(0.006)	(0.008)	(0.005)	(0.007)	(0.005)	(0.006)
isced5_6_m	0.011	0.008	0.013	0.002	0.003	0.029**	0.019*	0.023*
	(0.017)	(0.017)	(0.011)	(0.015)	(0.009)	(0.013)	(0.010)	(0.012)
Father's education (ref. category: isced 0_2)								
isced3_4_f	-0.012	-0.013	-0.006	-0.006	0.002	0.000	-0.002	0.001
	(0.008)	(0.008)	(0.005)	(0.007)	(0.004)	(0.006)	(0.005)	(0.005)
isced5_6_f	-0.012	-0.010	-0.008	-0.000	0.001	-0.000	0.008	0.000
	(0.012)	(0.013)	(0.008)	(0.011)	(0.006)	(0.010)	(0.007)	(0.009)
	(0.058)	(0.061)	(0.040)	(0.053)	(0.031)	(0.047)	(0.033)	(0.041)
Country by interview month dummies	x	x	x	x	x	x	x	x

Interaction between T and Distance from T	x	x	x	x	x	x	x	x
Obs	21,548	21,394	21,218	21,671	21,567	21,615	19,878	20,626

Notes: Standard errors in round brackets. Significance levels: p-value *** ≤ 0.01, ** ≤ 0.05, * ≤ 0.1.

Table C.2: The effect of expected longevity on health behaviours and forgone medical treatment. TSLS estimates.

Dep. Var.	(1) Shopping Less Often	(2) Walking Less Often	(3) Meeting People Less Often	(4) Always Distance	(5) Hands Washing & Sanitizer Usage	(6) Forgone Treatment	(7) Forgone Treatment GP	(8) Forgone Treatment SP
LongExp	0.071*	-0.075*	-0.021	-0.008	0.062***	-0.001	-0.001	-0.031
	(0.041)	(0.043)	(0.028)	(0.037)	(0.022)	(0.033)	(0.023)	(0.028)
Wave of LE assessment (ref. category: 4)								
wave 5	-0.035	-0.054	-0.020	-0.088**	0.044*	0.024	0.020	0.035
	(0.046)	(0.048)	(0.031)	(0.042)	(0.025)	(0.037)	(0.026)	(0.032)
wave 6	-0.062	-0.078*	-0.021	-0.066	0.056**	0.033	0.018	0.043
	(0.044)	(0.047)	(0.030)	(0.040)	(0.024)	(0.035)	(0.025)	(0.031)
wave 7	-0.097**	-0.094*	-0.018	-0.071*	0.068***	0.030	0.016	0.040
	(0.046)	(0.048)	(0.031)	(0.041)	(0.025)	(0.036)	(0.026)	(0.032)
wave 8	-0.071	-0.129***	-0.020	-0.072*	0.078***	0.038	0.016	0.048
	(0.044)	(0.046)	(0.030)	(0.040)	(0.024)	(0.035)	(0.025)	(0.031)
Age threshold in LE question (T) (ref. category: 75)								
80	0.195**	0.219***	-0.007	0.110	0.085**	0.090	0.087**	0.079
	(0.077)	(0.080)	(0.052)	(0.069)	(0.042)	(0.061)	(0.044)	(0.054)
85	0.007	-0.015	0.002	0.065	0.067*	-0.044	-0.061*	-0.036
	(0.064)	(0.067)	(0.043)	(0.057)	(0.034)	(0.051)	(0.037)	(0.044)
90	0.228***	0.148**	0.023	0.115**	0.010	-0.016	-0.027	-0.020
	(0.062)	(0.065)	(0.042)	(0.055)	(0.034)	(0.050)	(0.036)	(0.044)
Distance from T	-0.001	-0.006***	-0.002*	-0.001	0.003**	-0.000	-0.001	-0.001
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
Female	0.117***	0.068***	0.030***	0.056***	0.016***	0.046***	0.019***	0.038***
	(0.006)	(0.007)	(0.004)	(0.006)	(0.003)	(0.005)	(0.004)	(0.004)
Optimistic1	0.008	-0.021***	-0.001	0.021***	0.009**	0.004	-0.007**	0.006
	(0.007)	(0.007)	(0.004)	(0.006)	(0.004)	(0.005)	(0.004)	(0.005)
Optimistic2	0.027***	0.012	0.028***	0.025***	0.023***	0.016***	0.009**	0.013***
	(0.007)	(0.008)	(0.005)	(0.006)	(0.004)	(0.006)	(0.004)	(0.005)
Couple	0.048***	0.005	0.024***	0.019***	0.016***	0.001	-0.004	0.004
	(0.007)	(0.007)	(0.005)	(0.006)	(0.004)	(0.005)	(0.004)	(0.005)
Working	-0.086***	-0.024**	-0.099***	-0.039***	-0.009	-0.009	-0.005	-0.003
	(0.011)	(0.011)	(0.007)	(0.009)	(0.006)	(0.008)	(0.006)	(0.007)

Respondent's education (ISCED) (ref. category: isced0_2)								
isced3_4	-0.005	-0.025***	-0.005	-0.001	0.006	0.019***	0.011**	0.011**
	(0.007)	(0.008)	(0.005)	(0.007)	(0.004)	(0.006)	(0.004)	(0.005)
isced5_6	0.008	-0.060***	0.014**	0.006	0.012**	0.045***	0.015***	0.036***
	(0.009)	(0.009)	(0.006)	(0.008)	(0.005)	(0.007)	(0.005)	(0.006)
children	0.022*	0.014	0.012	-0.000	0.016**	0.004	0.005	0.013
	(0.013)	(0.013)	(0.009)	(0.011)	(0.007)	(0.010)	(0.007)	(0.009)
grandchildren	0.021**	-0.005	-0.011*	0.001	0.007	-0.000	0.008*	-0.008
	(0.009)	(0.009)	(0.006)	(0.008)	(0.005)	(0.007)	(0.005)	(0.006)
everhomeowner	0.030***	-0.034***	-0.001	-0.011	-0.001	0.004	-0.001	0.001
	(0.010)	(0.010)	(0.007)	(0.009)	(0.005)	(0.008)	(0.005)	(0.007)
eversmoked	-0.028***	-0.010	-0.012***	0.004	-0.001	0.000	-0.002	0.002
	(0.006)	(0.006)	(0.004)	(0.005)	(0.003)	(0.005)	(0.003)	(0.004)
Mother's birth cohort (ref. category: 1919less)								
1920-1924	-0.001	0.007	0.002	0.021***	-0.006	-0.017**	-0.008*	-0.015**
	(0.008)	(0.009)	(0.006)	(0.008)	(0.005)	(0.007)	(0.005)	(0.006)
1925-1929	0.023**	0.028**	-0.005	0.011	-0.008	-0.005	-0.000	-0.007
	(0.011)	(0.011)	(0.007)	(0.010)	(0.006)	(0.009)	(0.006)	(0.007)
1930-1934	0.006	0.014	-0.003	0.009	-0.010	-0.016	-0.012	-0.017*
	(0.014)	(0.015)	(0.010)	(0.013)	(0.008)	(0.011)	(0.008)	(0.010)
1935more	-0.003	0.031	-0.025**	-0.002	-0.005	-0.007	0.003	-0.018
	(0.018)	(0.019)	(0.012)	(0.016)	(0.010)	(0.015)	(0.010)	(0.013)
Father's birth cohort (ref. category: 1919less)								
1920-1924	0.004	0.005	0.004	-0.005	0.003	0.003	0.003	0.006
	(0.009)	(0.010)	(0.006)	(0.008)	(0.005)	(0.007)	(0.005)	(0.006)
1925-1929	-0.011	0.013	-0.000	0.006	0.002	-0.001	0.001	0.004
	(0.012)	(0.012)	(0.008)	(0.010)	(0.006)	(0.009)	(0.007)	(0.008)
1930-1934	0.003	0.011	-0.001	0.008	0.018**	0.003	-0.000	0.006
	(0.015)	(0.016)	(0.010)	(0.014)	(0.008)	(0.012)	(0.009)	(0.011)
1935more	-0.028	0.011	0.003	-0.017	-0.006	0.003	0.001	0.007
	(0.020)	(0.021)	(0.014)	(0.018)	(0.011)	(0.016)	(0.012)	(0.014)
Self-perceived health - COVID SURVEY (ref. category: Excellent)								
Very good	0.045***	0.053***	0.019**	0.003	0.018**	0.032***	0.019**	0.013
	(0.013)	(0.014)	(0.009)	(0.012)	(0.007)	(0.011)	(0.008)	(0.009)
Good	0.080***	0.077***	0.022**	-0.010	0.018**	0.046***	0.033***	0.018*
	(0.014)	(0.015)	(0.010)	(0.013)	(0.008)	(0.011)	(0.008)	(0.010)

Fair	0.141***	0.142***	0.047***	-0.002	0.022**	0.079***	0.055***	0.044***
	(0.018)	(0.018)	(0.012)	(0.016)	(0.009)	(0.014)	(0.010)	(0.012)
Poor	0.208***	0.216***	0.067***	0.035	0.008	0.086***	0.052***	0.050***
	(0.024)	(0.025)	(0.016)	(0.022)	(0.013)	(0.019)	(0.013)	(0.016)
Covid	0.021**	-0.008	0.013**	-0.013	0.008	0.038***	0.019***	0.029***
	(0.009)	(0.009)	(0.006)	(0.008)	(0.005)	(0.007)	(0.005)	(0.006)
New disease dignosed	0.022**	0.042***	0.001	0.023***	0.007	0.014*	0.003	0.013*
	(0.010)	(0.010)	(0.007)	(0.009)	(0.005)	(0.008)	(0.006)	(0.007)
Poor health during childhood	-0.000	-0.006	0.003	0.013**	0.001	-0.002	-0.004	-0.002
	(0.006)	(0.007)	(0.004)	(0.006)	(0.003)	(0.005)	(0.004)	(0.004)
Self-perceived health - wave of LE assessment (ref. category: Excellent)								
Very good	0.033**	-0.036**	-0.005	-0.020	0.009	0.011	0.006	0.003
	(0.016)	(0.016)	(0.011)	(0.014)	(0.008)	(0.012)	(0.009)	(0.011)
Good	0.066***	-0.008	-0.008	-0.019	0.019*	0.024	0.010	0.008
	(0.019)	(0.019)	(0.013)	(0.017)	(0.010)	(0.015)	(0.010)	(0.013)
Fair	0.080***	-0.002	-0.012	-0.017	0.035**	0.045**	0.026*	0.016
	(0.026)	(0.027)	(0.018)	(0.023)	(0.014)	(0.021)	(0.014)	(0.018)
Poor	0.138***	0.041	-0.006	0.015	0.042*	0.059*	0.042*	0.013
	(0.042)	(0.044)	(0.029)	(0.037)	(0.022)	(0.033)	(0.023)	(0.029)
Vaccinated during childhood	-0.027	-0.023	-0.005	0.019	0.014	-0.013	-0.005	-0.005
	(0.019)	(0.020)	(0.013)	(0.017)	(0.010)	(0.015)	(0.011)	(0.013)
Ever hospitalised	0.027***	0.012*	-0.002	0.013**	0.003	0.012**	0.001	0.011**
	(0.006)	(0.007)	(0.004)	(0.006)	(0.003)	(0.005)	(0.004)	(0.004)
Mother's birth education (ref. category: isced0_2)								
isced3_4_m	0.013	-0.001	-0.008	-0.008	-0.000	0.012*	0.006	0.006
	(0.009)	(0.009)	(0.006)	(0.008)	(0.005)	(0.007)	(0.005)	(0.006)
isced5_6_m	0.013	0.006	0.013	0.001	0.005	0.029**	0.019*	0.022*
	(0.017)	(0.018)	(0.011)	(0.015)	(0.009)	(0.013)	(0.010)	(0.012)
Father's birth education (ref. category: isced0_2)								
isced3_4_f	-0.015*	-0.010	-0.004	-0.005	-0.001	0.000	-0.002	0.002
	(0.008)	(0.009)	(0.006)	(0.007)	(0.004)	(0.007)	(0.005)	(0.006)
isced5_6_f	-0.015	-0.007	-0.007	0.000	-0.001	-0.001	0.008	0.001
	(0.012)	(0.013)	(0.008)	(0.011)	(0.007)	(0.010)	(0.007)	(0.009)
Country by interview month dummies	x	x	x	x	x	x	x	x
Interaction between								

T and Distance from T	x	x	x	x	x	x	x	x
Obs	21,548	21,394	21,218	21,671	21,567	21,615	19,878	20,626

Notes: Standard errors in round brackets. Significance levels: p-value *** ≤ 0.01, ** ≤ 0.05, * ≤ 0.1.

Appendix D. Acknowledgements.

We thank the discussant and participants to the 2nd Workshop APHEC on Health and Aging: the Sustainability and Equity Trade off (Genova, September 10-11, 2021), two anonymous reviewers and editors for their comments and suggestions on an earlier version of the paper.

This paper uses data from SHARE Waves 1, 2, 3, 4, 5, 6 and 7 (DOIs: 10.6103/SHARE.w1.710, 10.6103/SHARE.w2.710, 10.6103/SHARE.w3.710, 10.6103/SHARE.w4.710, 10.6103/SHARE.w5.710, 10.6103/SHARE.w6.710, 10.6103/SHARE.w7.710), see Börsch-Supan et al. (2013) for methodological details. The SHARE data collection has been funded by the European Commission through FP5 (QLK6-CT-2001-00360), FP6 (SHARE-I3: RII-CT-2006-062193, COMPARE: CIT5-CT-2005-028857, SHARELIFE: CIT4-CT-2006-028812), FP7 (SHARE-PREP: GA N°211909, SHARE-LEAP: GA N°227822, SHARE M4: GA N°261982, DASISH: GA N°283646) and Horizon 2020 (SHARE-DEV3: GA N°676536, SHARE-COHESION: GA N°870628, SERISS: GA N°654221, SSHOC: GA N°823782) and by DG Employment, Social Affairs Inclusion. Additional funding from the German Ministry of Education and Research, the Max Planck Society for the Advancement of Science, the U.S. National Institute on Aging (U01_AG09740-13S2, P01_AG005842, P01_AG08291, P30_AG12815, R21_AG025169, Y1-AG-4553-01, IAG_BSR06-11, OGHA_04-064, HHSN271201300071C) and from various national funding sources is gratefully acknowledged (see www.share-project.org).