Heterogeneous and Uncertain Health Dynamics and Working Decisions of Older Adults*

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Abstract

I study heterogeneity in health dynamics of older adults, focusing on the rate at which health deteriorates with age, and its effects on working decisions. After showing evidence of this unobserved heterogeneity, I use subjective survival expectations to infer health beliefs in a Bayesian-learning framework, and I flexibly estimate how working decisions depend on those beliefs. The results show individuals incorrectly believe their health will deteriorate too fast, and a numerical exercise suggests that eliminating that bias would increase labor-force participation by more than 2 percentage points. Providing biomarker information has only small effects on beliefs and working decisions.

JEL codes: D83, I14, J14, J26.

Keywords: Health dynamics, older adults, retirement, uncertainty, beliefs.

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1 Introduction

The population is aging rapidly, putting considerable strain on public budgets. The number of older adults out of the labor force who will need to be supported by each worker is projected to increase by around 40% between 2018 and 2050. Therefore, promoting employment at older ages has garnered large interest.[1] The success of policies promoting the employment of older adults depends on our correct understanding of the determinants of working decisions of this group, for whom health is an important factor.

In this paper, I study how the working decisions of older adults depend on their beliefs about future health, using data from the Health and Retirement Study (HRS). I am interested in studying if individuals expecting their health to deteriorate more rapidly make different working decisions than otherwise similar individuals, but who expect their health to deteriorate more slowly. There are several potential channels through which future health, and therefore health beliefs, may matter for working decisions. First, future health may affect the marginal utility of consumption and the disutility of work in future periods. Second, it may enter the intertemporal budget constraint by affecting wages due to changes in productivity and by changing health-related costs like medical expenses. Third, future health affects the probability of later survival. These channels could have opposite effects on current working decisions. For example, individuals may decide to remain working and save more, if they expect their health to deteriorate slowly and therefore anticipate living long, or if they expect their health to deteriorate rapidly and therefore anticipate higher health-related costs. Hence, the overall effect of health beliefs on working decisions of older adults is an empirical question.

For older adults, health deteriorates naturally with aging. Building on the evidence that health is heterogeneous and uncertain, with a mean that deteriorates and a variance that increases with age, I model health as a dynamic process with heterogeneous intercepts and heterogeneous slopes with age. The first contribution of the paper is to relax the full-information assumption, traditional in most of the literature, by assuming individuals do not know their health process (in particular, I assume they do not know their own health slopes), which adds an additional source of uncertainty beyond uncertainty due to unpredictable health shocks. I propose a Bayesian learning model where rational individuals update their beliefs about their health processes, i.e. their health dynamics, as they see their health changing over time. While these beliefs are time-varying objects unobserved to the econometrician, I leverage data on subjective survival expectations to pin down the learning

[1] See statistics from OECD (2019). In 2015, the OECD adopted an agenda promoting employment at older ages, to protect living standards and public finances (OECD (2015)).

parameters. The intuition is simple: future survival depends on future health, and hence, on health dynamics; therefore, expectations about survival speak to beliefs about health dynamics. Using the Simulated Method of Moments, I find a substantial amount of this additional uncertainty and a negative bias, which implies that on average individuals believe their health will deteriorate faster than the average rate in the population.

The second contribution of this paper is related to the link between health and working decisions of older adults, in an environment without full information. Building on the well-known result that health is an important determinant of working decisions, I study whether health beliefs matter for the working decisions of this group, conditioning on current health and focusing on the extensive margin. I estimate dynamic models for working decisions, both parametrically via probit and non-parametrically via neural networks, where unobserved health beliefs have a distribution that is integrated out. I find that beliefs do matter for working decisions, above and beyond the effects of current health, such that individuals who believe their health will deteriorate slowly have larger probabilities of working than otherwise similar individuals, but who believe their health will deteriorate rapidly. Furthermore, for individuals in their 50s who are not working, there is an interaction between health and beliefs about future health suggesting that adjustment costs of finding a job are important, as an improvement in health that is expected to be short-lived has lower effects than one that is expected to be long-lived.

In the current context of heterogeneous and uncertain health dynamics, a health shock affects working decisions in two ways: by changing current health, and by changing beliefs about future health. I decompose the effect of a health shock into these two channels and find that nearly all the effect goes through the first one. This results from a low signal-to-noise ratio of health, and it implies health by itself is not enough to resolve the uncertainty in health dynamics and correct the bias in beliefs. At the same time, in a simulation exercise in the spirit of impulse-response-functions, I show that eliminating the initial average bias in beliefs is associated with increased working probabilities of more than 2 percentage points, a relatively large effect that lasts beyond traditional retirement ages.

Finally, in the last part of the paper, I study the effects on health beliefs of health-related information, specifically information on blood-based biomarkers. I do this indirectly, by looking at its effects on subjective survival expectations and working decisions. First, I exploit exogenous variation in who receives this information, a variation that comes from the biomarker collection scheme within the HRS. A reduced-form analysis in the spirit of difference-in-differences shows positive effects of receiving *any* information on survival expectations, though these effects are only significant for highly educated individuals, and no significant effects are found on working decisions, suggesting that the information provided

is not enough to affects these variables. Then, I study the effects of receiving *bad* versus *good* biomarker results, for which I do not have exogenous variation. I find positive average differences among the two groups on both studied variables, particularly for low educated individuals, differences that are explained by sample selection. When controlling for the composition of these two groups, by regression-based estimates and propensity score matching, the effects disappear.

Outline. The paper proceeds as follows. Section 2 reviews the related literature putting this paper into context, while Section 3 describes the data and measurement of health. Section 4 estimates heterogeneous health dynamics, and Section 5 describes and estimates the learning model using subjective survival expectations. Section 6 presents the main results for working decisions as a function of health beliefs. Section 7 analyzes the provision of biomarker information within the HRS. Finally, Section 8 concludes.

2 Related literature

This paper is mainly related to two strands of literature. First, there is a literature studying health dynamics that highlights that health is heterogeneous and persistent; see, for example, Contoyannis, Jones, and Rice (2004), Halliday (2008), Hernández-Quevedo, Jones, and Rice (2008), and focusing on older adults, Heiss, Börsch-Supan, Hurd, and Wise (2009) and Lange and McKee (2011). The literature also shows that on average health deteriorates with age, and its dispersion increases (Deaton and Paxson, 1998a, Deaton and Paxson, 1998b and Halliday, 2011). Furthermore, health is a key determinant of survival, and failing to account for survival can bias estimates of the health process among older groups (Heiss, 2011, Heiss, Venti, and Wise, 2014. See also Lleras-Muney and Moreau, 2022). Building on this evidence, this paper begins by jointly modeling health and survival outcomes, explicitly accounting for both persistence and individual heterogeneity in the health process. It includes heterogeneity not only in intercepts but also in slopes with age, capturing the empirical observation that health variance increases with age. Halliday (2008) is one of the few papers that allows for this type of heterogeneity but finds only weak evidence of it; however, he uses a binary measure and focuses on a much younger population, whereas I focus on an older group for whom health changes with age are prevalent.

Second, this paper is related to an extensive literature studying the effects of health on work and retirement choices, which finds that poor health is associated with lower working probabilities. One concern in this literature is justification bias when using subjective health measures. To address this concern, several papers use objective measures as instruments for the subjective ones (Bound, Schoenbaum, Stinebrickner, and Waidmann, 1999, Disney,

Emmerson, and Wakefield, 2006, Zucchelli, Jones, Rice, and Harris, 2010, Harris, Zhao, and Zucchelli, 2021), and though some find evidence of this bias (Lindeboom and Kerkhofs, 2009), others do not (Dwyer and Mitchell, 1999). Blundell, Britton, Dias, and French (2023) find that the instrumented results are similar to those obtained by using subjective and objective measures, if a sufficiently large set of objective measures is used. They also find that a single index captures the relevant variation for employment, which is the strategy followed in this paper.

Another concern is the presence of unobserved individual-level heterogeneity in working decisions, that some papers explicitly account for. See, for example, Disney, Emmerson, and Wakefield (2006), Maurer, Klein, and Vella (2011), Haan and Myck (2009), Harris, Zhao, and Zucchelli (2021), the last two also accounting for persistence of working decisions. See also Lindeboom and Kerkhofs (2009). Blundell, Britton, Dias, and French (2023) find that accounting for heterogeneity by controlling for initial conditions is relevant when estimating the effects of health. In this paper, I explicitly account for the effects of health heterogeneity on working decisions.

While most of these papers consider only the effects of current health, the relevance of health dynamics for working decisions has also been discussed. Bound, Schoenbaum, Stinebrickner, and Waidmann (1999) and Disney, Emmerson, and Wakefield (2006) estimate working decisions as a function of current and lagged health and claim that the effect of the latter coefficient depends, among other reasons, on expectations about future health, as past health gives information about future health. See also Zucchelli, Jones, Rice, and Harris (2010). An innovation of this paper is to focus explicitly on expectations about future health, by allowing health dynamics to be heterogeneous and not fully known, which adds an additional source of uncertainty (on top of uncertainty due to health shocks), and by introducing the role of beliefs as an additional determinant of working decisions. Note, though, that I abstract from reverse causality and assume the health process is exogenous. This assumption implies that beliefs about future health and about future survival are exogenous (and not confounded by *planned* changes in *future* behavior), which allows me to use subjective survival expectations to pin down the belief parameters.

Other factors relevant for working and retirement decisions include institutional settings (Siddiqui, 1997, García-Gómez, 2011), financial aspects (French, 2005), household characteristics (Blau, 1998), health insurance (Blau and Gilleskie, 2001), spousal health insurance (Blau and Gilleskie, 2006) and health-related job characteristics (Helppie McFall, Sonnega, Willis, and Hudomiet, 2015). The last three are important in the context of this paper as they relate both to employment and health or health beliefs. These factors are not the focus of this paper, but I take them into account by controlling for wealth, health insurance,

spouse-related variables, and health-related job characteristics. I also allow for wealth and health insurance to change dynamically in the simulation exercise of Section 6.

Methodologically, this paper is related to the literature on empirical learning. Particularly, to those papers focusing on learning about own unobserved heterogeneity; for example, own ability and labor productivity (Arcidiacono, Aucejo, Maurel, and Ransom, 2025), own income profiles (Guvenen, 2007, Guvenen and Smith, 2014), patient-specific productivity of a drug or medical treatment (Crawford and Shum, 2005, Chan and Hamilton, 2006), own smoking effects in biomarker production (Darden, 2017), and family-specific component of infant mortality risk (Mira, 2007). These papers assume that individuals are rational Bayesian learners and have initial beliefs which they update over time based on available signals. Parametric assumptions allow econometricians to put structure into unobserved and high-dimensional beliefs. I follow a similar strategy, with changes in health being the signals, and the mean and variance of normally distributed initial beliefs being the key parameters. However, I do not specify and estimate a structural model. Within this literature, this paper is most closely related to Guvenen (2007), who examines an income process with heterogeneity in both levels and slopes with age, and studies how uncertainty in that process relates to consumption. His identification strategy depends on the relation between income and consumption. Instead, I use subjective survival expectations to pin down the belief parameters. Hence, identification does not depend on how health relates to working decisions, but on how it relates to survival.

Finally, there are also several papers looking at subjective survival expectations; see Hudomiet, Hurd, and Rohwedder (2023) for a recent review. Subjective survival expectations have been shown to have predictive power for survival and to be consistently updated with new health information (see, for example, Smith, Taylor, and Sloan, 2001, Hurd and McGarry, 2002). On the other hand, subjective expectations are subject to non-classical measurement error, including focal responses and rounding (see Kleinjans and Van Soest, 2014, Giustinelli, Manski, and Molinari, 2022, Hudomiet and Willis, 2013). In the model, these noisy measures are linked to the unobserved health beliefs through the relation between health and survival, and hence, I use these data to estimate the initial belief parameters. Consistent with the literature, I allow for non-classical measurement error and rounding, and I find differences in initial beliefs by education.

3 Data and health measurement

I use waves 4 to 12 of the Health and Retirement Study (2014) (HRS),[2] a US longitudinal survey representative of individuals 50 years and older. The survey includes questions about health, survival expectations, and labor participation, among others.

3.1 Factor model for health

Health is usually measured by self-assessed health, an ordinal variable taking five values from very poor to excellent. This variable has been shown to correlate with several outcomes, including labor-force participation; however, its limited range and subjective nature make it not ideal to study health dynamics with age. Instead, I use a battery of health-related measures included in the HRS, focusing on those related to physical health, and construct, via factor analysis, a summary health variable.[3] Table 1 describes the measures, which include self-assessed health, but also, other objective measures including number of chronic conditions and number of difficulties in activities of daily living, among others. These measures reflect a health concept that is relevant for the working decisions of older adults, related to how individuals perceive their physical health in their everyday activities.

Let h_{it} denote the (unobserved) health of individual i at age t and let M_{ijt} be the j^{th} (observed) measure of h_{it}, for $j = 1, \dots 11$. I assume a linear factor model structure,

$$M^*_{ijt} = \mu_j + \lambda_j h_{it} + \epsilon^h_{ijt}, \tag{1}$$

with $M_{ijt} = M^*_{ijt}$ for continuous measures, and

$$M_{ijt} = s \quad \text{if} \quad \tau^s_j \leq M^*_{ijt} \leq \tau^{s+1}_j, \tag{2}$$

for ordinal measures taking S values, with $\tau^0_j = -\infty, \tau^S_j = \infty$. The measures are observed at every age, and the intercepts μ_j and loadings λ_j are assumed to be age-invariant, as well as the thresholds τ^s_j for the ordinal variables. The measurement errors ϵ^h_{ijt} are assumed independent[4] and normally distributed $\epsilon^h_{ijt} \sim N(0, \sigma^2_{\epsilon j})$.

[2] The HRS (Health and Retirement Study) is sponsored by the National Institute on Aging (grant number NIA U01AG009740) and is conducted by the University of Michigan. For most of the analysis, I use the RAND HRS Longitudinal File (2014), which is an easy-to-use dataset based on the HRS core data. This file was developed at RAND with funding from the National Institute on Aging and the Social Security Administration.

[3] Constructing a summary variable from several measures is an approach commonly used in the literature; see, for example, Heiss, Venti, and Wise (2014), Lange and McKee (2011), and Blundell, Britton, Dias, and French (2023) for health, and Attanasio, Áureo de Paula, and Toppeta (2025) for skills.

[4] The only exception being the measurement errors of the eyesight measures, which are allowed to be corre-

Table 1: Descriptive statistics on health measures

Measure	Obs.	Mean	SD	Min	Max	Variable type
Number of chronic conditions	156,968	1.83	1.34	0	7	continuous
Self-assessed health	156,862	2.86	1.11	1	5	ordinal
Body mass index ($kg/m2$)	154,602	27.89	5.81	7	83	continuous
Eyesight in general	156,768	2.85	1.01	1	6	ordinal
Eyesight at a distance	156,833	2.57	1.01	1	6	ordinal
Eyesight up close	156,822	2.75	1.04	1	6	ordinal
Hearing	156,869	2.63	1.09	1	5	ordinal
Pain	156,550	0.63	0.97	0	3	ordinal
Difficulties in ADLs regarding mobility	156,748	1.09	1.45	0	5	continuous
Difficulties in ADLs of large muscles	156,737	1.28	1.33	0	4	continuous
Difficulties in other ADLs	151,923	0.40	0.66	0	2	continuous
Summary health variable h_{it}	148,866	10.57	0.75	6.82	11.87	continuous

Notes: Descriptive statistics on health measures and summary health variable. The sample includes 156,976 observations and comprises 31,210 individuals interviewed in person who are 50 years old or older. Chronic conditions include high blood pressure, heart attack, diabetes, stroke, lung disease, arthritis, and cancer. The categories for self-assessed health, eyesight and hearing variables are 1. excellent, 2. very good, 3. good, 4. fair, 5. poor, with an extra category 6. legally blind for eyesight variables. The categories for the level of pain are 0. no pain, 1. mail pain, 2. moderate, 3. severe. ADL stands for activities of daily living. ADLs regarding mobility include walking 1 block, several blocks, across room, climbing one flight of stairs, several flight of stairs. ADLs involving large muscles include pushing or pulling large objects, sitting for two hours, getting up from chair, and stooping, kneeling or crouching. Other ADLs include carrying 10 lbs. and reaching arms.

This system is not identified without further restrictions. To fix the location and scale of h_{it}, I set the intercept and loading of the (rescaled) number of chronic conditions,[5] such that larger values of h_{it} represent better health, and an increase of one unit in h_{it} can be broadly interpreted as having one less chronic condition.[6] We also need further normalizations for the ordinal measures, for which I fix $\sigma^2_{\epsilon j}$ and τ^1_j.[7]

I estimate equations (1) and (2) by confirmatory factor analysis (CFA) and the results are presented in Appendix Table A1. Estimates of latent health h_{it} are obtained as the predicted factor scores.

lated with each other.

[5] The rescaled measure corresponds to 7 minus the number of chronic conditions, for which the intercept and loading are fixed to 0 and 1, respectively.

[6] An alternative normalization would set the mean and variance of h_{it} at age 50 to be 0 and 1 respectively.

[7] Equivalently, we could allow all the thresholds to vary freely, but we would need to fix the intercepts μ_j of these measures.

3.2 Description of the main variables

Besides age and health, the two other main variables in this paper are survival expectations and working decisions. The HRS asks about subjective survival expectations in variable $plive10_{it}$. Specifically, the question asks *What is the percentage chance you will live to be (80, 85, 90, 95 or 100) or more?* The reference age is a function of the individual's age and the wave of the survey, and it is usually around 10 to 15 years into the future.[8]

I study the extensive margin of labor-participation decisions of older adults, and define a binary variable p_{it} as 1 for individuals working for pay at age t. This includes individuals working full- and part-time as well as individuals partially retired.[9]

The overall sample consists of 156,976 observations from an unbalanced panel of $N = 31,210$ individuals 50 years and older, interviewed in person[10] in some wave between waves 4 and 12. Table 2 presents descriptive statistics for the main variables.

Table 2: Summary statistics of the main variables

Variable	Notation	Observations	Mean	SD	Min	Max
Age	$t + 50$	156,976	67.44	10.35	50	109
Health	h_{it}	148,866	10.57	.75	6.82	11.87
Survival expectations	$plive10_{it}$	125,658	.47	.32	0	1
Working decisions	p_{it}	156,582	.37	.48	0	1

Notes: The sample includes 156,976 observations and comprises 31,210 individuals interviewed in person who are 50 years old or older. t is defined as 0 for age 50, $plive10$ is re scaled so it takes values between 0 and 1.

[8] The HRS also includes another question on survival expectations to the age of 75, only asked of individuals under 65 years old. I use this variable to check the fit of the beliefs model in Section 5.

[9] Hence, this variable identifies as 0 individuals unemployed, retired, disabled or not in the labor force.

[10] I exclude proxy interviews because these interviews do not ask questions about survival expectations.

4 Health dynamics

In this section, I study health dynamics, assuming an exogenous process[11] and focusing on changes in health due to aging in a flexible manner. I assume the following health process,[12]

$$h_{it} = \rho h_{it-1} + \alpha_i + \delta_i \cdot t + \tau \cdot t^2 + \epsilon_{it}, \tag{3}$$

where ϵ_{it} are health shocks, $\epsilon_{it} \sim N(0, \sigma_\epsilon^2)$. In this equation, α_i captures heterogeneous *levels* in health, while δ_i captures heterogeneous *slopes* with age, that is, heterogeneous dynamics. The heterogeneity in levels α_i is a well-recognized element of health in the literature, both among the general population (Hernández-Quevedo, Jones, and Rice, 2008) and among older individuals (Heiss, Venti, and Wise, 2014). The heterogeneity in slopes δ_i allows us to capture the increasing variance of health with age documented in the literature (Deaton and Paxson, 1998b, Halliday, 2011). As larger values of h_{it} represent better health and health decreases with age, $\delta_i < 0$.

I assume that, conditional on time-invariant characteristics x_i and initial health h_{i0}, α_i and δ_i are jointly normally distributed,

$$\begin{pmatrix} \alpha_i \\ \delta_i \end{pmatrix} \Big| x_i, h_{i0} \sim N\left(\begin{pmatrix} \mu_\alpha + \nu_\alpha' x_i + \omega_\alpha h_{i0} \\ \mu_\delta + \nu_\delta' x_i + \omega_\delta h_{i0} \end{pmatrix}, \begin{bmatrix} \sigma_\alpha^2 & \phi\sigma_\alpha\sigma_\delta \\ \phi\sigma_\alpha\sigma_\delta & \sigma_\delta^2 \end{bmatrix} \right), \tag{4}$$

where x_i is a vector of demographic characteristics including gender, race, Hispanic ethnicity, and education.

Furthermore, health is an important determinant for survival, especially for older adults, with individuals surviving at older ages having better health than individuals that don't survive that long. Hence, ignoring survival when studying health of older adults leads to biased estimates (Heiss, Venti, and Wise, 2014). I assume the survival process is given by

$$S_{it} = \mathbb{1}\{\gamma h_{it-1} + \theta_0 + \theta_1 \cdot t + \theta_2' x_i + \eta_{it} \geq 0\} S_{it-1}, \tag{5}$$

where η_{it} is a random shock, $\eta_{it} \sim N(0,1)$, independent of health shocks ϵ_{it} at all leads and lags. The parameter γ captures the dependence of survival on health.

I estimate equations (3), (4) and (5) jointly by Simulated Maximum Likelihood, in the subsample of individuals observed at age 50, for whom we have a measure of h_{i0}. This allows me to estimate the initial distribution of unobserved heterogeneity, before any survival selection happens, which I need for specifying the beliefs model in the next section.

[11] I further discuss this assumption at the end of Section 5.

[12] In what follows, given that HRS' waves are two years apart, I consider age as measured in two-year bins.

The main results are shown in Table 3. The table shows two things in terms of the unobserved heterogeneity. First, there is heterogeneity in both the intercepts and the slopes of the health process, with positive and significant standard deviations, σ_α and σ_δ. Second, these two sources of heterogeneity are uncorrelated, as shown by a non-significant ϕ, which implies knowing α_i does not provide additional information about δ_i. The table also shows that health decreases with age, as $\mu_\delta, \omega_\delta < 0$. Though these coefficients are not significant by themselves, combined they give an average δ_i of -0.061, significant at 1%. According to the table, health shocks have relatively low persistence ρ. Note that this formulation separates persistence due to time-invariant heterogeneity and due to time-varying shocks, which explains the low value of ρ.[13] The coefficient for health in the survival equation γ is positive and significant, implying that survival is more likely for healthier individuals. The full set of results is reported in Appendix Table B1. It shows that non-white individuals and individuals with low levels of education have worse health, health deteriorates faster for non-white individuals, and probabilities of survival are higher for women and Hispanic individuals.

By allowing for unobserved heterogeneity in δ_i, the model does indeed predict an increasing variance of health with age. To see this, Figure 1 plots the predicted variance of health for two cases: allowing for unobserved heterogeneity in slopes (left panel, baseline) and assuming instead no unobserved heterogeneity[14] (right panel). The figure shows that by ignoring unobserved slope-heterogeneity, we predict a rather constant variance of health, contrary to what is observed in the data.[15]

I include several robustness checks in Appendix B.2. First, I estimate a version of the model with heteroskedastic errors ϵ_{it}, allowing its variance to depend on age. The results show that this heteroskedasticity does not explain away the unobserved heterogeneity in slopes δ_i. Second, I estimate a version of the model adding the unobserved heterogeneity (α_i, δ_i) to the survival equation. The results show α_i and δ_i are not (jointly) significant; that is, I find no direct effect of heterogeneity in survival, once we control for health. This lack of significance has an important implication for the beliefs model in the next section: it means survival does not contain additional information about δ_i, beyond the information already

[13] In fact, estimating the model without unobserved time-invariant heterogeneity, that is setting $\sigma_\alpha = \sigma_\delta = \phi = 0$, gives an estimated $\rho = 0.86$. See Hernández-Quevedo, Jones, and Rice (2008) for a discussion of the different sources of persistence in health dynamics.

[14] This model allows for *observed* heterogeneity in slopes (given by ν_δ) but no *unobserved* heterogeneity ($\sigma_\delta, \omega_\delta \equiv 0$). The results for this specification are shown in columns (5) and (6) of Appendix Table B1.

[15] In an additional exercise, I observe that allowing for heterogeneous slopes but ignoring survival leads to an overestimation of the variance of health with age, as the prediction includes the left tail of the health distribution that has lower probability of survival.

Table 3: MLE results on health and survival

	Symbol	Coefficient	Pvalue
Persistence	ρ	0.196	0.000
Mean of α_i - constant term	μ_α	1.674	0.000
Mean of δ_i - constant term	μ_δ	-0.045	0.383
Mean of α_i - slope with h_{i0}	ω_α	0.647	0.000
Mean of δ_i - slope with h_{i0}	ω_δ	-0.001	0.754
SD of α_i	σ_α	0.264	0.000
SD of δ_i	σ_δ	0.050	0.000
$Corr(\alpha_i, \delta_i)$	ϕ	-0.005	0.960
SD of health shocks	σ_ϵ	0.300	0.000
Survival dependence on health	γ	0.404	0.000
N alive observations		11,816	
N dead observations		151	
N individuals		2,856	
-Log likelihood		5,556.4	

Notes: Main results of estimating the health and survival processes. The sample consists of 2,856 individuals observed at age 50 and their following consecutive observations until death or loss to follow up, for a total of 11,967 observations. Details and full set of results are given in Appendix B.

contained in health.[16,17] Finally, I estimate a similar model using self-assessed health instead of the summary health variable h_{it}. The results show the presence of heterogeneous slopes with age is robust to using only this measure.

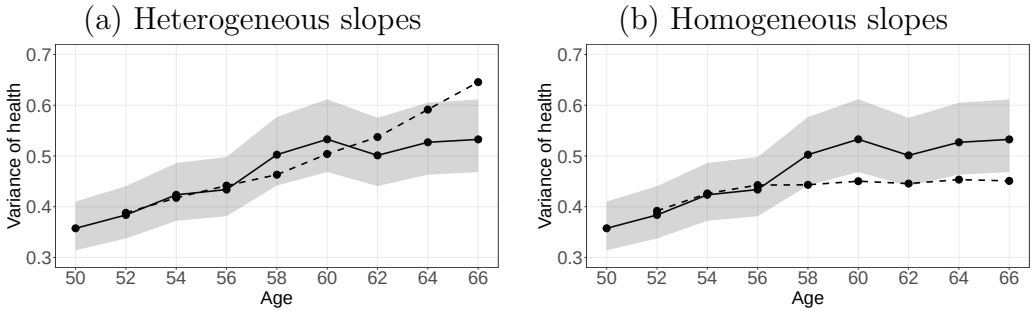
5 Uncertain health dynamics and beliefs

In standard models, agents are assumed to have complete information, which implies they know the parameters of their dynamic health processes. In this section, I relax this assumption.

[16] If this were not the case and survival contained additional information about δ_i, the learning model defined in Section 5 would not be valid, as it does not include survival as a signal.

[17] Note though that the estimation sample contains only a few transitions into death, so we cannot rule out that this lack of significance stems from a lack of power.

Figure 1: Variance of health in models with and without slope heterogeneity



Notes: The sample consists of 3,897 correlative observations from 433 individuals observed since they were 50 years old with health in all 9 waves (to avoid confounding by for mortality bias). The solid lines plot the health data, and the dotted lines plot the predicted values of health in each model, taking health at 50 as given.

5.1 Belief about health dynamics

I assume that at age 50 individuals know all the parameters of their health processes except for their own slope δ_i. The rationale behind this assumption is that common parameters can be learned from other individuals, and while levels α_i are heterogeneous, they have been observed for several decades. But if health starts deteriorating in old age,[18] individuals have not had the chance to learn about their δ_i's. This assumption is consistent with results from Halliday (2008), who studies health dynamics with discrete heterogeneity, using the Panel Study of Income Dynamics. He studies younger individuals, ages 22 to 60, and finds heterogeneity in levels but no heterogeneity in slopes with age. Moreover, in studying income profiles, Guvenen (2007) proposes a similar process for income with heterogeneous intercepts and slopes, both unknown, and finds the learning process for intercepts is much faster than the learning process for slopes, implying the assumption of known α_i is not restrictive.

As health changes with age, individuals do not know if the changes are due to health shocks or to their own health slope. I assume individuals are rational Bayesian learners with prior beliefs about δ_i given by $N(\hat{\delta}_{i0}, \hat{\sigma}_0^2)$,[19,20] which they update over time as they see their health changing. As the signals are also normally distributed (because health shocks are), according to Bayes' rule, individuals' posterior beliefs about their health slopes δ_i (henceforth, slope beliefs) are also normally distributed, $N(\hat{\delta}_{it}, \hat{\sigma}_t^2)$, with mean and variance

[18] For example, if $h_{it} = \rho h_{it-1} + \alpha_i + \mathbb{1}\{t \geq 0\}[\delta_i \cdot t + \tau \cdot t^2] + \epsilon_{it}$, for t positive or negative.

[19] The assumption of common-prior variance across individuals, i.e. that $\hat{\sigma}_0^2$ does not depend on i, though restrictive, is usual in the learning literature. See, for example, Guvenen (2007), Darden (2017), and Arcidiacono, Aucejo, Maurel, and Ransom (2025).

[20] Alternatively, I could assume prior beliefs follow a normal distribution truncated below at 0, as in Darden (2017). Under this assumption, the posterior distribution would also be a normal distribution truncated below at 0.

defined recursively by

$$\frac{\hat{\delta}_{it}}{\hat{\sigma}_t^2} = \frac{\hat{\delta}_{it-1}}{\hat{\sigma}_{t-1}^2} + \frac{(h_{it} - \rho h_{it-1} - \alpha_i - \tau t^2)t}{\sigma_\epsilon^2} \quad (6)$$

$$\frac{1}{\hat{\sigma}_t^2} = \frac{1}{\hat{\sigma}_{t-1}^2} + \frac{t^2}{\sigma_\epsilon^2}. \quad (7)$$

Equation (6) shows the posterior mean is a weighted average of the prior mean $\hat{\delta}_{it-1}$ and the signal derived from health h_{it}, with weights that depend on precision. The more certain an individual is to begin with (lower $\hat{\sigma}_{t-1}^2$), the more weight he gives to what he already knows, namely, the prior. The more precise health is as a signal (lower σ_ϵ^2), the more weight is given to its information. Equation (7) shows precision increases over time, and increases more when the signal is more precise, that is, when health is less noisy (lower σ_ϵ^2) and when individuals are older.

Conditional on health history, the key parameters determining beliefs are the parameters governing initial beliefs:

$$b = \mathbb{E}(\hat{\delta}_{i0} - \delta_i),$$
$$\lambda^2 = \frac{\hat{\sigma}_0^2}{Var(\delta_i)}.$$

The parameter b measures the bias in initial beliefs at the population level. If b is positive (resp. negative), individuals are upward (resp. downward) biased, and hence, they believe health deteriorates on average more slowly (resp. rapidly) than the average rate. The parameter λ measures the degree of initial uncertainty individuals face regarding δ_i, which affects their amount of learning over time. If $\lambda = 0$, there is no uncertainty in slopes δ_i and therefore no learning, though there is still uncertainty due to health shocks. The larger the value of λ, the more uncertain individuals are. Bayesian learning and normality assumptions allow us to reduce the dimensionality of the problem, giving structure to time-varying beliefs that are unobserved by the econometrician.

5.2 Estimation of belief parameters

To pin down these two parameters, b and λ, I use data on subjective survival expectations.[21] Given that future survival depends on future health, survival expectations depend on expectations about future health, and therefore, on beliefs about health dynamics.

[21] Subjective survival expectations have been shown to have predictive power for survival (Smith, Taylor, and Sloan, 2001, Hurd and McGarry, 2002). Appendix Table C1 shows the predictive power of $plive10_{it}$ for next-period survival S_{it+1} and next-period health h_{it+1}, conditional on current health h_{it}.

The intuition for identification using this data is as follows. Each period, individuals observe their health and update their beliefs regarding their unknown δ_i. This new information allows them to also update their beliefs about their future health, and hence their expectations about future survival. Thus, slope beliefs, unobserved by the econometrician, are closely linked to survival expectations, which are observed. This relation depends on the health and survival processes estimated in Section 4, and it is given in Appendix C.2. If individuals have a large positive (resp. negative) bias in beliefs, expecting their health to deteriorate too slowly (resp. fast), survival expectations are going to be larger (resp. lower). Hence, we can pin down b using levels of survival expectations. Similarly, the more uncertain individuals are, the more they update their slope beliefs given the same health signal,[22] and hence the larger is the correlation between changes in beliefs and changes in survival expectations.[23]

To estimate bias b and uncertainty λ, I use the Simulated Method of Moments (SMM). Given a set of parameters and health history $h_{i0}, h_{i1}, \dots h_{it}$, I can simulate moments of survival expectations $plive10_{it}$. This requires integrating out some variables that are unobserved by the econometrician[24], which I do by using Markov chain Monte Carlo (MCMC).[25]

As reported subjective survival probabilities are noisy measures, I allow for non-classical i.i.d. measurement error $\nu_{it} \sim N(\mu_{merror}, \sigma^2_{merror})$, such that the observed survival expectations are given by $\widetilde{plive10}_{it} = \max\{\min\{plive10_{it} + \nu_{it}, 1\}, 0\}$.[26] Furthermore, I follow Giustinelli, Manski, and Molinari (2022) and allow for rounding in the observed variable, where the amount of rounding is an individual characteristic, derived from their observed subjective expectations over the length of the panel. Individuals are classified according to their rounding behavior at the center and tails of the distribution in multiples of 1, 5, 10, 25 and 50 percent. The rounding behavior is then applied to the simulated probability $\widetilde{plive10}_{it}$.

I use six moments of subjective survival expectations, three in levels and three in dif-

[22] We can rewrite equation (6) as $\hat{\delta}_{it} = \hat{\delta}_{it-1} + K_t \cdot \hat{\zeta}_{it}$, where $K_t = \frac{\hat{\sigma}^2_{t-1} \cdot t}{\hat{\sigma}^2_{t-1} \cdot t^2 + \sigma^2_\epsilon}$ is increasing in $\hat{\sigma}^2_{t-1}$ and $\hat{\zeta}_{it}$ is individual i's perceived innovation in health at period t, $\hat{\zeta}_{it} = h_{it} - \mathbb{E}(h_{it}|\Omega_{it-1}) = h_{it} - \rho h_{it-1} - \alpha_i - \hat{\delta}_{it-1} \cdot t - \tau t^2$.

[23] Appendix C.3 further discusses identification of uncertainty λ.

[24] Mainly, α_i, δ_i and, for individuals who are observed starting after age 50, their initial health h_{i0} and combinations of their health shocks ϵ_{it} from 50 up to entering the sample.

[25] I assume $(\alpha_i, \delta_i, \hat{\delta}_{i0})$ are jointly normally distributed, with $Cov(\alpha_i, \hat{\delta}_{i0}) = Cov(\alpha_i, \delta_i)$. This assumption implies the information about δ_i contained in α_i is already incorporated in initial beliefs $\hat{\delta}_{i0}$. In Section 4 we estimated this covariance to be zero.

[26] Note that the measurement error shifts observed survival expectations by μ_{merror} on average. Similarly, the bias in initial beliefs b also shifts observed survival expectations. However, these two biases have different effects over time: the average shift due to measurement error is constant with age, given the i.i.d. assumption, whereas the average shift due to initial bias in beliefs is decreasing with age as individuals update their beliefs over time. Thus, we can separately identify both effects.

Table 4: SMM results on beliefs parameters

Parameter	Symbol	Low education			High education		
		Coeff.	Lower b.	Upper b.	Coeff.	Lower b.	Upper b.
Uncertainty	λ	0.344	0.327	0.362	0.107	0.105	0.109
Bias	b	-0.022	-0.023	-0.021	-0.063	-0.064	-0.062
Mean of measurement error	μ_{merror}	-0.070	-0.073	-0.068	0.006	0.005	0.006
SD of measurement error	σ_{merror}	0.258	0.256	0.260	0.179	0.178	0.180

Notes: Prior mean beliefs $\hat{\delta}_{i0}$ are unobserved to the econometrician, with a distribution that depends on bias b and uncertainty λ parameters, $\hat{\delta}_{i0}|\delta_i \sim N(\delta_i + b, \lambda^2\sigma_\delta^2)$. Subjective survival expectations $plive10_{it}$ are observed rounded and with measurement error. In each case, for computational reasons, the estimation uses consecutive waves of a subsample of 2,000 individuals chosen randomly among those with more observed periods, for sample sizes of 13,687 and 16,000 observations respectively. Moments are simulated using 20 draws of measurement error and 20 draws of unobserved heterogeneity. The bounds correspond to a 95% confidence interval, constructed using standard errors clustered at the individual level.

ferences, corresponding to the mean of $plive10_{it}$, its variance, and its covariance with h_{it}, and estimate bias b and uncertainty λ separately for individuals with high and low levels of education. Table 4 presents the estimation results. It shows individuals face a sizable amount of uncertainty, especially those with low education levels, and a negative initial bias; that is, individuals believe their health will deteriorate with age at a faster rate than what is true on average. This bias is larger for highly educated individuals.[27] In line with previous literature, subjective survival expectations are subject to large amounts of measurement error.

Table 5 presents the fit of the results. The top panel shows the fit of the targeted moments using $plive10_{it}$, whereas the bottom panel shows the fit of similar non-targeted moments using survival expectations to age 75. The table shows that the estimation performs reasonably well both for targeted and non-targeted moments.

The learning model and the results in this section rely on two simplifying assumptions: that health is exogenous and that health is the only source of information regarding δ_i. The first assumption is common in models of labor supply of older adults, and it is considered a reasonable simplification for this group, as studies that allow for health care effects on health find only small effects (French and Jones, 2017). This exogeneity assumption rules out the possibility of individuals changing their behavior to affect their health. If that were possible,

[27] The difference in average slopes for individuals with high and low education is 0.006 (though not significant according to Appendix Table B1).

Table 5: Moments' fit

	Low education			High education		
	Data moment	SE	Simulated moment	Data moment	SE	Simulated moment
(a) Targeted moments						
$\mathbb{E}(plive10)$	0.427	(0.00013)	0.436	0.545	(0.00011)	0.535
$\mathbb{E}(plive10^2)$	0.298	(0.00012)	0.280	0.382	(0.00012)	0.349
$\mathbb{E}(plive10 \cdot h)$	4.477	(0.00135)	4.595	5.945	(0.00125)	5.842
$\mathbb{E}(\Delta plive10)$	-0.017	(0.00005)	-0.013	-0.012	(0.00002)	-0.015
$\mathbb{E}((\Delta plive10)^2)$	0.110	(0.00006)	0.115	0.066	(0.00003)	0.071
$\mathbb{E}(\Delta plive10 \cdot \Delta h)$	0.012	(0.00004)	0.011	0.008	(0.00002)	0.003
(b) Untargeted moments						
$\mathbb{E}(plive75)$	0.572	(0.00026)	0.605	0.713	(0.00015)	0.759
$\mathbb{E}(plive75^2)$	0.432	(0.00029)	0.448	0.566	(0.00019)	0.615
$\mathbb{E}(plive75 \cdot h)$	6.007	(0.00286)	6.373	7.853	(0.00176)	8.346
$\mathbb{E}(\Delta plive75)$	-0.002	(0.00018)	0.019	-0.005	(0.00010)	0.014
$\mathbb{E}((\Delta plive75)^2)$	0.098	(0.00014)	0.111	0.052	(0.00007)	0.054
$\mathbb{E}(\Delta plive75 \cdot \Delta h)$	0.014	(0.00012)	0.007	0.006	(0.00004)	0.001

Notes: Same sample as in Table 4. In practice, panel (b) further restricts the sample to individuals who are asked $plive75_{it}$ *(the percentage chance you will live to be 75), that is, individuals up to 65 years old. Standard errors are clustered at the individual level.*

survival expectations would include individuals' *plans* of changing their *future* behavior in order to change their future health and survival chances. Hence, survival expectations alone would not be enough to pin down the belief parameters, and plans would be needed as well. As those planned behaviors are more likely to compensate for bad future outcomes, the results in this paper would be lower bounds on the magnitude of the underlying bias and uncertainty under an endogenous health process.

The second assumption, that health is the only source of information regarding δ_i, is common in learning models, and it rules out endogenous acquisition of health-related information, for example, by some individuals going to their doctors to better predict their future health. This assumption is partly addressed in Section 7 where I look at an additional and exogenous source of information that may shift beliefs.

6 Working decisions and beliefs about health

In this section, I study how the working decisions of older adults depend on their beliefs about future health. I am interested in studying if individuals expecting their health to deteriorate more rapidly make different working decisions than otherwise similar individuals, but who expect their health to deteriorate more slowly. The overall goal is to understand

how bias in these beliefs affects working decisions, and therefore, if eliminating that bias could significantly change those decisions.

I am interested in the effect among individuals attached to the labor market, and hence, I focus on a subsample of individuals under 80 years old with at least 20 years of working experience.

6.1 Effects of health beliefs on working decisions

In any model, decisions to work p_{it+1} depend on the variables known to individuals when they make their decisions.[28] Those variables include state variables age t, work p_{it} and health h_{it}, heterogeneity in health levels α_i, slope beliefs, $\hat{\delta}_{it}$ and $\hat{\sigma}_t$, and other controls.[29] However, some of these variables are unobserved to the econometrician, namely α_i, $\hat{\delta}_{it}$ and $\hat{\sigma}_t$, and need to be integrated out. This is possible for two reasons. First, the time-varying unobserved variables $\hat{\delta}_{it}$ and $\hat{\sigma}_t$ can be written as functions of time-invariant unobserved variables α_i and $\hat{\delta}_{i0}$, and observed health paths $h_{i1}, \dots h_{it}$. Second, the time-invariant unobserved variables α_i and $\hat{\delta}_{i0}$ have a known distribution (given by the results of Sections 4 and 5). The availability of longitudinal data, including data on survival expectations, is key to estimate the effect of health beliefs, which are time-varying and unobserved variables, on working decisions.

I estimate a model for p_{it+1} parametrically, by probit, where I approximate the distribution of α_i and $\hat{\delta}_{i0}$ conditional on all observed variables (including survival expectations) by using MCMC draws. To deal with initial conditions, I add an equation for working decisions when individuals are first observed. Panel (1) of Table 6 presents a summary of the results while the full set of results is presented in Appendix Table D2. The results show that beliefs do matter for working decisions of older adults, with a positive and significant coefficient for $\hat{\delta}_{it}$.[30] This positive sign implies that expecting better health, i.e. expecting health to deteriorate more slowly with age, is associated with larger probabilities of working.[31] Panel (2) shows that survival expectations $plive10_{it}$ are significant predictors of the probability of working; however, this significance does not hold when slope beliefs are accounted for, as shown by panel (3).[32] These results are consistent with survival expectations reflecting

[28] I assume working decisions p_{it+1} are made before health shocks are realized and health h_{it+1} is observed.

[29] Appendix Table D1 presents descriptive statistics for these controls.

[30] The assumptions of the learning model imply the posterior variance $\hat{\sigma}_t^2$ is constant across individuals of the same age t and education. As those variables are also relevant determinants of working decisions, I don't have enough variation to disentangle these two effects; any results would be based on functional-form assumptions alone. Therefore, I focus instead on interpreting the effects of the posterior mean.

[31] To analyze the intensive margin, I estimate a multinomial logit model with three outcomes: full-time work (35 hours a week or more), part-time work, and non-employment. Appendix Table D3 shows that mean beliefs $\hat{\delta}_{it}$ raise the probability of both full- and part-time work relative to non-work, though only the former is significant and other estimates are imprecise. Hence, I focus on the extensive margin.

[32] Note that survival expectations $plive10_{it}$ and slope beliefs $\hat{\delta}_{it}$ are correlated but not collinear, as according

Table 6: Main parametric results on the probability of working p_{it+1}

Variable	Symbol	(1)		(2)		(3)	
		Coefficient	Pvalue	Coefficient	Pvalue	Coefficient	Pvalue
Age	t	-0.089	0.000	-0.084	0.000	-0.088	0.000
Work	p_{it}	2.093	0.000	2.098	0.000	2.095	0.000
Health	h_{it}	0.138	0.000	0.250	0.000	0.142	0.005
Health intercept	α_i	0.300	0.000	0.102	0.014	0.303	0.000
Beliefs mean	$\hat{\delta}_{it}$	2.144	0.000			2.222	0.000
Beliefs var	$\hat{\sigma}_t^2/\sigma_\delta^2$	0.152	0.815			0.229	0.743
Survival expectations	$plive10_{it}$			0.095	0.001	-0.010	0.796
Controls		Yes		Yes		Yes	
N individuals		14,969		14,718		14,718	
N observations		58,040		55,592		55,592	

Notes: The sample consists of 58,064 observations from 14,969 individuals who have participated in the labor market for at least 20 years, are up to 80 years old, and have information on working p_{it} and p_{it+1}. Standard errors are clustered at the individual level.

individuals' beliefs about their future health. Thus, once those beliefs are accounted for, survival expectations do not provide additional information.

The results also confirm that health h_{it} has positive effects on the probability of working next period. Figure 2 explores these effects further by plotting average partial effects (APE) of health for individuals in their 50s, separately for those working $p_{it} = 1$ (panel (a)) and not working $p_{it} = 0$ (panel (b)). The figure shows an asymmetry in the interaction between health and beliefs for these two groups. For working individuals, there is a negative interaction between beliefs and health in determining future participation decisions, as health has lower marginal effects for individuals with better beliefs, that is, for individuals who believe their health will deteriorate more slowly. The opposite happens for non-working individuals, for whom this interaction is positive. Appendix Table D4 confirms these results: it shows positive and significant APEs that are decreasing (resp. increasing) in health h_{it} and beliefs $\hat{\delta}_{it}$ for individuals in their 50s who are working (resp. not working).

However, this pattern could be a result of the chosen parametric specification.[33] Hence, I turn to a more flexible non-parametric specification, via neural networks, which resembles a

to the model $plive10_{it}$ is a non-linear function of $\hat{\delta}_{it}$, h_{it}, α_i, $\hat{\sigma}_t^2$, and x_i. See Appendix C.2 for the exact expression.

[33] In any probit model, $sgn(\frac{\partial^2 \mathbb{P}(y=1)}{\partial x_1 \partial x_2}) = -sgn(\beta' x)sgn(\beta_1\beta_2)$. Hence, if $\beta_1, \beta_2 > 0$, the sign of this second derivative is the opposite of the sign of the argument $\beta' x$. Therefore, for any subsample of individuals for whom the probability is above (resp. below) 0.5, this sign is negative (resp. positive). This would be the case for individuals in their 50s who are (resp. are not) working.

maximum likelihood specification with logistic errors, but where the probability of success is a complex non-linear index of the inputs. To deal with time-invariant unobserved heterogeneity α_i and $\hat{\delta}_{i0}$, I use an EM iterative algorithm, where the M-step corresponds to estimating a neural network in an extended data base.[34,35] The flexibility of the model also allows me to easily control for additional variables,[36] including health insurance variables, spouse health insurance, and health-related job characteristics. Panels (c) and (d) of Figure 2 present the same average partial effects under this specification, and they show that the interaction is muted for working individuals, but it remains for non-working individuals.

One potential explanation for the pattern observed in the right column of Figure 2 is the presence of adjustment costs of going back to work. These adjustment costs could be due, for example, to lower wages caused by the loss of tenure, difficulties in finding jobs or in adapting to new work environments. If going back to work is costly, then the decision to go back to work depends on whether the expected benefits are larger than those costs. In turn, those expected benefits depend on how long individuals expect to remain working. For individuals who expect their health to deteriorate slowly, an improvement in health today will last for several periods, so they anticipate remaining in work. For individuals who expect their health to deteriorate rapidly, an improvement in health today will quickly dissipate, so they anticipate not wanting to work for long. Hence, better health today has different implications depending on health beliefs.

Note that by including α_i as a control, the model includes time-invariant heterogeneity in working decisions (for example, due to differences in risk aversion or taste for leisure), but one that is perfectly correlated with α_i. A more general time-invariant heterogeneity could be added to the probit model by assuming it follows a (conditional) normal distribution. However, that approach is not available for the more flexible and non-parametric neural-network model.

[34] The objective is to solve

$$\begin{aligned} arg\max_{\theta} log \int \mathbb{P}(p_i|\eta_i;\theta) f(\eta_i) d\eta_i &= arg\max_{\theta} \int log(\mathbb{P}(p_i|\eta_i;\theta)) f(\eta_i|p_i;\theta) d\eta_i \\ &\approx arg\max_{\theta} \sum_{\text{draws from } f(\eta_i|p_i;\theta)} log(\mathbb{P}(p_i|\eta_i;\theta)), \end{aligned}$$

where the last expression corresponds to the solution of a neural network in an extended data base which includes draws of the unobserved heterogeneity from the posterior distribution estimated in the E-step.

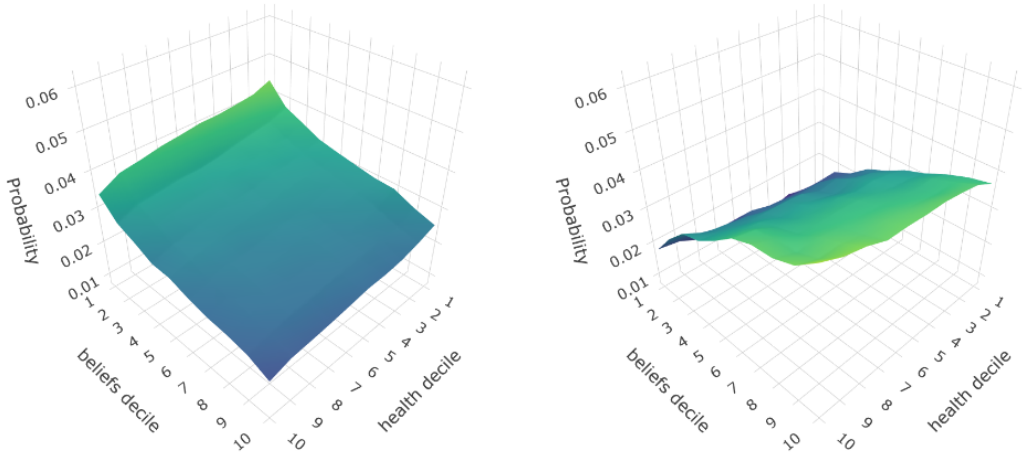
[35] This implementation uses the logic of standard EM-algorithms; however, in this case, there is no guarantee of a unique solution, and the likelihood does not necessarily increase with each iteration. Hence, this iterative approach must be thought of as a convenient implementation to get a solution to the problem.

[36] See Appendix Table D1.

Figure 2: Average partial effect of health h_{it} on the probability of working next period p_{it+1} for individuals in their 50s

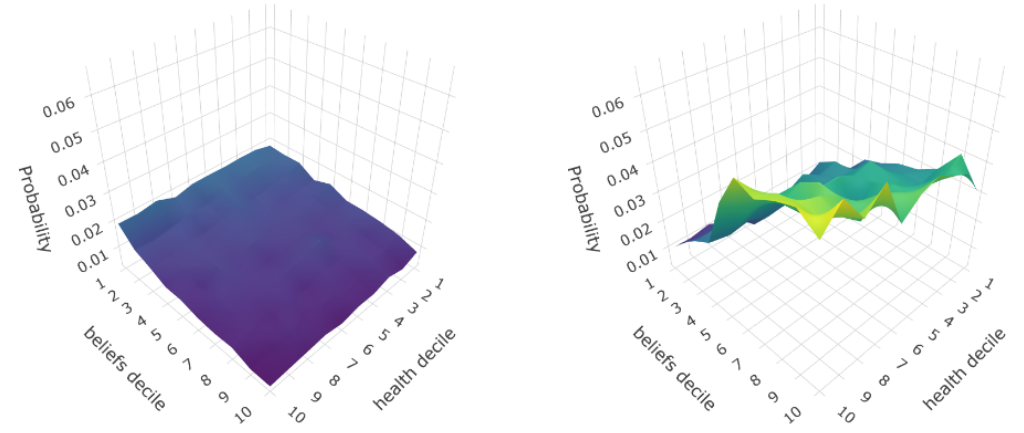
Probit results

(a) For working individuals $p_{it} = 1$ (b) For non-working individuals $p_{it} = 0$



Neural network results

(c) For working individuals $p_{it} = 1$ (d) For non-working individuals $p_{it} = 0$



Notes: In each plot, the x- and y-axis correspond to deciles of health h_{it} and mean slope beliefs $\hat{\delta}_{it}$ for the corresponding subsample of the plot among the sample of individuals attached to the labor market. The z-axis corresponds to the estimated average partial effect on the probability of working next period ($p_{it+1} = 1$).

6.2 The dual role of health shocks

In the context of uncertain health dynamics, a health shock ϵ_{it} has two roles in working decisions. On the one hand, a health shock ϵ_{it} has an effect through health h_{it}. On the other hand, an uncertain individual cannot perfectly distinguish between ϵ_{it} and δ_i within h_{it}. Hence, a shock ϵ_{it} is partly interpreted as new information regarding δ_i, which implies

that it has an effect through beliefs $\hat{\delta}_{it}$. The total effect of a health shock is a weighted sum of these two channels. Using Bayes' rule, we can write,

$$\frac{d\mathbb{P}(p_{it+1}=1|\Omega_{it})}{d\epsilon_{it}} = \underbrace{\frac{\partial \mathbb{P}(p_{it+1}=1|\Omega_{it})}{\partial h_{it}}}_{\text{health-state channel}} + \underbrace{\frac{\partial \mathbb{P}(p_{it+1}=1|\Omega_{it})}{\partial \hat{\delta}_{it}} \overbrace{\frac{t \cdot \hat{\sigma}_t^2}{\sigma_\epsilon^2}}^{\text{factor}}}_{\text{information channel}}, \tag{8}$$

where the factor term corresponds to the change in the posterior mean $\hat{\delta}_{it}$ given a marginal change in ϵ_{it}, and it is related to the signal-to-noise ratio of health as a signal.

Empirically, I find that on average less than 2% of the effects of health shocks ϵ_{it} in working decisions come through the information channel, because health shocks have only small effects on beliefs $\hat{\delta}_{it}$.[37] This last observation implies that health itself is not enough to quickly reduce the initial bias in beliefs, and hence this bias could have sizable effects on working decisions.

6.3 Eliminating the initial bias

Next, I study how eliminating bias in initial beliefs, that is, setting $\mathbb{E}(\hat{\delta}_{i0}) = \mathbb{E}(\delta_i)$, would matter for working decisions of older adults. To do this, I use an impulse-response-function approach, changing initial beliefs and simulating health, beliefs, and working decisions dynamically. To make the exercise more realistic, I predict two other time-varying outcomes that matter for working decisions (McClellan, 1998, Blau and Gilleskie, 2001), assets and health insurance,[38] while all other regressors are assumed fixed over time. For these two outcomes, I estimate a second neural network of their values at $(t+1)$ as a function of the same working regressors and p_{it+1}. As before, we can deal with time-invariant unobserved heterogeneity by the EM algorithm, though the results in this section consider a distribution conditional on health, survival expectations and working decisions only.[39] I estimate this neural network using the same sample as in Table D1, restricted to the observations that have values for these two variables one-period ahead. Then, for the subsample of individuals aged 52, I simulate these three outcomes over time under the baseline beliefs and under new beliefs shifted to have zero initial average bias.

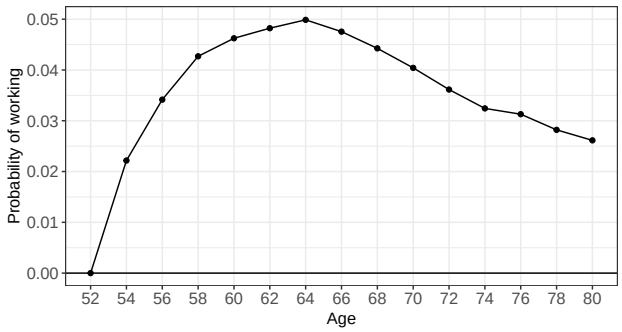
Figure 3 shows the difference in the simulated probability of working, which has an

[37] See Appendix Table D5 for results by age.

[38] The assets variable does not include wealth from individual retirement accounts, which is a separate wealth variable.

[39] That is, this distribution does not condition on the two outcomes of this second neural network, assets and health insurance. Incorporating this additional information should only have minor effects, as this was the case observed empirically for the working decisions estimated in the previous section.

Figure 3: Impulse-response function to a shift in prior beliefs eliminating overall bias b



Notes: Subsample of 1,184 individuals observed at 52 years old.

inverted-U shape. In the early 50s, the effect is small given that individuals are still mostly working. But as people start to retire, their new beliefs translate into larger probabilities of working that do not vanish completely with time and remain above 2 percentage points larger for individuals in their seventies. Appendix Figure D3 shows these effects come mostly from highly educated individuals, for whom the shift in beliefs was larger as they were initially more biased. This magnitude is fairly large considering that these individuals have an average probability of working of 41% at age 64 and 23% at age 70.[40] Furthermore, because these results come from eliminating a misconception at the population level, it is in principle an easier policy target than addressing individual biases. However, these results need to be interpreted with caution, as they are not a structural counterfactual but come from a simulation that assumes that many other variables are fixed over time, which is not the case in practice.

Overall, these results show that health beliefs matter for the working decisions of older adults, and that health itself is not a precise enough signal to correct the bias in beliefs. Furthermore, though not causal, the results of Figure 3 suggest that correcting biases in health beliefs could have important implications for the working decisions of older adults. In the next section, I use exogenous variation in an information shock that could potentially affect beliefs, and through them, affect working decisions.

[40] As a reference, using a structural model, French and Jones (2011) find that raising Medicare age from 65 to 67 leads individuals to work an additional 0.074 years over ages 60 to 69, whereas eliminating two years' worth of Social Security benefits increases time spent in the workforce by 0.076 years.

7 An information experiment: Blood-based biomarkers as signals of health

In this section, I study the effects of health-related information: information on blood-based biomarkers. I exploit that the HRS introduced the collection of blood samples for measuring biomarkers in wave 8. In particular, three biomarkers are measured and individuals are informed of their results: HDL cholesterol, total cholesterol, and blood glucose hbA1c.[41]

To control costs associated with the collection of biomarkers, in wave 8 the HRS randomly split the sample into two halves, and in each wave, it collects the biomarkers in only one half. This collection scheme generates exogenous variation in who receives the information, similar to an information experiment. I use this variation to indirectly study the effects on unobserved health beliefs by studying instead the effects on survival expectations $plive10_{iw}$ and on working decisions p_{iw}, variables that depend on health beliefs according to Sections 5 and 6. This exogenous variation allows me to measure effects without the assumptions imposed so far. Note that in this section, I modify the notation slightly, denoting the time dimension as w, to emphasize the survey waves as opposed to individuals' age, as in other sections.

One caveat in using this variation is that, traditionally, the HRS has been a phone interview,[42] while an in-person interview is needed to collect blood samples. Interview-mode could affect individuals' answers, for example due to experimenter demand, in particular, on questions regarding opinions and expectations. Hence, difference in interview-mode between treated and control individuals could confound the information effects of the experiment. However, the timing of the information provision allows us to separately identify the interview-mode effect from the information effect, because the information is only provided to individuals after the fieldwork.[43] That is, individuals do not have the information at the wave when the blood is collected, but in the following wave.

Figure 4 presents the timing of the biomarker collection and the information experiment, and it helps us visualize the identification strategy. First, a difference-in-differences analysis

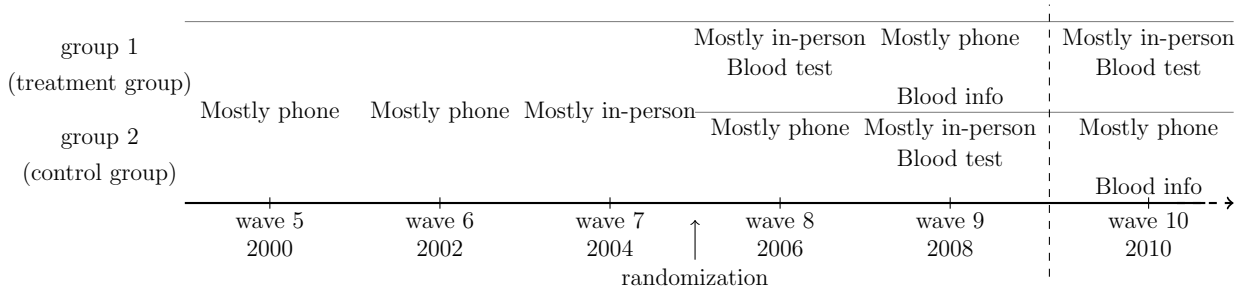
[41] Two other biomarkers are measured: C-reactive protein (CRP), a general marker of systemic inflammation, and Cystatin C, an indicator of kidney functioning. However, individuals are not informed of their results on these two biomarkers; hence, they do not provide additional information.

[42] There are exceptions to this general rule, with in-person interviews conducted for first interviews of new cohorts, people who request in-person interviews, and individuals residing in nursing homes. A shift to in-person interviews also occurred in 2004 in an attempt by the HRS to increase individuals' consent to link their survey responses to administrative data. These differences in interview mode are not relevant for the analysis if they are applied in the same way across the two groups.

[43] The results are provided around a month after the survey has ended (see Edwards, 2018 for details).

using waves 7 and 8 identifies the interview-mode effect. Second, assuming the interview-mode effect is the same across waves, a difference-in-differences analysis using waves 7 and 9 identifies the same interview-mode effect (with the opposite sign) plus the effect of receiving the additional information. Hence, we can identify the information effect by adding these two terms. To avoid confounding with the effects of information provided in later waves, I restrict the analysis up to wave 9.

Figure 4: Timing of the biomarker collection and information experiment



Therefore, I estimate the following equation:

$$y_{iw} = \beta_0 + \beta_1 d_{g_i} + \beta_{2w} d_w + \beta_{3w} d_{g_i} \cdot d_w + \gamma x_i + \epsilon_{iw}, \tag{9}$$

where i denotes an individual, w denotes a wave, d_{g_i} is a dummy for the treatment group, and d_w are wave dummies (with wave 5 as a reference). With this specification, the interview-mode effect is given by β_{3w_8}, and the information effect is given by $\beta_{3w_8} + \beta_{3w_9}$, where the interview-mode effects in each group cancel each other out. While we cannot test for parallel trends, parallel pre-trends hold if $\beta_{3w_6} = \beta_{3w_7} = 0$, and randomization in the selection of the two groups implies $\beta_1 = 0$.

Table 7 presents the estimation results of equation (9) for both $plive10_{iw}$ and p_{iw}, separately by education level. In all cases, the groups are similar and pre-trends are parallel. When looking at the results for survival expectations $plive10_{iw}$, for individuals with a college degree, there is a positive and significant information effect of 5.12 percentage points. For individuals without a college degree, the effect is still positive but close to zero and insignificant. These positive signs are aligned with what we already know about beliefs: on average, individuals' beliefs about health and survival are biased downward. Therefore, providing more information shifts those expectations up. Furthermore, the difference by education is aligned with the results in Table 4 that shows that highly educated individuals are initially more negatively biased (with respect to their own group) than less educated individuals. Nevertheless, we can't rule out as an alternative explanation that more educated individuals

have a higher ability to process this information.[44]

When looking at the results for working decisions p_{iw}, the positive coefficients are also consistent with the negative bias in beliefs and the working results shown in the previous sections, as providing information should, on average, shift the beliefs up and increase working probabilities. However, the effects are not significant, suggesting the signal is not large enough to have a meaningful effect.[45]

A different question, as opposed to the overall effects of receiving *any* information, relates to differences in effects depending on whether the information conveys *good* or *bad* news regarding health. However, what is good or bad news may be individual-specific in an unobserved way. For example, a total cholesterol level of 220 -above the 200 level flagged by the HRS as the normal limit- may be bad news for an individual who was expecting his cholesterol to be normal, but good news for an individual who was expecting his cholesterol to be much higher, for example, due to previously measured levels, family history of high cholesterol, or simply because of differences in expectations, which this paper argues are heterogeneous.

Hence, instead I focus on the average effects of receiving any biomarker result outside of the normal range, which I refer to as bad (instead of good) biomarker results, independently of individuals' expectations. Still, the (unintended) experiment does not provide exogenous variation to answer this question, as it does not include a control arm of individuals who get their biomarkers measured but who are not informed of their results. Appendix Table E1 shows the results of further decomposing the treatment group into individuals who have a bad biomarker result versus those who do not, a distinction we cannot make in the control group.[46] The table shows that those who received a bad result were already different in wave 5. Furthermore, their survival expectations and working probabilities fell more in the following waves, even before being informed of their results, suggesting that they already learned at least some of the information signaled by the biomarkers.

To study the average effects of receiving bad versus good biomarker results, in what follows, I restrict the sample to the random subset of individuals whose blood is collected and their biomarker results are informed (group 1 in Figure 4). I construct three different estimates to capture these effects, and the results are shown in Table 8. First, I take the

[44] A similar analysis for the number of doctor visits finds no interview-mode nor information effects for either group. Still, more educated individuals may be better able to incorporate the new information with the help of their physicians, even if the number of doctor visits is the same.

[45] The interview-mode has an effect on survival expectations but not on working decisions. This lack of effect on working decisions is expected, given the more objective nature of working outcomes versus survival expectations.

[46] One possibility would be to use the biomarker results in wave 9 to attempt the same distinction for the control group. However, biomarker results change between waves, invalidating this strategy.

Table 7: Information and interview-mode effects of biomarker experiment

	Survival expectation ($plive10_{iw}$)		Working decision (p_{iw})	
	Below college	College	Below college	College
	(1)	(2)	(3)	(4)
Group 1 (β_1)	-0.003	-0.013	0.004	-0.008
	(0.008)	(0.012)	(0.013)	(0.023)
Wave 6 (β_{2w_6})	-0.012	-0.021	-0.068	-0.086
	(0.005)	(0.008)	(0.007)	(0.012)
Wave 7 (β_{2w_7})	-0.014	-0.017	-0.116	-0.116
	(0.006)	(0.008)	(0.008)	(0.014)
Wave 8 (β_{2w_8})	-0.061	-0.074	-0.157	-0.187
	(0.006)	(0.009)	(0.009)	(0.015)
Wave 9 (β_{2w_9})	-0.032	-0.047	-0.200	-0.215
	(0.006)	(0.010)	(0.009)	(0.016)
Group 1, wave 6 (β_{3w_6})	-0.001	0.014	0.003	0.018
	(0.007)	(0.011)	(0.010)	(0.016)
Group 1, wave 7 (β_{3w_7})	-0.003	-0.003	0.010	0.010
	(0.008)	(0.011)	(0.011)	(0.019)
[(a)] Group 1, wave 8 (β_{3w_8})	0.013	0.033	0.003	0.032
	(0.008)	(0.012)	(0.012)	(0.021)
[(b)] Group 1, wave 9 (β_{3w_9})	-0.011	0.018	0.012	0.004
	(0.008)	(0.013)	(0.012)	(0.022)
Controls	Yes	Yes	Yes	Yes
N observations	31,810	10,115	31,805	10,113
N individuals	6,362	2,023	6,362	2,023
R-squared	0.020	0.025	0.033	0.034
F test pre-trends	0.0612	1.3788	0.4850	0.5933
P-value	0.9407	0.2522	0.6157	0.5526
Interview mode effect (a)	0.0127	0.0331	0.0028	0.0315
P-value	0.1131	0.0058	0.8143	0.1260
Information effect (a)+(b)	0.0015	0.0512	0.0144	0.0358
P-value	0.9185	0.0208	0.5283	0.3691

Notes: Results of estimating equation (9). Controls include gender, education, race and ethnicity. The sample consists of individuals with non-proxy interviews who are at least 50 years old in wave 8 and who give a valid answer to $plive10_{iw}$ *every wave between waves 5 and 9. Standard errors (shown in parentheses) are clustered at the household level.*

difference in mean wave-9 outcomes between the group who get bad results and the group who get good results (see row 1). Simple mean comparisons in survival expectations and working probabilities between these two groups show positive and sometimes significant differences, with larger values for those who are informed of bad results. These results seem counter-intuitive; however, as mentioned before, the "treatment" of receiving bad instead of good results is not random, and a positive difference between the two groups was already observed by wave 5 (see Appendix Table E1).

Second, I consider a parametric estimate that controls for individual characteristics by modeling next-wave outcomes (survival expectations or working decisions) as a linear function of current survival expectations and working decisions, age, health-related variables, work-related variables, individual fixed effects, and a treatment indicator for receiving bad results. I estimate these dynamic models using the Arellano-Bond estimator[47] and find negative and insignificant treatment effects for survival expectations, and positive and sometimes significant effects for working decisions (see row 2). Note that the results from these parametric specifications assume homogeneous treatment effects within education groups, not allowing for other differences, for example, due to unobserved time-varying expectations, which this paper argues are key.

Lastly, for each outcome, I estimate an Average Treatment Effect on the Treated (ATT), by propensity score matching with one neighbor, where the propensity score is estimated with a probit model on wave-8 characteristics. This estimator, though still assumes a parametric specification for identifying the closest neighbor, does not impose a homogeneous treatment effect. The results show that when comparing individuals with a similar probability of receiving a bad result, the magnitudes are -in most cases- largely reduced and become non-significant (see row 3). Overall, though Table 8 shows some positive effects of receiving bad biomarker results on working decisions for individuals without a college degree, those results are not robust to the estimation method, and they disappear with more flexible specifications.

8 Conclusion

This paper studies how beliefs about heterogeneous and uncertain health dynamics affect working decisions of older adults.

I start by modeling health as a heterogeneous dynamic process that deteriorates rapidly for some individuals but slowly for others. This time-invariant heterogeneity in slopes with age implies that the variance of health increases with age, an empirical observation made in

[47] In these equations, along with working decisions and survival expectations, health insurance and variables describing work characteristics of working periods are considered predetermined variables.

Table 8: Outcome differences of getting bad versus good biomarker results

	Survival expectation ($plive10_{iw}$)		Working decision (p_{iw})	
	Below college	College	Below college	College
Difference in means	0.020	0.022	0.037	0.054
	(0.011)	(0.018)	(0.016)	(0.032)
Regression-based estimates	-0.002	-0.017	0.025	0.040
	(0.013)	(0.018)	(0.012)	(0.025)
ATT	0.020	0.008	0.000	0.015
	(0.014)	(0.019)	(0.018)	(0.034)

Notes: Same sample as in Table 7, restricted to the group for whom biomarkers are measured. The first row shows differences in average wave-9 outcomes between individuals who get bad biomarker results (non-random treated) and individuals who get good results (non-random control). The second row shows parametric estimates of treatment effects based on linear dynamic models using Arellano-Bond estimators. The third row shows estimates of the treatment effect on the treated by propensity-score matching using one neighbor, where the propensity score is estimated with a probit model on wave-8 characteristics. Robust standard errors are shown in parentheses. See Appendix E.2 for details.

the literature. In modeling these dynamics, I simultaneously estimate survival as a function of health to account for survival bias.

Once I have shown heterogeneity, I study individuals' uncertainty about their own health dynamics. I assume individuals are rational Bayesian learners with beliefs about their health slopes, which they update over time as they see their health changing. As future survival depends on future health, and therefore on health dynamics, I leverage data on subjective survival expectations to estimate the learning parameters. I find that individuals are uncertain and negatively biased, that is, on average they believe their health will deteriorate faster than the average rate in the population.

Then, I study how health beliefs relate to working decisions of older adults, after controlling for current health and focusing on the extensive margin. I find beliefs matter for these decisions, and that expecting health to deteriorate more slowly is associated with larger probabilities of working. The results also show a positive interaction between health and beliefs for non-working individuals in their 50s, for whom marginal effects of improving health are larger the slower they believe their health will deteriorate with age. This interaction suggests that adjustment costs may be a deterrent against going back to work for this group.

Two other exercises are informative in the context of health beliefs and working decisions. First, a decomposition exercise shows that the effects of health shocks on working decisions go almost entirely through current health, with negligible effects through health beliefs.

This result comes from health being a noisy signal. Second, a simulation exercise shows that eliminating the initial average bias in beliefs would increase labor participation by more than to 2 percentage points, an effect that would last beyond traditional retirement ages.

Overall, health beliefs matter for working decisions, but they are biased, and health itself is not enough to reduce that bias. Hence, in the last part of the paper I look at the provision of information on blood-based biomarkers within the HRS, as an alternative to reduce that bias and affect working decisions. Using exogenous variation from the biomarker collection scheme, I find that receiving *any* information has only mild effects, increasing subjective survival expectations only for highly educated individuals. On the other hand, controlling for sample selection, I find no robust evidence of effects of receiving *bad* versus *good* biomarker results.

The results on this paper are a first approximation to study the effects of health beliefs on working decisions of older adults. As health beliefs are unobserved, this paper relies on two key assumptions, rational expectations and exogeneity of the health process. These assumptions rule out effects of work and other behaviors in health, and they limit our ability to study changes in cognition. Other tools and other data are needed to move in this direction.

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ONLINE APPENDIX

A Health measurement

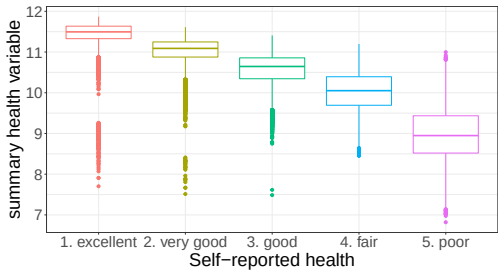
Table A1: CFA results for health measurement

Measure M_{ijt}	Intercept μ_j	Loading λ_j
Rescaled number of chronic conditions [(a)]	0.000	1.000
Self-assessed health	8.043	-1.121
Body mass index ($kg/m2$)	36.659	-1.684
Eyesight in general	5.803	-0.670
Eyesight at a distance	5.089	-0.600
Eyesight up close	5.265	-0.604
Hearing	4.841	-0.561
Pain	4.987	-0.855
Difficulties in ADLs regarding mobility	8.294	-1.394
Difficulties in ADLs of large muscles	7.820	-1.263
Difficulties in other ADLs	3.247	-0.550

Note: The estimation sample consists of 148,666 observations (30,657 individuals) from Table 1 that have information on all health measures. (a) The first measure corresponds to 7 minus the number of chronic conditions. For this measure, the intercept and loading are fixed to 0 and 1, respectively, so larger values represent better health. All other coefficients are significant at 1%.

Figure A1 presents a box plot for h_{it} per value of self-assessed health. The figure shows both measures are highly correlated but h_{it} captures more variation than what is captured by the self-assessed measure, especially among those with worse health. As discussed in Section 4, the heterogeneity in health dynamics is robust to the use of self-assessed health instead of the summary variable h_{it}.

Figure A1: Summary health variable h_{it} by category of self-assessed health



Notes: Same sample as in Table A1.

B Health dynamics

B.1 Baseline results

Table B1 presents the MLE results for three different specifications. The left panel shows the baseline results, including survival and unobserved heterogeneity in slopes. As mentioned in the main text, these results show there is unobserved heterogeneity in levels α_i and slopes δ_i, both uncorrelated. There is also correlation between health at age 50, h_{i0}, and α_i, but h_{i0} is uncorrelated with δ_i. Furthermore, survival is strongly dependent on lagged health. In terms of other observable characteristics, non-white individuals and individuals with low levels of education have worse health, health deteriorates faster for non-white individuals, and the probabilities of survival are higher for women and Hispanic individuals. For completeness, the middle panel shows the results allowing for unobserved slope heterogeneity but ignoring survival, while the right panel shows the results including survival but ignoring unobserved slope heterogeneity.[1] Columns (5) and (6) show that if we ignore slope heterogeneity, we overestimate the persistence of health.

B.2 Robustness checks

Table B2 presents the results of three robustness checks to the baseline model of health dynamics. First, I estimate the model allowing for heteroskedastic errors in the health equation, with a variance that varies linearly with age. The results (in the left panel) show that this heteroskedasticity does not explain away the heterogeneity in health slopes δ_i. Second, I estimate the model allowing for the heterogeneous levels and slopes to directly affect survival. The results (in the middle panel) show there is no such (joint) effect, hence, survival does not provide additional information on δ_i. Finally, I use self-assessed health h_{it}^{SAH} instead of the summary variable h_{it} and estimate an ordinal model. The results (in the right panel) show that the presence of slope heterogeneity is robust to using this measure alone.

[1] The model on the right panel allows for heterogeneity in slopes by observed characteristics, but it does not allow *unobserved* heterogeneity in slopes.

Table B1: MLE results on health and survival under different assumptions

	Heterogeneous slopes with survival eq		Heterogeneous slopes without survival eq		Homogeneous slopes with survival eq	
	Coefficient (1)	Pvalue (2)	Coefficient (3)	Pvalue (4)	Coefficient (5)	Pvalue (6)
ρ	0.196	0.000	0.199	0.000	0.331	0.000
τ	0.001	0.309	0.001	0.311	0.001	0.341
μ_α	1.674	0.000	1.660	0.000	1.476	0.000
$\nu_{\alpha female}$	-0.025	0.132	-0.026	0.127	-0.022	0.155
$\nu_{\alpha white}$	0.048	0.019	0.048	0.017	0.045	0.016
$\nu_{\alpha hispanic}$	-0.023	0.453	-0.023	0.453	-0.029	0.320
$\nu_{\alpha less\_HS}$	-0.124	0.000	-0.124	0.000	-0.106	0.000
ω_α	0.647	0.000	0.646	0.000	0.530	0.000
μ_δ	-0.045	0.383	-0.043	0.416	-0.050	0.000
$\nu_{\delta female}$	0.007	0.129	0.007	0.123	0.007	0.070
$\nu_{\delta white}$	0.014	0.023	0.014	0.025	0.010	0.052
$\nu_{\delta hispanic}$	0.014	0.139	0.013	0.143	0.010	0.208
$\nu_{\delta less_H S}$	-0.006	0.441	-0.006	0.432	-0.003	0.645
ω_δ	-0.001	0.754	-0.002	0.724		
σ_α	0.264	0.000	0.264	0.000	0.240	0.000
σ_δ	0.050	0.000	0.050	0.000		
ϕ	-0.005	0.960	-0.015	0.887		
σ_ϵ	0.300	0.000	0.300	0.000	0.320	0.000
γ	0.404	0.000			0.418	0.000
θ_0	-1.983	0.000			-2.133	0.000
θ_1	-0.057	0.000			-0.057	0.000
$\theta_{2female}$	0.279	0.000			0.277	0.000
θ_{2white}	0.059	0.453			0.064	0.417
$\theta_{2hispanic}$	0.328	0.017			0.375	0.010
θ_{2less_HS}	-0.136	0.119			-0.138	0.114
N alive observations	11,816		11,816		11,816	
N dead observations	151		0		151	
N individuals	2,856		2,856		2,856	
-Log likelihood	5,556.4		4,842.2		5,596.7	

Notes: The sample consists of 2,856 individuals observed at age 50 and their following consecutive observations until death or loss to follow up, for a total of 11,967 observations. The demographic variables include an indicator for female, for white race, for Hispanic ethnicity, and for education lower than high school. Standard errors are clustered at the individual level.

Table B2: MLE robustness checks

Dependent variable:	Health h_{it}		Health h_{it}		Self-assessed health h_{it}^{SAH}	
	Coefficient (1)	Pvalue (2)	Coefficient (3)	Pvalue (4)	Coefficient (5)	Pvalue (6)
ρ	0.197	0.000	0.196	0.000	0.209	0.000
τ	0.001	0.308	0.001	0.343	0.010	0.001
μ_α	1.635	0.000	1.651	0.000	-1.163	0.000
$\nu_{\alpha female}$	-0.025	0.143	-0.025	0.145	-0.042	0.504
$\nu_{\alpha white}$	0.047	0.020	0.046	0.024	0.185	0.006
$\nu_{\alpha hispanic}$	-0.024	0.444	-0.023	0.460	-0.218	0.032
$\nu_{\alpha less\_HS}$	-0.123	0.000	-0.121	0.000	-0.456	0.000
ω_α	0.649	0.000	0.649	0.000	1.149	0.000
μ_δ	-0.038	0.477	-0.039	0.490	-0.051	0.174
$\nu_{\delta female}$	0.007	0.135	0.007	0.150	0.034	0.036
$\nu_{\delta white}$	0.014	0.022	0.015	0.020	0.000	0.989
$\nu_{\delta hispanic}$	0.014	0.136	0.013	0.143	0.045	0.107
$\nu_{\delta less_H S}$	-0.006	0.419	-0.007	0.418	0.009	0.679
ω_δ	-0.002	0.671	-0.002	0.685	-0.040	0.000
σ_α	0.265	0.000	0.266	0.000	0.965	0.000
σ_δ	0.050	0.000	0.051	0.000	0.144	0.000
ϕ	-0.025	0.811	-0.033	0.759	-0.252	0.004
σ_ϵ	0.300	0.000	0.300	0.000	1.000	
σ_ξ	-0.000	0.001				
γ	0.415	0.000	0.562	0.000	0.366	0.000
θ_0	-2.104	0.000	-1.998	0.000	1.214	0.000
θ_1	-0.058	0.000	-0.046	0.010	-0.065	0.000
$\theta_{2female}$	0.288	0.000	0.291	0.000	0.244	0.000
θ_{2white}	0.055	0.486	0.065	0.424	0.074	0.330
$\theta_{2hispanic}$	0.314	0.020	0.325	0.019	0.385	0.004
θ_{2less_HS}	-0.124	0.160	-0.132	0.139	-0.137	0.108
ι_1			-0.196	0.391		
ι_2			0.035	0.988		
O_2					1.699	0.000
$O_3 - O_2$					1.732	0.000
$O_4 - O_3$					2.053	0.000
N alive observations	11,816		11,816		11,816	
N dead observations	151		151		151	
N individuals	2,856		2,856		2,856	
-Log likelihood	5,556.3		5,554.5		12,815.1	
Pvalue of H_0			0.43			

Notes: Same sample as in Table B1. In columns (1) and (2), $Var(\epsilon_{it}) = \sigma_\epsilon^2 + t \cdot \sigma_\xi^2$. In columns (3) and (4) the survival equation (5) is $S_{it} = \mathbb{1}\{\gamma h_{it-1} + \iota_1 \alpha_i + \iota_2 \delta_i + \theta_0 + \theta_1 \cdot t + \theta_2' x_i + \eta_{it} \geq 0\} S_{it-1}$, and the null hypothesis corresponds to $H_0 : \iota_1 = \iota_2 = 0$. In columns (5) and (6) the health equation (3) is replaced by $\tilde{h}_{it}^{SAH} = \rho h_{it-1}^{SAH} + \alpha_i + \delta_i \cdot t + \tau \cdot t^2 + \epsilon_{it}$, where $\sigma_\epsilon^2 = 1$, $\tilde{h}_{it}^{SAH}$ is a latent variable, h_{it}^{SAH} is the observed ordinal value with larger values represent better health, and O_2, O_3, O_4 are the threshold values. Standard errors are clustered at the individual level.

C Uncertain dynamics and learning model details

C.1 Predictive power of subjective survival expectations $plive10_{it}$

Table C1: Correlation between $plive10_{it}$ and future outcomes

	Next-period health h_{it+1}				Next-period survival S_{it+1}			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Survival expectations	0.112	0.107	0.114	0.056	0.030	0.023	0.021	0.021
	(0.005)	(0.005)	(0.005)	(0.007)	(0.003)	(0.003)	(0.003)	(0.003)
Health	0.763	0.735	0.714	0.081	0.077	0.062	0.065	0.067
	(0.003)	(0.003)	(0.003)	(0.006)	(0.002)	(0.002)	(0.002)	(0.003)
Age		-0.005	-0.006	-0.029		-0.005	-0.005	-0.008
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Female			-0.032				0.035	
			(0.003)				(0.002)	
White			0.067				-0.001	
			(0.004)				(0.002)	
Hispanic			-0.023				0.022	
			(0.006)				(0.003)	
Education: less than high school			-0.109				0.002	
			(0.005)				(0.003)	
N observations	91,246	91,246	91,138	91,246	98,619	98,619	98,508	98,619
N individuals	24,095	24,095	24,033	24,095	25,645	25,645	25,581	25,645
Regression type	RE	RE	RE	FE	RE	RE	RE	FE

Note: Panel regressions under random effects (RE) or fixed effects (FE) specifications. Same sample as in Table 2, including information on next-period survival S_{it+1}, if available. Standard errors (shown in parentheses) are clustered at the individual level.

C.2 Formula for $plive10_{it}$

Let Ω_{it} be the information set of individual i after observing his health up to period t. From equation (3), we can write for $l > t$

$$h_{il} = \underbrace{\rho^{l-t}h_{it} + \alpha_i \sum_{k=0}^{l-t-1} \rho^k + \tau \sum_{k=0}^{l-t-1} (l-k)^2\rho^k}_{\text{known under } \Omega_{it}} + \underbrace{\delta_i \sum_{k=0}^{l-t-1} (l-k)\rho^k + \sum_{k=0}^{l-t-1} \rho^k \epsilon_{i(l-k)}}_{\text{unknown under } \Omega_{it}}. \quad \text{(A1)}$$

Let s denote the reference age asked in $plive10_{it}$. Then, by equations (5) and (A1),

$$plive10_{it} \equiv \mathbb{P}(S_{is}=1|\Omega_{it}) = \prod_{l=t}^{s-1}\mathbb{P}(S_{il+1}=1|S_{il}=1,\Omega_{it}) = \prod_{l=t}^{s-1}\Phi\left(\frac{M_{itl}}{W_{tl}^{1/2}}\right), \quad \text{(A2)}$$

where

$$\begin{aligned} M_{itl} &= \gamma\left(\rho^{l-t}h_{it} + \alpha_i\sum_{k=0}^{l-t-1}\rho^k + \hat{\delta}_{it}\sum_{k=0}^{l-t-1}(l-k)\rho^k + \tau\sum_{k=0}^{l-t-1}(l-k)^2\rho^k\right) + \theta_0 + \theta_1(l+1) + \theta_2' x_i \\ W_{tl} &= \gamma^2\hat{\sigma}_t^2\left(\sum_{k=0}^{l-t-1}(l-k)\rho^k\right)^2 + \gamma^2\sigma_\epsilon^2\sum_{k=0}^{l-t-1}\rho^{2k} + 1 \end{aligned}$$

Note that M_{itl} and W_{tl} are functions of h_{it}, α_i, $\hat{\delta}_{it}$, $\hat{\sigma}_t^2$, x_i and the parameters of the model Θ. Hence, $plive10_{it} = plive10_{it}(\alpha_i, h_{it}, \hat{\delta}_{it}, \hat{\sigma}_t^2, x_i; \Theta)$.

C.3 Identification of uncertainty λ

Proposition C.1 provides a formal identification result for λ using data on expected survival *rates*.

Proposition C.1 (Identification of λ) *Let the health and survival processes be given by equations (3) and (5), and assume individuals are Bayesian learners with prior beliefs about δ_i following $N(\hat{\delta}_{i0}, \hat{\sigma}_0^2)$. Let Ω_{it} be the information set of individual i after observing his health up to period t. Thus, $\alpha_i, \hat{\delta}_{it}, \hat{\sigma}_t^2 \in \Omega_{it}$. Consider the subjective expectations about survival rates between periods $t+2$ and $t+3$, from the point of view of $t+1$ and t, that is, the expected survival rates 1 and 2 periods ahead.*

$$\begin{aligned} b_{it+1}^{(1)} &\equiv \mathbb{P}(S_{it+3}=1|S_{it+2}=1,\Omega_{it+1}), \\ b_{it}^{(2)} &\equiv \mathbb{P}(S_{it+3}=1|S_{it+2}=1,\Omega_{it}). \end{aligned}$$

Define $\Delta B_{it+1} = \Phi^{-1}(b_{it+1}^{(1)}) - w_t\Phi^{-1}(b_{it}^{(2)})$, the weighted difference of these expected survival rates, where Φ is the standard normal CDF and w_t is a known constant across individuals.

Then, there exist a function $F(\lambda, t, \Theta)$, such that, conditional on x_i, h_{it}, $b_{it}^{(1)}$ and $b_{it}^{(2)}$,

$$Cov(\Delta B_{it+1}, \Delta h_{it+1}) = F(\lambda, t, \Theta), \quad \text{(A3)}$$

with $F(\lambda, t, \Theta)$ increasing in λ.

Proof: First, note that we can write the beliefs updating equations (6) and (7) as

$$\hat{\delta}_{it} = \hat{\delta}_{it-1} + K_t \cdot \hat{\zeta}_{it} \tag{A4}$$

$$\hat{\sigma}_t^2 = (1 - K_t \cdot t)\hat{\sigma}_{t-1}^2, \tag{A5}$$

where $K_t = \frac{\hat{\sigma}_{t-1}^2 \cdot t}{\hat{\sigma}_{t-1}^2 \cdot t^2 + \sigma_\epsilon^2} = \frac{t\hat{\sigma}_t^2}{\sigma_\epsilon^2}$, $K_t \leq 1$, and $\hat{\zeta}_{it}$ is individual i's perceived innovation in health at period t, $\hat{\zeta}_{it} = h_{it} - \mathbb{E}(h_{it}|\Omega_{it-1}) = h_{it} - \rho h_{it-1} - \alpha_i - \hat{\delta}_{it-1} \cdot t - \tau t^2$.

Then, applying the same derivation as in equation (A2) and defining $c_t^1 = \frac{W_{t+1t+2}^{1/2}}{\gamma}$ and $c_t^2 = \frac{W_{tt+2}^{1/2}}{\gamma}$, which are constant across individuals, we can write

$$\begin{aligned} c_t^1 \Phi^{-1}(b_{it+1}^{(1)}) - c_t^2 \Phi^{-1}(b_{it}^{(2)}) &= \underbrace{\rho\big(h_{it+1} - \rho h_{it} - \alpha_i - \hat{\delta}_{it}(t+1) - \tau(t+1)^2\big)}_{\text{due to persistence}} \\ &\quad + \underbrace{(\hat{\delta}_{it+1} - \hat{\delta}_{it})(t+2)}_{\text{due to learning}}. \end{aligned} \tag{A6}$$

Using equations (A4) and (A5),

$$\begin{aligned} c_t^1 \Phi^{-1}(b_{it+1}^{(1)}) - c_t^2 \Phi^{-1}(b_{it}^{(2)}) &= \Big(\rho + K_{t+1}(t+2)\Big)\hat{\zeta}_{it+1} \\ &= \Big(\rho + K_{t+1}(t+2)\Big)\Big(h_{it+1} - \frac{1}{\gamma}\big(W_{tt+1}^{1/2} \cdot \Phi^{-1}(b_{it}^{(1)}) - \theta_0 - \theta_1(t+2) - \theta_2' x_i\big)\Big). \end{aligned}$$

Rearranging the terms and taking covariance, conditional on x_i, h_{it}, $b_{it}^{(1)}$ and $b_{it}^{(2)}$ (belonging to Ω_{it}),

$$Cov(\Delta B_{it+1}, \Delta h_{it+1}) = G(\lambda, t, \Theta) \cdot Var(\Delta h_{it+1}) \equiv F(\lambda, t, \Theta),$$

where $w_t = \frac{c_t^2}{c_t^1}$, $G(\lambda, t, \Theta) = \frac{\rho + (t+2)K_{t+1}}{c_t^1}$, $\frac{\partial G}{\partial \lambda} \geq 0$ (strictly greater than zero when $\lambda > 0$) and $Var(\Delta h_{it+1})$ does not depend on λ (which govern the distribution of beliefs but not the distribution of realized health). ■

The proposition says that, given Θ, we can identify λ with enough longitudinal data on health and subjective expectations about these survival *rates*, as the left hand side of equation (A3) would be observed and the right hand side is increasing in the one unknown parameter λ. Furthermore, this equation says that the key moment for identification is the covariance between changes in health and changes in expectations about survival *rates*.

Equation (A6) shows individuals update their survival expectations for two reasons. The first reason is that health is a persistent process; thus, any change in health will have future repercussions on health and therefore on survival. If health is not a persistent process, that

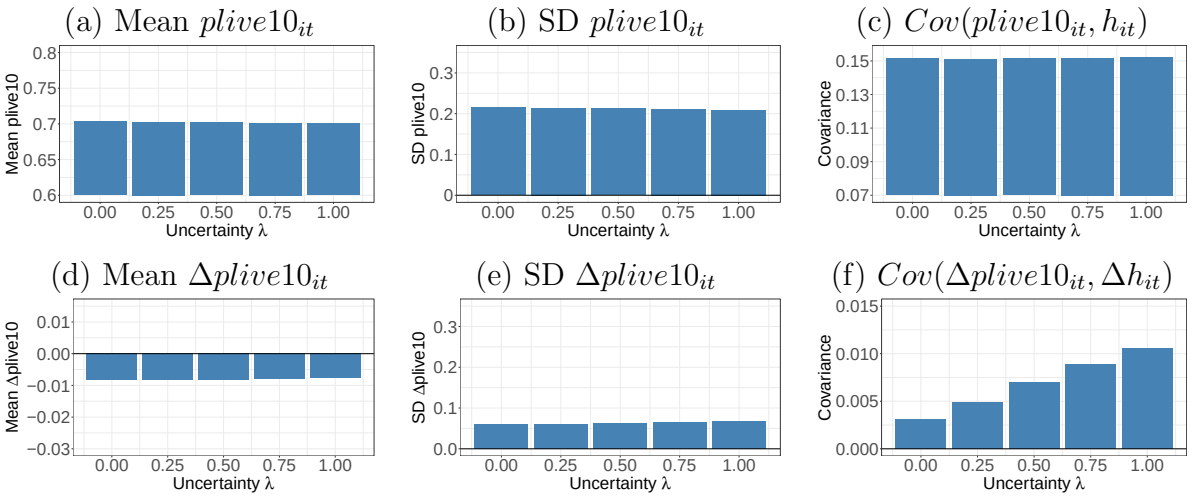
is $\rho = 0$, this channel disappears. The second reason is that learning implies a change in future predictions of health and therefore of survival. If there is no uncertainty in beliefs, that is $\lambda = 0$, there is no learning and this channel disappears. The more uncertain beliefs are, i.e. for larger values of λ, the larger is the change in expected survival given the same change in health.

In practice, we do not have data on subjective expectations about survival *rates*, but we do have data on (unconditional) subjective expectations about survival and the same intuition applies there. Next, I describe a simulation exercise showing that the intuition of proposition C.1 extends to the available data on survival expectations.

In the exercise, I first simulate individual-level heterogeneity (α_i, δ_i) and health h_{it}, according to equations (3), (4) and (5). Then, for different values of the uncertainty parameter λ, I simulate initial beliefs $(\hat{\delta}_{i0}, \hat{\sigma}_0^2)$ assuming $b = 0$.[2] I update those beliefs over time and construct $(\hat{\delta}_{it}, \hat{\sigma}_t^2)$ using the simulated h_{it} and the Bayesian updating equations (6) and (7). Finally, I use these simulated beliefs, to construct survival expectations $plive10_{it}$ according to equation (A2). Figure C1 presents the results. In the figure, each graph depicts the uncertainty parameter λ in the x-axis, and a simulated moment in the y-axis. The six graphs correspond to the six moments used for estimation. The top row considers moments in levels, and the bottom row considers moments in differences. The figure clearly shows that, as with data on expectations on survival *rates*, the covariance between changes in health and changes in expectations is increasing in the uncertainty parameter λ, and therefore, a key moment for identification.

[2] I also assume $Cov(\alpha_i, \hat{\delta}_{i0}) = Cov(\alpha_i, \delta_i)$, and set it to zero according to the results of Section 4.

Figure C1: Simulated moments of $plive10_{it}$ by uncertainty λ in data-generating process



Notes: Moments in simulated data following the structure of the available data in the HRS. In each figure, the x-axis shows the value of the uncertainty parameter λ used in the data-generating process. In all cases, the bias parameter b is set to zero.

D Working decisions

Table D1: Descriptive statistics on additional controls of working decisions

Variable	Observations	Mean	SD	Min	Max	Probit
Panel (a)						
Work	58,064	0.46	0.50	0	1	Y
Female	58,064	0.51	0.50	0	1	Y
Education: less than high school	58,064	0.19	0.39	0	1	Y
Education: some college	58,064	0.54	0.50	0	1	N
White	58,064	0.83	0.38	0	1	N
Hispanic	58,064	0.07	0.25	0	1	N
Marital status: married	58,040	0.71	0.45	0	1	Y
Marital status: separated or divorced	58,040	0.12	0.33	0	1	Y
Marital status: widowed	58,040	0.13	0.34	0	1	Y
Number of household members	58,064	2.17	1.05	1	14	N
Total number of years worked	58,064	39.59	9.17	20	68	N
Spouse works	57,043	0.31	0.46	0	1	N
Spouse has health insurance	57,312	0.18	0.39	0	1	N
Income from pension	58,064	5.72	47.00	0	10,000	$Y^{(*)}$
Income from Social Security	58,064	6.14	6.02	0	58	$Y^{(*)}$
Wealth from IRA	58,064	70.92	208.25	0	10,000	$Y^{(*)}$
Other wealth	58,064	372.01	762.64	-1,963	10,000	$Y^{(*)}$
Health insurance: employer covering retirement	55,991	0.15	0.35	0	1	N
Health insurance: employer not covering retirement	55,991	0.08	0.28	0	1	N
Health insurance: employer (already 65)	55,991	0.16	0.36	0	1	N
Health insurance: government	55,991	0.45	0.50	0	1	N
Health insurance: other	55,991	0.11	0.32	0	1	N
Panel (b)						
Income from work	26,971	30.46	55.74	0	5,823	$Y^{(*)}$
Tenure	26,586	12.97	12.27	0	66	N
Self-employed	26,893	0.23	0.42	0	1	N
Occupation: managerial	20,599	0.16	0.37	0	1	N
Occupation: professional	20,599	0.21	0.41	0	1	N
Occupation: sales	20,599	0.12	0.32	0	1	N
Occupation: clerical	20,599	0.16	0.37	0	1	N
Occupation: services	20,599	0.14	0.34	0	1	N
Occupation: farming, mechanics, construction, operators	20,599	0.22	0.41	0	1	N
Occupation: FF.AA.	20,599	0.00	0.02	0	1	N
Job requires physical effort	26,632	0.17	0.38	0	1	N
Job requires lifting heavy loads	26,632	0.07	0.25	0	1	N
Job requires stooping or kneeling	26,631	0.14	0.34	0	1	N
Job requires good eyesight	26,650	0.68	0.47	0	1	N
Job involves lots of stress	26,681	0.16	0.37	0	1	N

Note: Descriptive statistics on variables used in estimating working decisions in Section 6. The sample consists of 58,064 observations from 14,969 individuals who have participated in the labor market for at least 20 years, are up to 80 years old, and have information on working p_{it} and p_{it+1}. Panel (a) comprises all 58,064 observations, and panel (b) comprises 26,971 observations from working periods (defined as 0 otherwise). Income and wealth variables are measured in thousands of 2002 dollars. Wealth variables are capped at $10 million dollars. All variables are included in the neural network specification, while only a subset of them are included in the probit specification. (∗) In the probit specification, I control for quartiles of total income, corresponding to the sum of income from work, pensions and Social Security, and for quartiles of total wealth, corresponding to the sum of wealth from IRA and total wealth.

Table D2: Parametric results on the probability of working p_{it+1}

Variable	(1)		(2)		(3)	
	Coefficient	Pvalue	Coefficient	Pvalue	Coefficient	Pvalue
Main equation						
Intercept	-4.748	0.000	-4.471	0.000	-4.831	0.000
Age	-0.089	0.000	-0.084	0.000	-0.088	0.000
Work	2.093	0.000	2.098	0.000	2.095	0.000
Health	0.138	0.000	0.250	0.000	0.142	0.005
Educ LHS	-0.161	0.001	-0.063	0.003	-0.169	0.003
MS married	0.036	0.360	0.050	0.213	0.055	0.183
MS divorced	0.062	0.146	0.072	0.103	0.078	0.083
MS widowed	0.034	0.447	0.044	0.337	0.046	0.321
Q1 income	0.113	0.000	0.107	0.000	0.108	0.000
Q2 income	0.005	0.826	0.001	0.967	0.007	0.751
Q3 income	0.025	0.203	0.020	0.331	0.027	0.199
Q1 wealth	0.103	0.000	0.104	0.000	0.113	0.000
Q2 wealth	0.072	0.001	0.069	0.001	0.078	0.001
Q3 wealth	-0.002	0.907	-0.006	0.765	-0.002	0.907
Female	-0.069	0.000	-0.086	0.000	-0.066	0.000
Health intercept α_i	0.300	0.000	0.102	0.014	0.303	0.000
Beliefs mean $\hat{\delta}_{it}$	2.144	0.000			2.222	0.000
Beliefs var $\hat{\sigma}_t^2/\sigma_\delta^2$	0.152	0.815			0.229	0.743
Survival expectations $plive10_{it}$			0.095	0.001	-0.010	0.796
Initial condition						
Intercept	-4.400	0.000	-4.123	0.000	-4.374	0.000
Age	-0.192	0.000	-0.189	0.000	-0.192	0.000
Health	0.376	0.000	0.465	0.000	0.368	0.000
Educ LHS	-0.016	0.862	0.022	0.512	0.006	0.953
MS married	0.049	0.448	0.042	0.517	0.043	0.512
MS divorced	0.042	0.554	0.036	0.614	0.040	0.580
MS widowed	-0.056	0.454	-0.065	0.385	-0.066	0.386
Q1 income	-1.590	0.000	-1.592	0.000	-1.593	0.000
Q2 income	-1.053	0.000	-1.056	0.000	-1.053	0.000
Q3 income	-0.614	0.000	-0.615	0.000	-0.612	0.000
Q1 wealth	0.403	0.000	0.383	0.000	0.389	0.000
Q2 wealth	0.247	0.000	0.229	0.000	0.234	0.000
Q3 wealth	0.067	0.078	0.060	0.117	0.062	0.109
Female	0.084	0.002	0.077	0.005	0.092	0.001
Health intercept α_i	0.281	0.000	0.125	0.069	0.297	0.015
Beliefs mean $\hat{\delta}_{it}$	1.593	0.000			1.885	0.010
Beliefs var $\hat{\sigma}_t^2/\sigma_\delta^2$	-0.623	0.580			-0.812	0.476
Survival expectations $plive10_{it}$			-0.018	0.680	-0.092	0.094

Notes: Same sample as in Table 6. Standard errors are clustered at the individual level.

Table D3: Main results on the probability of working next period - intensive margin

Variable	Symbol	Full-time vs non-work		Part-time vs non-work		Full-time vs part-time	
		Coeff. β^{ft}	Pvalue	Coeff. β^{pt}	Pvalue	Coeff. $\beta^{ft} - \beta^{pt}$	Pvalue
Age	t	-0.251	0.659	-0.084	0.500	-0.167	0.771
Work full time	p_ft_{it}	4.818	0.002	2.511	0.323	2.307	0.433
Work part time	p_pt_{it}	2.900	0.011	3.655	0.000	-0.755	0.636
Health	h_{it}	0.231	0.712	0.293	0.733	-0.062	0.950
Health intercept	α_i	0.711	0.544	0.402	0.873	0.309	0.903
Beliefs mean	$\hat{\delta}_{it}$	4.785	0.015	3.222	0.507	1.563	0.791
Beliefs var	$\hat{\sigma}_t^2/\sigma_\delta^2$	-2.821	0.995	2.834	0.948	-5.655	0.990

Notes: Parametric results for a categorical dependent variable with three values: full-time work, part-time work, and non-employment (reference). Full- and part-time work are given by the binary variables p_ft_{it} and p_pt_{it}, respectively. Errors are assumed to follow a type I extreme value distribution. The sample (58,040 observations from 14,969 individuals) and regressors are the same as in the probit specification of Table D2 column (1). The last two columns are constructed using the parameter estimates. Standard errors are clustered at the individual level.

Table D4: APE of health h_{it} on the probability of working next period, $p_{it+1} = 1$

Sample:	Ages 50 to 59		Ages 60 to 65		Ages 66 to 75	
	$p_{it} = 1$	$p_{it} = 0$	$p_{it} = 1$	$p_{it} = 0$	$p_{it} = 1$	$p_{it} = 0$
APE health	0.0286	0.0305	0.0376	0.0231	0.047	0.0146
	(0.0079)	(0.013)	(0.0079)	(0.0118)	(0.0068)	(0.0091)
Slope with health	-0.0043	0.0042	-0.0044	0.004	-0.0034	0.0032
	(0.0011)	(0.0013)	(0.0016)	(0.0017)	(0.0023)	(0.0018)
Slope with beliefs	-0.0674	0.0655	-0.0676	0.0623	-0.0525	0.0493
	(0.0083)	(0.0107)	(0.0152)	(0.0174)	(0.0285)	(0.0209)

Notes: results from the probit specification of Table D2 column (1). Standard errors in parentheses, clustered at the individual level. APE health is the average of $\frac{\partial \mathbb{P}(p_{it+1}=1)}{\partial h_{it}}$, slope with health is the average of $\frac{\partial^2 \mathbb{P}(p_{it+1}=1)}{\partial h_{it}^2}$, and slope with beliefs is the average of $\frac{\partial^2 \mathbb{P}(p_{it+1}=1)}{\partial \hat{\delta}_{it} \partial h_{it}}$.

Table D5: Decomposition of the effects of a health shock ϵ_{it} on working decisions p_{it+1}

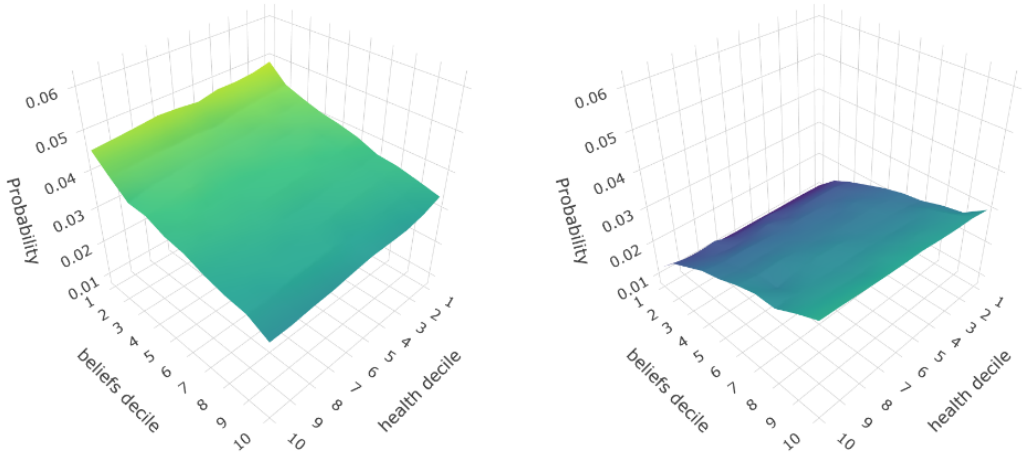
Age	Avg partial effects		Factor	Decomposition		Avg partial effects		Factor	Decomposition	
	Health h_{it}	Beliefs $\hat{\delta}_{it}$		Health channel	Info. channel	Health h_{it}	Beliefs $\hat{\delta}_{it}$		Health channel	Info. channel
	Working individuals $p_{it}=1$ *with low education*					*Working individuals* $p_{it}=1$ *with high education*				
52	0.011	0.015	0.003	0.996	0.004	0.009	0.012	0.000	1.000	0.000
54	0.013	0.017	0.007	0.991	0.009	0.010	0.014	0.001	0.999	0.001
56	0.014	0.019	0.009	0.988	0.012	0.012	0.017	0.001	0.999	0.001
58	0.016	0.021	0.012	0.984	0.016	0.014	0.019	0.001	0.998	0.002
60	0.017	0.023	0.014	0.981	0.019	0.015	0.021	0.002	0.998	0.002
62	0.017	0.023	0.015	0.980	0.020	0.016	0.022	0.002	0.997	0.003
64	0.019	0.024	0.016	0.981	0.019	0.017	0.022	0.002	0.997	0.003
66	0.019	0.024	0.016	0.981	0.019	0.017	0.022	0.002	0.997	0.003
68	0.020	0.025	0.015	0.982	0.018	0.017	0.021	0.003	0.997	0.003
70	0.019	0.023	0.015	0.983	0.017	0.016	0.020	0.003	0.996	0.004
72	0.020	0.024	0.014	0.984	0.016	0.016	0.020	0.003	0.996	0.004
74	0.018	0.023	0.013	0.985	0.015	0.015	0.019	0.003	0.996	0.004
	Non-working individuals $p_{it}=0$ *with low education*					*Non-working individuals* $p_{it}=0$ *with high education*				
52	0.039	0.040	0.003	0.997	0.003	0.044	0.047	0.000	1.000	0.000
54	0.028	0.027	0.007	0.994	0.006	0.037	0.040	0.001	0.999	0.001
56	0.022	0.021	0.009	0.991	0.009	0.031	0.033	0.001	0.999	0.001
58	0.018	0.017	0.012	0.989	0.011	0.026	0.027	0.001	0.999	0.001
60	0.016	0.014	0.014	0.988	0.012	0.022	0.022	0.002	0.998	0.002
62	0.015	0.014	0.015	0.986	0.014	0.017	0.016	0.002	0.998	0.002
64	0.011	0.010	0.016	0.987	0.013	0.013	0.012	0.002	0.998	0.002
66	0.009	0.007	0.016	0.988	0.012	0.011	0.009	0.002	0.998	0.002
68	0.007	0.006	0.015	0.989	0.011	0.008	0.007	0.003	0.998	0.002
70	0.006	0.004	0.015	0.989	0.011	0.007	0.005	0.003	0.998	0.002
72	0.005	0.003	0.014	0.991	0.009	0.005	0.004	0.003	0.998	0.002
74	0.004	0.003	0.013	0.991	0.009	0.004	0.003	0.003	0.998	0.002

Notes: The columns on health and information channels correspond to the terms in equation (8), expressed as a proportion of the total partial effect. These estimates come from the neural network specification, applied to the sample from Table D1.

Figure D1: Average partial effect of health h_{it} on the probability of working next period p_{it+1} for individuals 60 to 65 years old

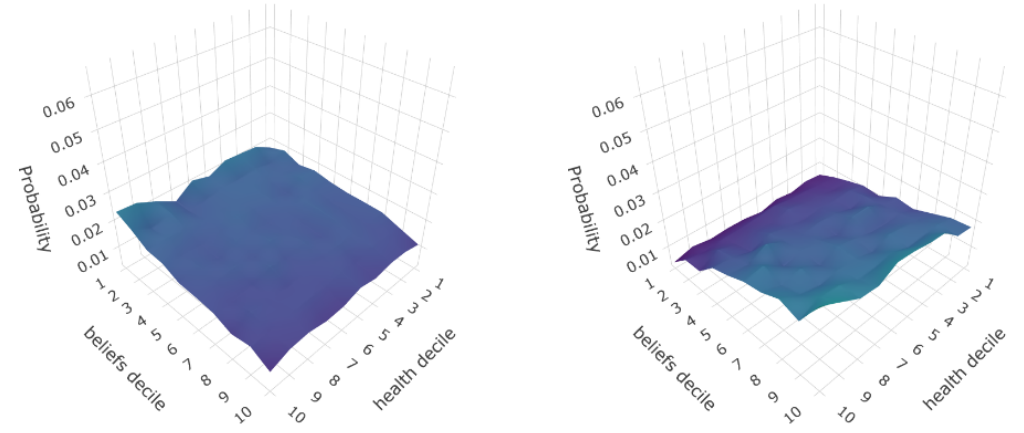
Probit results

(a) For working individuals $p_{it} = 1$ (b) For non-working individuals $p_{it} = 0$



Neural network results

(c) For working individuals $p_{it} = 1$ (d) For non-working individuals $p_{it} = 0$

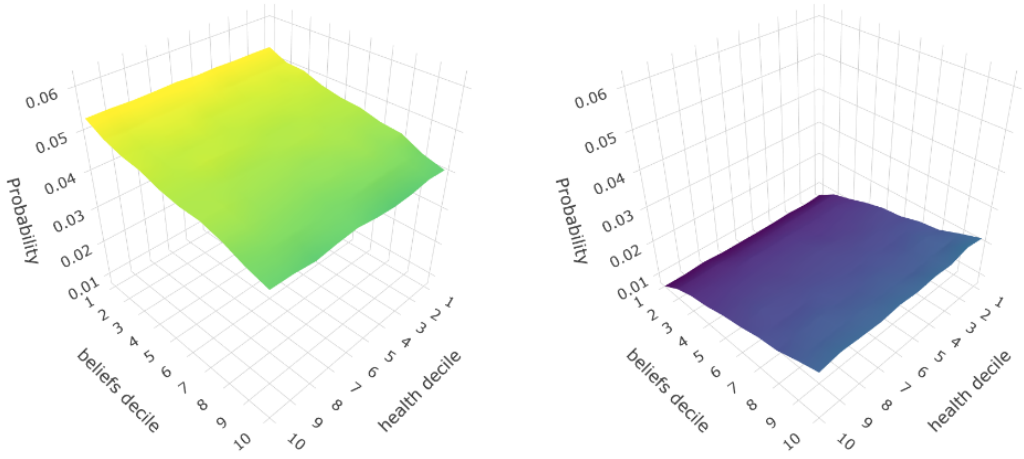


Notes: In each plot, the x- and y-axis correspond to deciles of health h_{it} and mean slope beliefs $\hat{\delta}_{it}$ for the corresponding subsample of the plot among the sample of individuals attached to the labor market. The z-axis corresponds to the estimated average partial effect on the probability of working next period ($p_{it+1} = 1$).

Figure D2: Average partial effect of health h_{it} on the probability of working next period p_{it+1} for individuals 66 to 75 years old

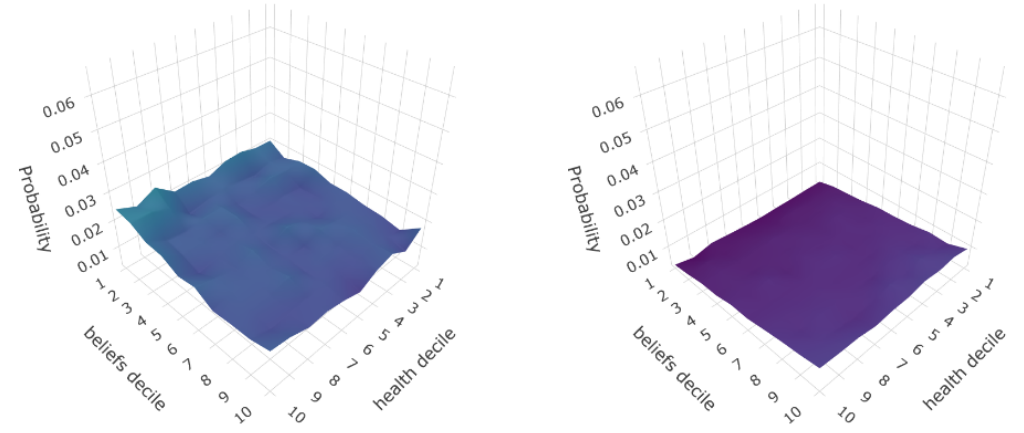
Probit results

(a) For working individuals $p_{it} = 1$ (b) For non-working individuals $p_{it} = 0$



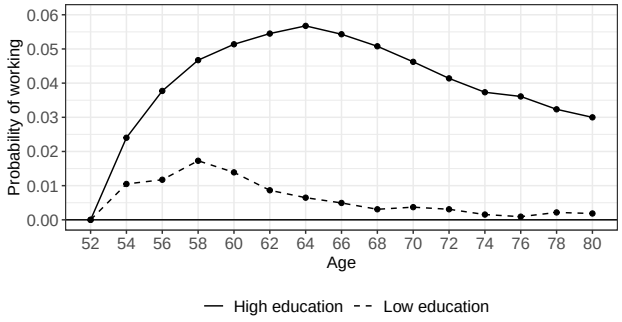
Neural network results

(c) For working individuals $p_{it} = 1$ (d) For non-working individuals $p_{it} = 0$



Notes: In each plot, the x- and y-axis correspond to deciles of health h_{it} and mean slope beliefs $\hat{\delta}_{it}$ for the corresponding subsample of the plot among the sample of individuals attached to the labor market. The z-axis corresponds to the estimated average partial effect on the probability of working next period ($p_{it+1} = 1$).

Figure D3: Impulse-response function to eliminating overall bias b, results by education



Notes: Subsample of 1,184 individuals observed at 52 years old.

E Bad versus good biomarker results

E.1 Distinguishing bad vs good biomarker results in the DD setup

I estimate the following generalization of equation (9):

$$y_{iw} = \beta_0 + \beta_1 d_{g_i} + \beta_2 d_{g_i} \cdot d_{b_i} + \beta_{3w} d_w + \beta_{4w} d_{g_i} \cdot d_w + \beta_{5w} d_{g_i} \cdot d_w \cdot d_{b_i} + \gamma x_i + \epsilon_{iw}, \quad \text{(A7)}$$

where, as before, d_{g_i} is a dummy for the treatment group (those who get their blood collected in wave 8 and their results informed between waves 8 and 9), and d_w are wave dummies. d_{b_i} is a dummy for the subgroup of treated individuals who get a bad result in any of the 3 biomarkers. That is, total cholesterol equal or above 200 mg/dL, HDL cholesterol below 40 mg/dL, or blood glucose hbA1c equal or above 7%. Note that the interpretation of the coefficients has changed relative to Equation (9). For example, β_1 compares wave-5 outcomes of treated individuals who get good results with all control individuals, whether their (unobserved) biomarkers are good or bad. Thus, β_1 does not reflect the randomization of the treatment. Consequently, the interest in this equation lies not in the comparison between treatment and control groups, but in the comparison between treated individuals who receive bad versus good results.

Table E1 presents the results of estimating equation (A7). It shows some initial differences between those who get bad and good results (see the coefficients for $d_{g_i} \cdot d_{b_i}$). Additionally, it suggests that the information contained in the bad results is at least partially learned by some individuals before being informed of their results, as their survival expectations and working probabilities fell more in the following waves (see the coefficients for $d_{g_i} \cdot d_{b_i} \cdot d_{w7}$ and $d_{g_i} \cdot d_{b_i} \cdot d_{w8}$.)

E.2 Effects of bad vs good biomarker results

For estimating the effects of receiving bad versus good biomarker results, I focus on the subsample of individuals who got this information after wave 8 and consider three alternative estimates.

Difference in means. Corresponds simply to an estimate of

$$\mathbb{E}(y_{iw_9} | d_{b_i} = 1) - \mathbb{E}(y_{iw_9} | d_{b_i} = 0).$$

Table E1: Biomarker experiment distinguishing bad vs good test results

	Survival expectation ($plive10_{iw}$)		Working decision (p_{iw})	
	Below college	College	Below college	College
	(1)	(2)	(3)	(4)
Group 1 (d_{g_i})	-0.018	-0.018	-0.021	-0.028
	(0.009)	(0.013)	(0.015)	(0.025)
Group 1, bad results ($d_{g_i} \cdot d_{b_i}$)	0.038	0.015	0.065	0.059
	(0.011)	(0.017)	(0.018)	(0.031)
Wave 6 (d_{w_6})	-0.012	-0.021	-0.068	-0.086
	(0.005)	(0.008)	(0.007)	(0.012)
Wave 7 (d_{w_7})	-0.014	-0.017	-0.116	-0.116
	(0.006)	(0.008)	(0.008)	(0.014)
Wave 8 (d_{w_8})	-0.061	-0.074	-0.157	-0.187
	(0.006)	(0.009)	(0.009)	(0.015)
Wave 9 (d_{w_9})	-0.032	-0.047	-0.200	-0.215
	(0.006)	(0.010)	(0.009)	(0.016)
Group 1, wave 6 ($d_{g_i} \cdot d_{w_6}$)	0.005	0.012	0.004	0.013
	(0.008)	(0.012)	(0.011)	(0.018)
Group 1, wave 7 ($d_{g_i} \cdot d_{w_7}$)	-0.000	-0.005	0.021	0.016
	(0.009)	(0.012)	(0.012)	(0.020)
Group 1, wave 8 ($d_{g_i} \cdot d_{w_8}$)	0.021	0.032	0.013	0.040
	(0.009)	(0.014)	(0.013)	(0.022)
Group 1, wave 9 ($d_{g_i} \cdot d_{w_9}$)	-0.005	0.017	0.021	0.003
	(0.009)	(0.014)	(0.014)	(0.024)
Group 1, bad results, wave 6 ($d_{g_i} \cdot d_{b_i} \cdot d_{w_6}$)	-0.016	0.004	-0.005	0.013
	(0.010)	(0.015)	(0.014)	(0.022)
Group 1, bad results, wave 7 ($d_{g_i} \cdot d_{b_i} \cdot d_{w_7}$)	-0.006	0.005	-0.029	-0.017
	(0.011)	(0.016)	(0.015)	(0.028)
Group 1, bad results, wave 8 ($d_{g_i} \cdot d_{b_i} \cdot d_{w_8}$)	-0.023	0.003	-0.027	-0.025
	(0.011)	(0.017)	(0.016)	(0.030)
Group 1, bad results, wave 9 ($d_{g_i} \cdot d_{b_i} \cdot d_{w_9}$)	-0.016	0.003	-0.026	0.003
	(0.011)	(0.017)	(0.018)	(0.032)
Constant	0.586	0.580	0.552	0.759
	(0.011)	(0.020)	(0.018)	(0.036)
N observations	31,810	10,115	31,805	10,113
N individuals	6,362	2,023	6,362	2,023
R-squared	0.021	0.025	0.034	0.035
% of treated individuals with bad results	37.7	34.4	37.7	34.4

Notes: Results of estimating equation (A7). Controls include gender, education, race and ethnicity. The sample consists of individuals with non-proxy interviews who are at least 50 years old in wave 8 and who give a valid answer to $plive10_{iw}$ every wave between waves 5 and 9. Standard errors (shown in parentheses) are clustered at the household level.

Regression-based estimates. I consider the following dynamic equations for survival expectations $plive10_{iw}$ and working decisions p_{iw}:

$$\begin{aligned} plive10_{iw+1} &= \alpha_i + \beta_0 \cdot d_{b_iw} + \beta_1 \cdot plive10_{iw} + \beta_2 \cdot p_{iw} + \beta_3 \cdot x_{iw} + \beta_4 \cdot iwmode_{iw+1} + \epsilon_{iw} \\ p_{iw+1} &= \nu_i + \gamma_0 \cdot d_{b_iw} + \gamma_1 \cdot plive10_{iw} + \gamma_2 \cdot p_{iw} + \gamma_3 \cdot x_{iw} + \gamma_4 \cdot iwmode_{iw+1} + u_{iw} \end{aligned}$$

where α_i and ν_i are time-invariant fixed effects, d_{b_iw} is a dummy for the subgroup of individuals who get a bad result in any of the 3 biomarkers in wave 8 and zero otherwise, and $iwmode_{iw}$ is a dummy for interviews done by phone as opposed to in person. The time-varying vector x_{iw} includes age, age squared, wave dummies, health, number of doctor visits, indicators for having been diagnosed with diabetes, for taking diabetes medication, and the controls described in Appendix Table D1. Of these variables, health insurance and the characteristics of working periods (see panel (b) of Table D1) are assumed to be predetermined, along with survival expectations and working decisions, while the other regressors are assumed to be strictly exogenous. The error terms ϵ_{iw} and u_{iw} are assumed independent of each other and i.i.d. over time. The coefficients β_0 and γ_0 capture the treatment effects of receiving bad biomarker results, which are homogeneous across individuals under this specification. The two equations are estimated independently using the GMM estimator of Arellano-Bond.

ATT by propensity score matching. I estimate the ATT on wave-9 outcomes of receiving bad biomarker results by a propensity score matching estimator with one neighbor. The propensity score is estimated with a probit model on wave-8 values of working decisions, survival expectations, age, age squared, gender, race, ethnicity, education, marital status, health, number of doctor visits, binary variables for not having health insurance, for having been diagnosed with diabetes, for already taking diabetes medication, for having had a cholesterol test[3], and binary variables indicating whether work requires physical effort, lifting heavy loads, stooping or kneeling, good eyesight, and whether it involves lots of stress.

[3] The information on cholesterol test comes from wave 7, as it is only available for few individuals in wave 8.