HETEROGENEOUS AND UNCERTAIN HEALTH DYNAMICS AND WORKING DECISIONS OF OLDER ADULTS*

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Abstract

As the population ages, there is a general concern and effort on trying to lengthen the labor-force participation of older adults, for whom health is an important determinant of working decisions. In this paper, I introduce heterogeneity in health dynamics with age and argue that uncertainty about this heterogeneity affects the working decisions of older adults. Using the Health and Retirement Study, I first show evidence of heterogeneity in the rate health changes with age, and use subjective survival expectations to infer health beliefs in a Bayesian-learning framework. I then estimate how working decisions depend on those beliefs flexibly, using a neural-network approach that does not require additional structure. The results show beliefs have substantial negative bias, that is, on average, individuals incorrectly believe their health will deteriorate too fast. Furthermore, eliminating that bias would increase labor-force participation by up to 2 percentage points. In the last part of the paper, I further look at a policy that could affect beliefs: the provision of information on blood glucose and cholesterol levels. The results show that this information has only small effects on beliefs and working decisions, and, consequently, policies with larger effects on beliefs are needed to delay retirement.

Keywords: health dynamics, older adults, retirement, uncertainty, beliefs

JEL Classification: D83, I14, J14, J26

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1 Introduction

The population is aging rapidly. Worldwide, the median age was 40 years old in 2018 and it is estimated to be 45 years old by 2050.[1] And though participation of older adults in the labor market has also been recently increasing,[2] still, the number of older people out of the labor force who will need to be supported by each worker is projected to rise by around 40% between 2018 and 2050.[3] This aging pattern puts a lot of strain on public budgets, and, as a result, there is a large interest in promoting employment at older ages.[4] The success of policies promoting 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. For older adults, health deteriorates naturally with aging, affecting retirement choices[5] and expectations.[6] Yet, little is known about how heterogeneous health dynamics of older adults are, and how this heterogeneity affects their working decisions.

This paper documents individual-level heterogeneity in health dynamics among older adults and studies how individuals' beliefs about their own health dynamics affect their working decisions. To do this, the paper proceeds in three parts. In the first part, I show evidence that health dynamics are indeed heterogeneous among older adults. That is, while some individuals see their health slowly deteriorating with age, other individuals see their health deteriorating much more rapidly. I argue this heterogeneity, which has been mostly ignored in the literature, is an important factor in the working decisions of older adults. Furthermore, what matters for those decisions is how much individuals know about their own health profiles. Hence, in the second part of the paper, I study uncertainty in health dynamics by developing a Bayesian learning model in which individuals have beliefs about their own health profiles and update those beliefs as they see their health changing with age. I leverage data on survival expectations to infer these beliefs and to quantify how uncertain individuals are. Then, in the third part of the paper, I estimate the effects those beliefs have on working decisions of older adults. I estimate this relation flexibly, by using machine learning tools that provide data-driven results. The use of expectation data to infer beliefs and the use of flexible machine learning tools for estimation of working decisions imply no assumptions have been made about the relation between beliefs and working decisions. Therefore, the results are not driven by any such assumption.

Using the Health and Retirement Study (HRS), the first part of the paper leverages the longitudinal nature of the data to estimate a dynamic model of health allowing for more general forms of heterogeneity.[7] In particular, I assume health is a persistent process with individual-level heterogeneity both in levels and in changes with age. The results show significant heterogeneity, in both dimensions. Further-

[1] For the US, those numbers are 38 and 42 years, respectively (OECD (2019)).
[2] The averaging retirement age increased by 2.5 years over the last two decades (OECD (2019)).
[3] See OECD (2019).
[4] For example, in 2015, the OECD adopted an agenda to promote employment at older ages, to protect living standards and public finances.
[5] See McClellan (1998), Siddiqui (1997), Bound et al. (1999); Disney et al. (2006), Zucchelli et al. (2010), and Maurer et al. (2011)).
[6] See Dwyer and Mitchell (1999) and McGarry (2004).
[7] Most of the literature allows only for individual heterogeneity in health levels. See, for example, Contoyannis et al. (2004) and Heiss (2011). An exception is Halliday (2008), who allows for heterogeneity in levels, in changes with age, and in persistence, but assuming only a few discrete unobserved types.

more, the heterogeneity in changes helps explain the increasing variance of health with age, a pattern observed in the population but ignored by traditional models of health.

The panel estimates on the first part of the paper provide evidence of individual-level heterogeneity on health dynamics, but they do not address the question of how much individuals know about their own health profiles. In the second part of the paper, I study this question using a Bayesian learning model[8] with initial beliefs that allow for bias (through the mean) and uncertainty (through the variance). Data on subjective survival expectations,[9] available in the HRS, allow me to identify the parameters governing these beliefs. Intuitively, future survival depends on future health; hence, expectations about future survival depend on beliefs about future health, and therefore, on beliefs about health profiles. Thus, according to the model, survival expectations are a complex function of health and health beliefs. Hence, I use Simulated Method of Moments to estimate the parameters of those beliefs. On the one hand, average survival expectations speak to bias in beliefs. On the other hand, covariance between changes in health and changes in expectations speak also to uncertainty. To see this, note that, given a change in health, individuals update their survival expectations for two reasons. First, because the persistence of health implies that future health is affected by a health change today. Second, because the uncertainty and the learning model imply that beliefs are updated with a health change today. Moreover, the larger the persistence and the larger the uncertainty, the larger the change in survival expectations. Hence, moments of survival expectations are they key source for identification of beliefs. My results show individuals are uncertain, updating their beliefs over time, and they are negatively biased, that is, on average, they believe their health will deteriorate faster than the average rate on the population.[10]

The heterogeneity and uncertainty in health dynamics imply that beliefs about health profiles enter the decisions of forward-looking individuals. In the third part of the paper, I study how these beliefs affect the working decisions of older adults. In particular, this step requires estimating the relationship between working decisions and all the information available to individuals at the moment they make those decisions, including their beliefs about their health profiles. Under the Bayesian assumption of the learning model, those beliefs are summarized by their mean and variance. I estimate this relation flexibly, by using a machine learning approach that, in the present context, generalizes logit with a non-linear index. To deal with the fact that some of the inputs are unobserved by the econometrician (mainly, the individual-level heterogeneity in initial beliefs), I use an iterative approach in the spirit of EM algorithms. An attractive feature of this framework is that it does not depend on any specific assumption about the relation between beliefs and labor choices, and hence, it is robust to misspecification. Furthermore, the

[8] The health process in this paper is similar to the income process studied by Guvenen (2007) who shows that, while learning of heterogeneous levels occurs fairly rapidly, learning of heterogeneous slopes with age is much slower.

[9] Survival expectations have been shown to have predictive power for individuals' survival and to be consistently updated with new health information. See, for example, Hurd et al. (2001), Hurd and McGarry (2002), and Smith et al. (2001). Furthermore, survival expectations are correlated with several outcomes for older individuals, including retirement (Hurd et al. (2004), O'Donnell et al. (2008), van Solinge and Henkens (2009)), claiming of Social Security (Hurd et al. (2004), Delavande and Willis (2007)), and wealth accumulation (Bloom et al. (2006))

[10] This result on negative bias in initial beliefs also implies individuals underestimates their survival probabilities to begin with. The result is consistent with Elder (2013) and Ludwig and Zimper (2013) who find that, on average, older adults under 65 years old underestimate their survival chances while adults older than 80 years old overestimate their survival chances. This overestimation by elderly adults is also reflected in my results but it is explained by measurement error, as discussed in section 5.

framework can also be applied to study other outcomes that may depend on health beliefs, like savings and health insurance of older adults. To the best of my knowledge, this is the first paper studying the effect of beliefs about heterogeneous health dynamics on working decisions of older adults.

I discuss three results related to beliefs and working decisions of older adults. The first result shows that beliefs matter in working decisions, and that expecting health to deteriorate more slowly is associated with larger probabilities of work. Furthermore, for individuals in their 50s that are not working, there is an interaction between beliefs and health. On the one hand, the effects of beliefs on working probabilities are larger for individuals with worse health. On the other hand, the effects of health on working probabilities are larger for individuals who believe their health will deteriorate relatively slowly. These results, not explained by standard mechanisms, suggest that adjustment costs of finding a job are important in individuals' decisions of going back to work. This observation highlights an advantage of the current framework and the data-driven estimation method, as a good complement for structural models.

A second result is related to the resolution of uncertainty about health profiles and the precision of health as a signal. A health shock has two effects on working decisions: it affects working decisions by changing the stock of health through persistence, and it affects working decisions by changing beliefs about future health by changing information about health profile. I decompose the effect of a health shock in these two channels, persistence and information, and find that nearly all the effect goes through the persistence channel. Intuitively, this result comes from the signal-to-noise ratio of health being low, and it implies that health by itself is not enough to resolve the uncertainty and correct the bias in beliefs. In a third set of results, I apply the machine learning tools to predict not only work but also assets and health insurance, and I use those results to compare baseline working probabilities with probabilities after eliminating initial overall bias in beliefs. I find that eliminating initial bias increases participation by 2 percentage points, and effect that lasts beyond traditional retirement ages.

Given that (i) individuals are uncertain about their health profiles, (ii) they have biased initial beliefs, (iii) health changes are not enough to resolve uncertainty, and (iv) beliefs matter for working decisions, a natural question that follows is: can we provide additional information to individuals in order to correct their beliefs and affect their working decisions? In the last part of the paper I look at this question in the context of an information experiment available in the HRS. Starting in 2006, the HRS collects and analyzes blood samples of their interviewees and informs them about their results about blood glucose and cholesterol levels. While the implementation in the HRS was not designed as an information experiment,[11] in order to save costs, the blood sample is collected for a random half of the sample each wave, providing us with exogenous variation. A reduced form analysis in the spirit of differences-in-differences[12] shows small and insignificant effects of this additional information on survival expectations and working decisions. Consistently, a model-based analysis also shows small and insignificant results. The model, however, provides us with an interpretation for these results: the magnitude of this blood-based signal is

[11] A proper information experiment would randomize who gets their results back among those for whom their results are available. In the HRS context, there is randomization on who gets their blood collected, but all of them receive their results back.

[12] As discussed in section 8, the design needs to control also for changes in interview mode.

too small.

The fact that this particular information policy does not have an effect on beliefs and working decision of older adults does not mean that other policies could not have an effect. Such policies could include information policies aimed at correcting bias in beliefs about aggregate values in the population, or more individualized information. Information policies have been studied in other settings; for example, Delavande and Kohler (2015) discuss information campaigns for beliefs about HIV risk, and Bates (2020) discusses information provided to schools about teachers effectiveness. Information policies have also been studied in the context of surveys; for example, Armona et al. (2018) provide in-survey information on actual changes in home prices, and Wiswall and Zafar (2014) provide information to students on major characteristics. In the case of the HRS, this could include providing information about biomarkers on kidney function and systemic inflammation, as well as genetic information, all already collected in the survey but with results that are not informed to individuals.

Contribution to the literature. This paper is related to three strands of the literature. First, it is related to the literature studying health dynamics, a literature that consistently finds persistence and heterogeneity in health, both among the general population (Halliday (2008), Hernández-Quevedo et al. (2008), Contoyannis et al. (2004)) and among older adults (Heiss et al. (2009), Heiss (2011), Heiss et al. (2014), Lange and McKee (2011)). However, most of this literature allows only for limited heterogeneity. An exception is Halliday (2008) who allows for discrete types of multivariate heterogeneity, including heterogeneity in health changes with age. Contrary to my results, he finds only weak evidence of this heterogeneity. However, he focuses on a much younger population, while I focus on older individuals for whom health changes with age are prevalent. Thus, a first contribution of this paper is to highlight heterogeneity in health dynamics for older adults. An additional contribution to this literature is related to health measurement. Traditionally, health has been considered a latent variable measured with one binary variable (Halliday (2008), Hernández-Quevedo et al. (2008), Heiss et al. (2009), Heiss (2011)), though, more recently, several measured of health are being used (Heiss et al. (2014), Lange and McKee (2011), Blundell et al. (2017)). In this paper, I also use several measures of health to better capture the richness of health and its dynamics, hence, contributing in this direction.

Second, this paper is related to the literature on empirical learning. In a broad sense, the paper is related to the literature on the importance of beliefs for individuals' choices and economic outcomes.[13] More specifically, the paper is related to the literature studying individuals' learning of own unobserved heterogeneity; for example, regarding abilities (Stinebrickner and Stinebrickner (2014), Arcidiacono et al. (2016)), productivity (Arcidiacono et al. (2016)) and income profiles (Guvenen (2007), Guvenen and Smith (2014)). My paper is more closely related to Guvenen and Smith (2014) who study an income process with heterogeneous levels and heterogeneous growth rates. As in the case of health, the more flexible heterogeneity helps explain the income pattern of increasing variance over time. However, an

[13] Outcomes studied by this literature include occupational choices and college attrition (Breen and García-Peñalosa (2002), Arcidiacono et al. (2017), Arcidiacono et al. (2016)), labor supply of women and employment transitions (Gong et al. (2019), Conlon et al. (2018)), birth control choice and risky sexual behaviors (Delavande (2008), Paula et al. (2014), Delavande and Kohler (2015)), and investment decisions (Delavande and Rohwedder (2011)).

important difference with that paper is the source of identification of profile uncertainty. Guvenen and Smith (2014) use consumption data to identify uncertainty in income profiles. Instead, I use data on expectations to identify uncertainty in health profiles. This is important because my goal is to study the effect of uncertainty regarding health dynamics on working decisions of older adults, and hence, using that outcome to identify beliefs would mean my results could suffer from misspecification issues. By using expectations data, my results are robust to such issues. I also allow for individuals to be biased overall in their initial beliefs, consistent with findings from the literature on survival expectations (see Elder (2013) and Ludwig and Zimper (2013)). Additionally, this paper contributes to a more recent literature on the provision of information and its effects on beliefs (see, for example, Delavande and Kohler (2015), Wiswall and Zafar (2014), Bates (2020)), extending this literature to the provision of health-related information.

Finally, the paper is related to the literature on health and other outcomes of older adults. Particularly, the paper is related to the literature studying the effects of health on work and retirement choices (Bound et al. (1999), French (2005), Disney et al. (2006), Maurer et al. (2011)) and expectations (Dwyer and Mitchell (1999), McGarry (2004)). Although this literature considers future health as uncertain, it assumes a known stochastic process for health. On the contrary, this paper allows for a stochastic health process that is not fully known, introducing the role of health beliefs as an additional determinant of those decisions. More broadly, this paper is also related to a series of papers studying health-related outcomes for older individuals. These papers estimate structural models assuming discrete values for health with homogeneous transition probabilities. Examples include papers studying the effect of health insurance on retirement (French and Jones (2011), De Nardi et al. (2016a)), Social security and labor supply (van der Klaauw and Wolpin (2008)) portfolio choice (Yogo (2016)) and long-term care (Ameriks et al. (2020), Lockwood (2018)). Though health is not the main explanatory variable of interest in these papers, the results here suggest that beliefs about health may also play a role. Furthermore, the data-driven methodology suggested in this paper is a good and not-costly complement to such analyses.

Organization. The paper proceeds as follows. Section 2 presents the framework and section 3 describes the data. Section 4 provides evidence of heterogeneity in health dynamics, and section 5 provides evidence of uncertainty. Section 6 presents the main results for working decisions as function of beliefs and section 7 expands those results. Section 8 analyzes the information experiment available in the HRS. Section 9 concludes.

2 Framework

This paper introduces two elements into a standard model of labor-participation decisions in late life: individual-level heterogeneity in health dynamics and individuals' uncertainty regarding their own health profile. This section formalizes this idea and describes a framework in which older adults choose labor participation based on their health and on their beliefs about how their health will change with age. Let i denote an individual and let t denote his age. I focus on individuals fifty years and older and define t as zero for age fifty.

2.1 Health process with heterogeneous dynamics

Health is a dynamic process that, as people get older, naturally deteriorates in a heterogeneous way across individuals. In particular, I assume,

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

where the parameter $\rho \in (0,1)$ captures persistence in health, α_i captures heterogeneous levels in health, δ_i captures heterogeneous changes of health with age, and ϵ_{it} represents health shocks. Both the persistence of health and its heterogeneity in levels are well recognized elements of health in the literature, both among the general population (see, for example, Hernández-Quevedo et al. (2008)) and among older individuals (see, for example, Heiss et al. (2014)). The first novel element in this paper is to allow for heterogeneous slopes of health with age, δ_i. Larger values of h_{it} represent better health, and health decreases with age. Therefore, $\delta_i < 0$.

Throughout the paper, I assume health is exogenous. In a review of the literature on health, health insurance and retirement, French and Jones (2017) mention that much of the retirement literature assumes that health is exogenous, and their model makes that same assumption. In a review of the literature on savings after retirement, De Nardi et al. (2016b) conclude that most of the studies on the effects of health care on health find small effects. A similar argument is made in French and Jones (2011). The exogeneity assumption implies we can estimate equation (1) without the need to model endogenous regressors.[14]

2.2 Uncertain health dynamics and beliefs

The second novel element is to allow for individuals to be uncertain about their own health dynamics. I assume individuals observed their health h_{it}, but the do not observe their health shocks ϵ_{it} nor they observe their individual heterogeneity (α_i, δ_i). Given that health deteriorates in old age, I assume 50-years old individuals do not know δ_i, which has not affected them before.[15] For simplicity, I assume they know their heterogeneous level α_i,[16] as they have observed their health for several decades.

Under uncertainty, rational individuals form beliefs about their health slopes δ_i (henceforth, slope beliefs) and update those beliefs as they see their health changing with age. In particular, I assume individuals are Bayesian learners, with initial beliefs (at age 50) about δ_i equal to $N(\hat{\delta}_{i0}, \hat{\sigma}_0^2)$.[17] By further assuming that health shocks ϵ_{it} are i.i.d normally distributed, posterior beliefs in period t after observing health h_{it} are also normally distributed, $N(\hat{\delta}_{it}, \hat{\sigma}_t^2)$, with mean and variance defined recursively

[14] The assumption is also relevant for the identification of beliefs, as discussed in section 5.

[15] 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, aged 22 to 60, and finds no heterogeneous slopes with age.

[16] This assumption can be generalized. In studying income profiles, Guvenen (2007) proposes a similar process with heterogeneous intercepts and slopes, both unknown. He finds the learning process for intercepts is much faster than the learning process for slopes.

[17] The assumption of common-prior variance across individuals is usual in the learning literature. See for example, Guvenen (2007) and Arcidiacono et al. (2016). It is, however, an important assumption for the identification results provided later.

by

$$
\begin{aligned}
\frac{\hat{\delta}_{it}}{\hat{\sigma}_t^2} &= \frac{\hat{\delta}_{it-1}}{\hat{\sigma}_{t-1}^2} + \frac{(h_{it} - \rho h_{it-1} - \alpha_i)t}{\sigma_\epsilon^2} && (2) \\
\frac{1}{\hat{\sigma}_t^2} &= \frac{1}{\hat{\sigma}_{t-1}^2} + \frac{t^2}{\sigma_\epsilon^2}. && (3)
\end{aligned}
$$

Equation (2) 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 is health as a signal (lower σ_ϵ^2) more weight is given to its information. Equation (3) 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,

$$
\begin{aligned}
b &= \mathbb{E}(\hat{\delta}_{i0} - \delta_i) && (4) \\
\lambda^2 &= \frac{\hat{\sigma}_0^2}{Var(\delta_i)}. && (5)
\end{aligned}
$$

The parameter b measures the bias in initial beliefs at the population level. If $b = 0$, individuals are overall unbiased, in the sense that $\mathbb{E}(\hat{\delta}_{i0}) = \mathbb{E}(\delta_i)$. If b is positive (negative), individuals are upward (downward) biased and, hence, they believe health deteriorates on average more slowly (faster) than the average rate. The parameter λ measures the degree of initial uncertainty individuals face regarding δ_i, which affects the amount of learning they do over time. If $\lambda = 0$ there is no uncertainty and, therefore, no learning. The larger the value of λ the more uncertain individuals are and the more weight they give to new information. The Bayesian learning assumption allows me to reduce the dimensionality of the problem, giving structure to time-varying beliefs that are unobserved by the econometrician.

2.3 Embedding health uncertainty in a model of labor supply

In a life-cycle model, forward-looking individuals attempt to predict variables that will affect their future utility or future set of options in order to choose their best current action. The need for those predictions is given by the inherent uncertainty on many key variables. In this paper, I focus on working decisions of older adults and argue that a key source of uncertainty for this group is related to their future health. In particular, I focus on the heterogeneous way health changes with age δ_i and how beliefs about them, given by $N(\hat{\delta}_{it}, \hat{\sigma}_t^2)$, relate to their working decisions.

Consider a model where individual i must choose consumption c_{it} and labor participation p_{it} every period. I focus on the extensive margin of labor participation and assume p_{it} is a binary decision. The health of individual i is given by h_{it}, which follows equation (1). The main components of this life-cycle model are the following.

Preferences. Individual i's flow utility is given by a function U that depends on his participation and consumption decisions, p_{it} and c_{it}, as well as on his health h_{it}. Furthermore, preferences depend on past labor participation, for example, to reflect psychological costs of going back to work after retirement and adjusting to a new work environment. I summarize this dependence by allowing p_{it-1} to enter the utility function. Hence, flow utility is given by $U(p_{it}, c_{it}, h_{it}, p_{it-1})$. The individual discounts the future, and when he dies his remaining assets a are left as a bequest.

Budget constraint. Let a_{it-1} denote individual i's assets at the end of period $t-1$. If the individual chooses to work, he receives labor income, which depends on his past labor income w_{it-1}, his health h_{it} due to the effects of health on productivity, and his past participation p_{it-1}, due to wage penalties of reentering the labor market after retirement. His assets at the end of the period depend also on his consumption choice, his other sources of income, including pension and social security, and other health-related costs.

Uncertainty. Individuals are uncertain about their future health, in part because of unpredictable health shocks ϵ_{it}, and in part because they don't know their health slopes δ_i. They form beliefs about their slopes δ_i and update those beliefs as they see their health changing over time according to equations (2) and (3). Future wages are also uncertain, following a first-order Markov process.

Timing. At the beginning of period t, an individual must choose participation p_{it} and consumption c_{it} before health shocks are realized and health h_{it} is observed. Then, beliefs are updated. At the end period t, individual i may or may not die.

Information set. The information set of individual i at the beginning of period t is given by his history up to $t-1$ in terms of labor participation p_i^{t-1} (superscripts denote histories), consumption c_i^{t-1}, and health h_i^{t-1}, as well as labor income w_i^{t-1}. It also includes his known value α_i and his prior-beliefs parameters $\hat{\delta}_{i0}$ and $\hat{\sigma}_0^2$. The relevant information from this set can be summarized in his state variables, given by

$$\Omega_{it-1} \quad = \quad \left\{p_{it-1}, a_{it-1}, w_{it-1}, h_{it-1}, \hat{\delta}_{it-1}, \hat{\sigma}^2_{t-1}, \alpha_i\right\}.$$

Slope uncertainty implies δ_i does not belong to Ω_{it-1}, but beliefs about δ_i do, with those beliefs summarized by $\hat{\delta}_{it-1}$ and $\hat{\sigma}^2_{t-1}$. Note that I am assuming only heterogeneity in health; thus, no other individual-level heterogeneity is stated in Ω_{it-1}. A natural extension of this research is to allow for more flexible dimensions of heterogeneity, and it is left for future work.

The solution to this problem are policy rules for labor participation p_{it} and consumption c_{it}, which are functions of the state variables and the parameters of the model θ (including the discount factor and parameter entering flow utility, health process, the budget constraint, and so on), which I omit for ease of notation. Focusing on p_{it}, which is the object of interest in this paper,

$$\mathbb{P}(p_{it}=1|\Omega_{it-1}) \quad = \quad \mathbb{P}(p_{it}=1|p_{it-1}, a_{it-1}, w_{it-1}, h_{it-1}, \hat{\delta}_{it-1}, \hat{\sigma}^2_{it-1}, \alpha_i) \tag{6}$$

Similarly, policy rules for other decisions, including consumption and assets, can be written as functions of the state variables Ω_{it-1}.

With these elements, the model is a standard model of labor participation in late life and includes several channels through which health can play a role. First, health directly affects utility by changing the marginal utility of consumption and the disutility of work. Second, it enters the budget constraint via health-related costs and via effects on labor income due to changes in productivity. Third, health affects the probabilities of survival. The overall effect of health on individuals' participation decisions depends on all of these channels. The novel element in this paper is that beliefs about future health also play a role. They could have a positive or negative effect depending on the relative importance of these channels in the individual's problem. For example, if an individual predicting better future health wants to work longer, the sign of beliefs would be positive. This would be the case if the dominant effect were the desire to save more given the longer life expectancy implied by better health. If an individual predicting worse future health wants to work longer, the sign would be negative. This would be the case if the dominant effect were the desire to save more given the higher cost of future healthcare implied by worse health.

2.4 Objective of the paper

Under this framework, the objectives of the paper are the following:

(i) To document heterogeneity in health dynamics among older adults, particulary heterogenity in δ_i.

(ii) To study older adults' beliefs about their health dynamics, in particular, to estimate their initial bias b and their initial uncertainty λ.

(iii) To examine whether these beliefs have an effect on working decisions of older adults, by studying the effect of marginal changes in beliefs on those decisions,[18]

$$\frac{\partial \mathbb{P}(p_{it}=1|\Omega_{it-1})}{\partial \hat{\delta}_{it-1}} \tag{7}$$

The overall goal of this paper is to estimate equation (7) flexibly, without imposing any additional structure on the model of labor supply. A flexible estimation provides results that are robust to misspecification issues on that model. The paper uses a data-driven estimation method that allows me to achieve that flexibility. Furthermore, as it is discussed in section 6, this data-driven approach allows the data to suggests mechanisms that may be overlooked otherwise. Nevertheless, this framework could also be applied under a structural approach, by adding assumptions about the different elements in the model. A structural approach, on the other hand, has the advantage of allowing for interesting counterfactual

[18] I focus on the marginal effect of the posterior mean $\hat{\delta}_{it-1}$ and not of the posterior variance $\hat{\sigma}^2_t$. The reason for this choice is that the posterior variance $\hat{\sigma}^2_{t-1}$ is common across individuals. Thus, I do not have variation in the data to separately identify its effects from the effects of age t, without relying on functional form assumptions.

analysis. Hence, the objective of the current approach is not to compete with structural models, but to complement them. Thus, a natural extension of this paper is to estimate such an structural model, which is left for future research.

In this context of uncertain health dynamics, an additional interesting question is related to the dual role of health shocks ϵ_{it-1} in working decisions. On the one hand, a health shock ϵ_{it-1} affects h_{it-1}, which in turn affects h_{it} through persistence of the health process. This persistence effect disappears if $\rho = 0$. On the other hand, an uncertain individual can not perfectly distinguish between ϵ_{it-1} and δ_i within h_{it-1}. Hence, the effect of a shock ϵ_{it-1} on h_{it-1} is partly interpreted as new information regarding δ_i, affecting beliefs $\hat{\delta}_{it-1}$. This information channel disappears if $\lambda = 0$. Using Bayes' rule, we can write,

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

where the *factor* term corresponds to the change in the posterior mean $\hat{\delta}_{it-1}$ given a marginal change in ϵ_{it-1}, and it is related to the signal to noise ratio of health as signal. The term is larger when there is more uncertainty about the unknown δ_i and when the variance of the health shocks are smaller. How much of these channels explain the total effect of a health shock on working decisions of older adults is, then, an empirical question.

3 Data and descriptive statistics

For this study, I use data from waves 4 to 12 of the Health and Retirement Study (HRS), a longitudinal survey representative of the population 50 years and older in the US. This survey interviews individuals and their spouses every two years and includes several measures of health, questions about expectations, information about labor participation and retirement, as well as income and wealth variables.[19] For most of the analysis, I use the RAND version of these data. In this section, I briefly describe the variables used in this study.

3.1 Data on health

The most common measure of health used in the literature is *self-assessed health*, an ordinal variable taking five values from very poor to excellent. It has been shown to correlate with several outcomes, including education, income, savings, retirement and health insurance. Still, its limited range makes it not ideal in studying health dynamics with age. The HRS, however, provides a larger battery of health-related questions, which I exploit to construct a summary measure of health via factor analysis that I use throughout the paper. This approach of using several measures to construct a summary variable is not unique to this paper; see, for example, Heiss et al. (2014), Lange and McKee (2011) and Blundell et al. (2017). Table 1 presents summary statistics for these health-related questions and for the summary

[19] I exclude proxy interviews because questions on survival expectations are not asked in these interviews.

Table 1: Summary statistics for health-related questions

Variable	Observations	Mean	SD	Min	Max
Number of chronic conditions	156,968	5.17	1.34	0	7
Self-assesed health	156,862	2.86	1.11	1	5
Body mass index (kg/m^2)	154,602	27.89	5.81	7	83
Eyesight in general	156,768	2.85	1.01	1	6
Eyesight at a distance	156,833	2.57	1.01	1	6
Eyesight up close	156,822	2.75	1.04	1	6
Hearing	156,869	2.63	1.09	1	5
Pain	156,550	0.63	0.97	0	3
Difficulties in ADLs regarding mobility	156,748	1.09	1.45	0	5
Difficulties in ADLs of large muscles	156,737	1.28	1.33	0	4
Difficulties in other ADLs	151,923	0.40	0.66	0	2
Summary health measure h_{it}	148,866	5.22	0.67	2.96	6.18

Note: Summary statistics for the health measures including the summary health measure. The sample comprises 30,657 individuals interviewed in-person, in wave 4 or later, that are 50 years old or older. Chronic conditions include: high blood pressure, heart attack, diabetes, stroke, lung disease, arthritis, cancer. The categories for self-assesed health and hearing include: 1. excellent, 2. very good, 3. good, 4. fair, 5. poor. These are also the categories for eyesight variables, but those include alternative 6. legally blind. 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: walk 1 block, several blocks, across room, climb one flight of stairs, several flight of stairs. ADLs involving large muscles include: push or pull large object, sit for two hours, get up from chair, stoop kneel or crouch. Other ADLs include: carry ten lbs and reach arms.

health measure. Note these measures reflect a health concept that is the relevant one for the working decisions of older adults, related to how individuals feel and how they perceive their health in relation to their everyday activities. The appendix provides details on the estimation of the summary measure h_{it} via factor analysis. The scale of h_{it} is set to be the inverse scale of the number of chronic conditions, which ranges from 0 to 7. That is, larger values of h_{it} represent better health, and an increase of one unit in h_{it} corresponds to one less chronic condition. Figure 1 shows a box plot for h_{it} per value of *self-assessed health*. Both measures are highly correlated, but h_{it} captures more variation than what we can capture with a discrete measure.

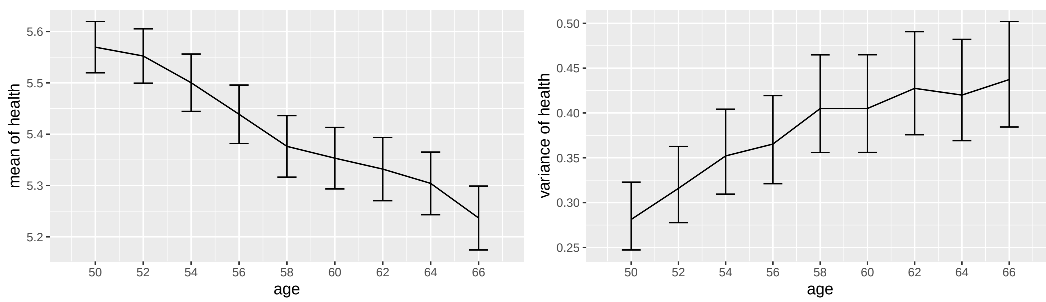
Figure 2 shows the mean and variance of health h_{it} by age.[20] Given the two-years time between waves, throughout this paper I consider age as measured in two-years bins. These plots are the starting point for thinking about health for older adults: they show that with age, the average health in the population decreases while the variance of health in the population increases. This pattern of decreasing mean and increasing variance is robust to sample composition and also holds for most of the individual measures. Similarly, Figure 3 shows percentiles of health by age, which also reflect an increasing variance over time. While not conclusive, the pattern in these plots suggests a process with heterogeneous slopes with age,

[20] The standard errors in this figure, as well as the following results in this paper, need yet to be adjusted for the estimation of the summary health measure, something that I am working on.

Figure 1: Summary health variable h_{it} by *self-assessed health* category

Note: Sample of 148,866 observations from Table 1.

Figure 2: Mean and variance of health by age



(a) Mean of h_{it} by age

(b) Variance of h_{it} by age

Note: Results from a balanced sample of 433 individuals observed at 50 years with at least 9 consecutive waves. The bars represent the 95% confidence intervals.

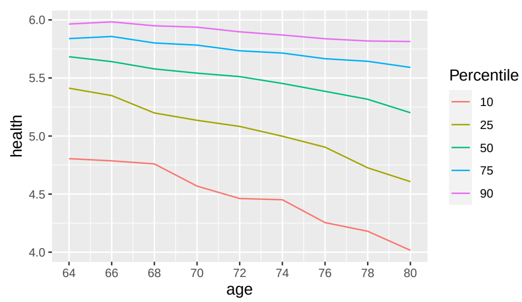
which I empirically investigate in section 4. Finally, Figure 4 shows the mean of health for different cohorts of individuals. The figure suggests survival bias, because cohorts of individuals surviving to older ages have better health than cohorts that may not survive that long. The relevance of addressing survival bias for older individuals is well-recognized in the literature (see, for example, Heiss et al. (2014)), and address it also, as explained in the next section.

3.2 Data on subjective survival expectations

The HRS includes a battery of questions relative to subjective expectations, including subjective survival expectations, which I use in this paper. The question asks *What is the percentage chance you will live to be (80, 85, 90, 95 or 100) or more?*, where the reference age is a function of the individual's age and the wave of the survey. This reference age is usually around 10 to 15 years into the future.[21] This variable suffers from rounding and focal point issues (Manski and Molinari (2010), Kleinjans and Van Soest (2014)), as it is shown in Figure 5. However, they have been shown to have predictive power for individuals' survival (Hurd et al. (2001), Hurd and McGarry (1995)) and to be consistently updated

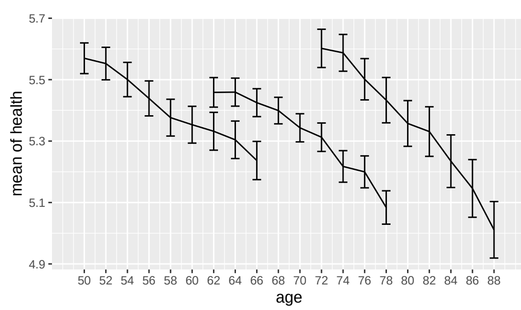
[21] The HRS also includes a question on survival expectations to the age of 75. However, I do not use this variable for the main analysis given that this question is only asked to individuals under 65 years old. Thus, using this variable would restrict my sample considerably.

Figure 3: Health percentiles by age



Note: Results from a balanced sample of 414 individuals observed at age 64 with at least 9 consecutive waves.

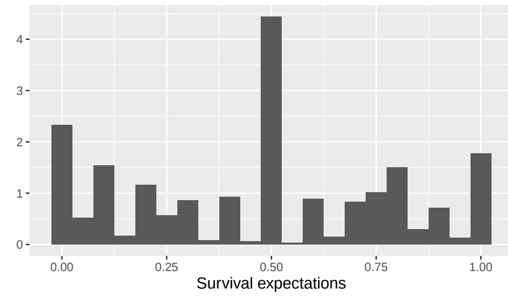
Figure 4: Mean of health with age for different cohort of individuals



(a) Mean of h_{it} with age

Note: Results from three balanced samples of individuals with at least 9 consecutive waves: 433 individuals observed from age 50, 509 individuals observed from age 62, and 153 individuals observed from 72. The bars represent the 95% confidence intervals. Standard errors need to be adjusted to account for the estimation of the health summary measure.

Figure 5: Histogram of survival expectations to age 85



Note: Sample comprises 54,754 observations from individuals interviewed in-person, in wave 4 or later, that are 50 years old or older, and who are asked for a reference age of 85 years old. The variable is rescaled to take values between 0 and 1 instead of 0 and 100.

with new health information (Hurd and McGarry (2002), Smith et al. (2001)). Furthermore, survival expectations are correlated with several outcomes for older individuals, including retirement (Hurd et al. (2004), O'Donnell et al. (2008), van Solinge and Henkens (2009)), claiming of Social Security (Hurd et al. (2004), Delavande and Willis (2007)), and wealth accumulation (Bloom et al. (2006)).

3.3 Data on other determinants of working decisions

In this paper, the main objective is to study how beliefs regarding health profiles affect the working decisions of older adults. As described in section 2, this requires estimating the policy rule of participation p_{it} as a function of past participation p_{it-1}, health h_{it-1}, heterogeneity in health levels α_i, beliefs regarding health profiles $(\hat{\delta}_{it}, \hat{\sigma}_t^2)$, as well as other variables in the information set Ω_{it-1}, including assets a_{it-1} and labor income w_{it-1}. Table 2 presents summary statistics for these other variables in Ω_{it-1} that I use in section 6 in predicting working outcomes of older adults.

4 Health process with heterogeneous dynamics

This section estimates a health process with heterogeneous intercepts and slopes. As Figure 4 suggests, for a population of older adults, we need to control for survival bias, which I address by jointly modeling the two processes, given the lack of a suitable instrument affecting survival chances but not health.

4.1 Empirical strategy

Let S_{it} be a binary variable for surviving up to the beginning of period t with $S_{i0} = 1$ and let the health and survival processes be given by

$$h_{it} = \rho h_{it-1} + \alpha_i + \delta_i \cdot t + \tau \cdot t^2 + \epsilon_{it}, \qquad \epsilon_{it} \ it\text{-iid } N(0, \sigma_\epsilon^2) \tag{9}$$

$$S_{it} = \mathbb{1}\{\gamma h_{it-1} + \theta_0 + \theta_1 \cdot t + \theta_2' x_i + \eta_{it}\} S_{it-1}, \qquad \eta_{it} \ it\text{-iid } N(0, 1) \tag{10}$$

Table 2: Summary statistics for variables used in studying working decisions

Variable	Mean	SD	Min	Max
Panel (a)				
Age	66.26	7.49	52	80
Work	0.38	0.49	0	1
Female	0.52	0.5	0	1
Education: less than highschool	0.20	0.40	0	1
Education: some college	0.55	0.50	0	1
White	0.84	0.37	0	1
Hispanic	0.06	0.24	0	1
Marital Status: married	0.70	0.46	0	1
Marital Status: separated or divorsed	0.12	0.33	0	1
Marital Status: widow	0.14	0.35	0	1
Number of household members	2.15	1.03	1	12
Total number of years worked	39.79	9.17	20	68
Spouse works	0.28	0.45	0	1
Spouse has health insurance	0.17	0.38	0	1
Income from pension	6.08	50.49	0	10000
Income from Social Security	6.65	5.95	0	58.3
Wealth	366.51	730.98	-1585.01	10000
Health insurance: employer coverting retirement	0.14	0.35	0	1
Health insurance: employer not coverting retirement	0.07	0.25	0	1
Health insurance: employer (already 65)	0.17	0.37	0	1
Health insurance: government	0.47	0.5	0	1
Health insurance: other	0.11	0.31	0	1
Panel (b)				
Income from work	30.51	39.83	0	1190.68
Tenure	14.31	12.4	0	66.1
Self-employed	0.22	0.42	0	1
Occupation: managerial	0.16	0.36	0	1
Occupation: professional	0.21	0.4	0	1
Occupation: sales	0.12	0.32	0	1
Occupation: clerical	0.16	0.37	0	1
Occupation: services	0.14	0.35	0	1
Occupation: farming, mechanics, construction, operators	0.22	0.41	0	1
Occupation: FF.AA.	0.00	0.02	0	1
Job requires physical effort	0.17	0.38	0	1
Job requires lifting heavy loads	0.07	0.25	0	1
Job requires stooping or kneeling	0.13	0.34	0	1
Job requires good eyesight	0.68	0.47	0	1
Job involves lots of stress	0.16	0.37	0	1

Note: Summary statistics for the variables used in estimating working decisions in section 6. The sample consists of observations from 12,623 individuals that have participated in the labor market for at least 20 years, excluding missing values in any of these variables. *Panel (a)* comprises 48,607 observations, and *Panel (b)* comprises 18,415 observations from working periods. Income and wealth variables are measured in thousands of 2002 dollars. Wealth variables are capped at 10 millions dollars.

with individual-level heterogeneity (α_i, δ_i),

$$\begin{pmatrix} \alpha_i \\ \delta_i \end{pmatrix} \Big| x_i, h_{i0} \sim N\left(\begin{pmatrix} \mu_\alpha + \nu'_\alpha x_i + \omega_\alpha h_{i0} \\ \mu_\delta + \nu'_\delta x_i + \omega_\delta h_{i0} \end{pmatrix}, \begin{bmatrix} \sigma^2_\alpha & \phi\sigma_\alpha\sigma_\delta \\ \phi\sigma_\alpha\sigma_\delta & \sigma^2_\delta \end{bmatrix} \right). \tag{11}$$

The health process is persistent, measured by the parameter ρ, and it has heterogeneous levels α_i and heterogeneous slopes with age δ_i. The survival process depends on health, through the parameter γ_1, and it depends on age, through θ_1. The health and survival shocks, ϵ_{it} and η_{it}, are assumed independent. The variables in x_i are time-invariant binary variables for female, white, Hispanic, and an education level below high school graduation. These variables potentially affect health (through the individual-level heterogeneity) and survival. I also allow for the unobserved heterogeneity to depend on health h_{i0} (health at age 50) in order to address initial-conditions concerns.

Under these assumptions, the panel structure of the data identifies the distribution of α_i and δ_i. Let Θ be the set of parameters of this random-coefficients model.[22] I estimate these parameters by maximizing the likelihood:

$$\max_{\Theta} \sum_{i=1}^{N} log\Big(\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \prod_{t=1}^{T_i} \mathbb{P}\left(h_{it}, S_{it} | h_{it-1}, S_{it-1} = 1, x_i, \alpha, \delta\right) \cdot \phi(\alpha, \delta | x_i, h_{i0}) d\alpha d\delta \Big).$$

4.2 Results

I use a sample of 8,901 correlative observations from 1,671 individuals observed since they were 50 years old ($t = 0$).[23] Over the span of the following eight waves, 112 of these individuals died. The main results are shown in Table 3 and full results are shown in the appendix. The table shows, first, heterogeneity in both the intercepts and the slopes of the health process, with positive and significant σ^2_α and σ^2_δ. Second, these two sources of heterogeneity are uncorrelated, which implies knowing α_i does not provide additional information on δ_i. Health decreases with age and the persistence of the health process is relatively low, with $\rho = 0.22$. The results in the appendix further show low levels of education are associated with worse health every period, health decreases faster for white individuals, and women and Hispanic individuals have higher probabilities of survival on average. Those results also show h_{i0} is correlated with α_i, but it does not provide information on δ_i.

I want to emphasize two aspects of this model: the inclusion of heterogeneous slopes with age and the joint estimation with survival. To understand how these two aspects influence my results, I estimate two additional versions of the model: (i) one excluding the equation for survival but allowing for heterogeneous slopes with age, and (ii) another one assuming homogenous slopes with age but including an equation for survival. The results are in the appendix and show qualitatively similar results for the coefficients that are common across specifications. Their main difference is that ignoring slope heterogeneity increases the point estimate of the persistence parameter ρ by over 50% (from 0.22 to 0.37). However, a key takeaway is that these models achieve very different fits of health over time. This takeaway is more

[22] $\Theta = \{\rho, \tau, \sigma^2_\epsilon, \gamma, \theta_0, \theta_1, \theta_2, \mu_\alpha, \mu_\delta, \nu_\alpha, \nu_\delta, \omega_\alpha, \omega_\delta, \sigma^2_\alpha, \sigma^2_\delta, \phi\}$

[23] I approximate the double integral by using one thousand draws from a bivariate normal distribution.

Table 3: MLE results on health and survival

	Symbol	Coefficient	Pvalue
Persistence	ρ	0.222	0.000
Mean* of α_i	μ_α	0.967	0.000
Mean* of δ_i	μ_δ	-0.059	0.006
SD of α_i	σ_α	0.236	0.000
SD of δ_i	σ_δ	0.043	0.000
$Corr(\alpha_i, \delta_i)$	ϕ	-0.034	0.605
SD of health shocks	σ_ϵ	0.266	0.000
Survival dependence on health	γ_1	0.656	0.002
Controls		Yes	
N alive observations		8,901	
N dead observations		112	
N individuals		1,671	
-Log likelihood		3,021.1	

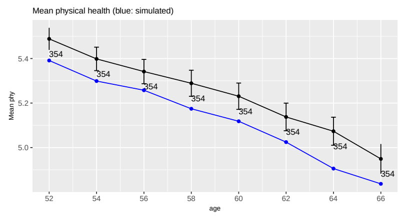
Note: Main results of estimating equations (9), (10) and (11). Full set of results are shown in the appendix.

clearly seen in Figure 6, which repeats the exercise for a sample of individuals observed from 66 years old and plots the predicted mean and variance of health with age. The figure shows that ignoring survival leads to a downward bias of average health and an upward bias of its variance, consistent with a model that includes the lower tail of the health distribution, which is dropped from the data as people die. The figure also shows that when ignoring slope heterogeneity, we predict a rather constant variance of health, contrary to what the data show. In that sense, these plots support a model with slope heterogeneity, though they don't discard alternative explanations for the increasing variance with age. As a robustness check, I estimate a version with heteroskedastic error ϵ_{it} allowing for its variance to depends on age. The results shows increasing variance of health shocks do not explain away the heterogeneity in slopes δ_i.

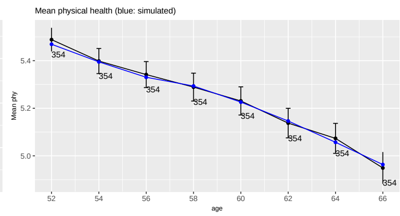
Finally, I add two robustness checks included in the appendix. First, I estimate a similar model using *self-assessed health* instead of the constructed summary measure of health. The results show the presence of heterogeneous slopes with age is robust to the use of this measure alone. Second, I estimate a version of the model adding the unobserved heterogeneity (α_i, δ_i) directly to the survival equation. The results show (α_i, δ_i) is not (jointly) significant, which implies being alive does not provide an additional signal on the heterogeneous slopes.

Overall, these results show evidence of slope heterogeneity, but they do not reveal anything about how much individuals know or don't know about their own slope δ_i, which I address next.

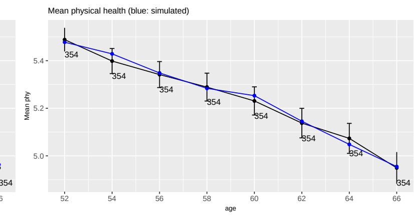
Figure 6: Mean and variance of health in models with different assumptions about slope heterogeneity and survival



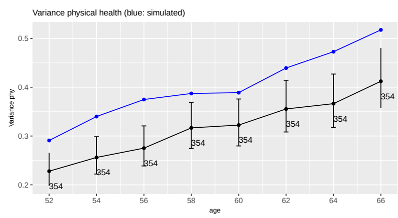
(a) Heterogeneous slopes without survival equation



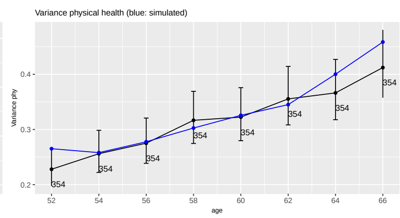
(b) Heterogeneous slopes and survival equation



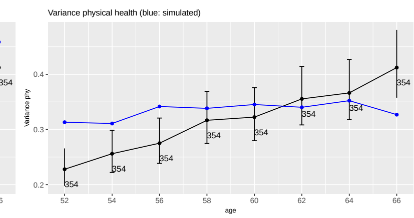
(c) Homogeneous slopes and survival equation



(d) Heterogeneous slopes without survival equation



(e) Heterogeneous slopes and survival equation



(f) Homogeneous slopes and survival equation

Note: The sample consists of 26,950 correlative observations from 7,301 individuals observed since they were 66 years old. Over the span of the following eight waves, 996 of them died. The black lines plot the health data and the blue lines plot the predicted values of health in each model.

5 Uncertain health dynamics and beliefs

To study the effect of beliefs on labor-participation decisions of older adults, the main difficulty is that those beliefs are unobserved by the econometrician. The Bayesian learning model implies beliefs are updated over time using health, starting from initial beliefs, $N(\hat{\delta}_{i0}, \hat{\sigma}_0^2)$. Hence, a key issue is the identification of those initial beliefs, in particular, the identification of the parameters b and λ. These parameters are defined by

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

and they measure how biased are initial beliefs and how much individuals know about their slopes at age 50. Because the health process does not reveal slopes beliefs, this section proposes the use of *survival expectations*, available in the HRS. Equation (10) implies survival is a health-related process. Therefore, expectations about future survival are related to expectations about future health; thus, they are related to slope beliefs.

5.1 Empirical strategy

The exact wording of the HRS questions follows:

[$plive10_{it}$] *What is the percentage chance you will live to be (80, 85, 90, 95 or 100) or more?*, where the reference age depends on the individual's age t at the time of the survey (and wave), and it is approximately 10 years in the future. Let s denote this reference age. Then, this question corresponds to

$$plive10_{it} = \mathbb{P}(S_{is}=1|\Omega_{it}) = \prod_{l=t+1}^{s}\mathbb{P}(S_{il}=1|S_{il-1}=1,\Omega_{it}) = \prod_{l=t+1}^{s}\mathbb{P}(\gamma_1 h_{il}+\eta_{il+1}\geq 0|\Omega_{it}).$$

where we omitted the regressors in the survival equation (besides health) for ease of notation. Applying the equation for health (9) recursively, we can write:

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

From the view point of Ω_{it}, the second term is random, with a normal distribution that depends on $(\hat{\delta}_{it},\hat{\sigma}_t^2)$ (and the parameters of the model). Because age-t beliefs depend on health history h_i^t and initial beliefs $N(\hat{\delta}_{i0},\hat{\sigma}_0^2)$, this second term is a function of λ and b. Therefore, $plive10_{it}$ are complex non-linear functions of slope beliefs,

$$plive10_{it} = plive10_{it}(\alpha_i,h_{it},\hat{\delta}_{it},\hat{\sigma}_t^2) = plive10_{it}(\alpha_i,h_i^t,\hat{\delta}_{i0},\hat{\sigma}_0^2).$$

Each period, individuals observe their health and update their beliefs regarding their unknown δ_i. This new information allows them to also update their expectations about their future health, and hence, their expectations about future survival. Thus, slopes beliefs, unobserved by the econometrician, are closely linked to survival beliefs, which are observed by the econometrician. Intuitively, the bias parameter b affects expected health and, hence, the average survival expectation. Thus, levels of *survival expectation* identify bias b. Next, I discuss identification of the uncertainty parameter λ.

In what follows, I assume $(\alpha_i,\delta_i,\hat{\delta}_{i0})$ are jointly normally distributed, with $Cov(\alpha_i,\hat{\delta}_{i0}) = Cov(\alpha_i,\delta_i)$ (which is zero according to the results in section 4). This assumption implies the information about δ_i contained in α_i is already incorporated in initial beliefs $\hat{\delta}_{i0}$.

Identification using subjective expectations about survival rates (ideal data)

I start by discussing identification using ideal data, which I do not actually observe. Let Ω_{it} be the information set of individual i after observing his health up to period t. Thus, $\alpha_i,\hat{\delta}_{it},\hat{\sigma}_t^2\in\Omega_{it}$.

Proposition 5.1 (Identification of λ) *Let health and survival process by given by equations (9) and (10), and assume individuals are Bayesian learners with prior beliefs about δ_i following $N(\hat{\delta}_{i0},\hat{\sigma}_0^2)$. Consider the subjective expectations about survival rates:*

$$bsr_{it} \equiv \mathbb{P}(S_{it+3}=1|S_{it+2}=1,\Omega_{it})$$
$$bsr_{it+1} \equiv \mathbb{P}(S_{it+3}=1|S_{it+2}=1,\Omega_{it+1}).$$

Then,

$$Cov(\Delta_w \Phi^{-1}(bsr_{it+1}), \Delta h_{it+1}) \quad = \quad \mathbb{C}_t Var(\Delta h_{it+1}),$$

where the time-varying constant $\mathbb{C}_t$ *is increasing in* λ.

The proof is in the appendix. The proposition says we can identify λ with longitudinal data on subjective expectations about survival rates and health. The key equation behind this result,

$$\Delta_w \Phi^{-1}(bsr_{it+1}) = \underbrace{\rho(h_{it+1} - \rho h_{it} - \alpha_i - \hat{\delta}_{it}(t+1) - \beta x_{it+1})}_{\text{due to persistency}} + \underbrace{(t+2)(\hat{\delta}_{it+1} - \hat{\delta}_{it})}_{\text{due to learning}}, \tag{12}$$

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. Note that if $\rho = 0$, this channel disappears. The second reason is that learning implies a change in future predictions of health and therefore of survival. Note that if $\lambda = 0$, $\hat{\delta}_{it+1} = \hat{\delta}_{it}$ and this channel disappears.

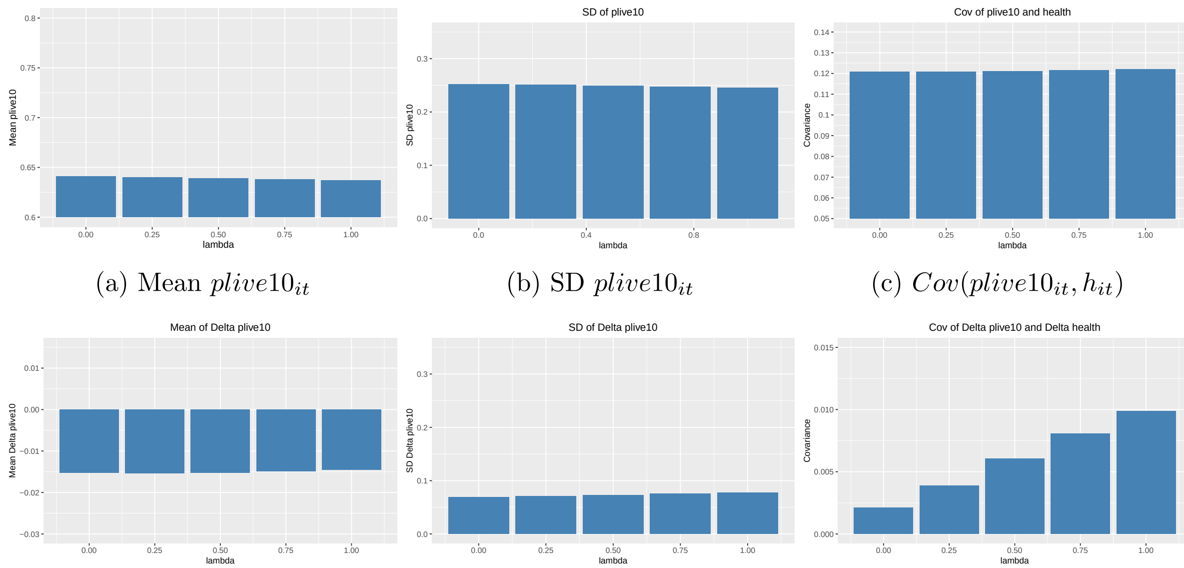
Identification using subjective expectations about survival probabilities (available data)

We can not use the previous result directly, because the HRS does not exactly measure subjective expectations about survival rates. However, Figure 7 shows the intuition of proposition 5.1 extends to the available data. It shows the results of a simulation exercise, where I simulated data on h_{it} and $plive10_{it}$ for different values of the uncertainty parameter λ, plotted in the x-axis of each figure. The six plots correspond to the six moments used later for estimation. The top row considers moments in levels, and the bottom row considers moments in differences. The figure clearly shows that, as before, the covariance between changes in health and changes in survival expectations depends on the underlying uncertainty.

This model has two simplifying assumptions. First, the model assumes the health process is exogenous, with no choice variable that affects the evolution of health; that is, no investment is purposefully made in the form of health behaviors (like exercising or smoking) and working decisions do not affect health. This assumption is not uncommon in the literature on labor market decisions among older individuals, and it emphasizes changes in health due to aging. By ruling out the possibility of individuals changing their behavior in order to affect their health, the strict exogeneity assumption implies the correlation between changes in health and changes in survival expectations are not confounded by changes in individuals' planned behaviors. Second, the model assumes health is the only signal available to individuals and with no endogenous acquisition of health information (e.g., demand for preventive care). This assumption is more restrictive in this context, and I address it in the last section of the paper by looking at another source of information that may shift beliefs, hence, reducing reliance on the model.

Under these assumptions, $plive10_{it}$ is a function of initial beliefs $N(\hat{\delta}_{i0}, \hat{\sigma}_0^2)$, heterogeneous intercept α_i, and health history up to t, $(h_{i0}, \dots h_{it})$. Hence, for any value of b and λ, I can use the estimated health

Figure 7: Simulated moments of $plive10_{it}$ by uncertainty λ in data-generating process



(a) Mean $plive10_{it}$ (b) SD $plive10_{it}$ (c) $Cov(plive10_{it}, h_{it})$

(d) Mean $\Delta plive10_{it}$ (e) SD $\Delta plive10_{it}$ (f) $Cov(\Delta plive10_{it}, \Delta h_{it})$

Note: Moments in simulated data following the structure of the available data in the HRS. The x-axis in each figure 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.

process to simulate draws α_i and $\hat{\delta}_{i0}$, and then use those variables to simulate $plive10_{it}$.[24] I estimate the parameters governing initial beliefs, b and λ, by simulated method of moments. I use six moments, three in levels and three in differences, corresponding to the mean of $plive10_{it}$, its variance, and its covariance with h_{it}.[25] Details of the implementation are given in the appendix.

Subjective survival expectations are measured with substantive error, which is well established in the literature (see, for example, Manski and Molinari (2010)). Similar to Kleinjans and Van Soest (2014), 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

$$\widetilde{plive10}_{it} = \max\{\min\{plive10_{it} + \nu_{it}, 1\}, 0\}.$$

Note 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 on age, given the i.i.d. assumption, while the average shift due to initial bias in beliefs is decreasing with age as individuals observe their health and update their beliefs. Thus, we can separately identify both effects.

[24] The distribution of $\hat{\delta}_{i0}$ depends on b and λ. Hence, I first simulate α_i and δ_i conditional on health history $h_{i0}, \ldots h_{iT_i}$, and then for a given value of b and λ, I draw $\hat{\delta}_{i0}$ conditional on α_i, δ_i, and h_{i0}.

[25] As described in the appendix, most individuals are first observed in sample at age t_0 older than 50, and I modify the simulation process for them accordingly. Overall, I target these six moments averaged across time for different subgroups of individuals, depending on the age t_0 I first observe them, for a total of 78 moments.

Table 4: Estimated parameters of prior beliefs

	Symbol	Coefficient	Lower bound	Upper bound
Uncertainty	λ	0.338	0.336	0.340
Bias	b	-0.061	-0.061	-0.060
Mean of measurement error	μ_{merror}	0.121	0.118	0.123
SD of measurement error	σ_{merror}	0.177	0.176	0.177

Note: Prior beliefs about slopes are unobserved $N(\delta_i^k+b, \lambda^2\sigma_\delta^2)$, whereas subjective survival expectations $plive10_{it}$ are observed but measured with error. The estimation uses a subsample of 2,000 individuals with eight periods, chosen randomly for computational reasons. Moments are simulated using 20 draws of measurement error and 20 draws of unobserved heterogeneity. The bounds correspond to a 95% confidence interval.

5.2 Results

The estimation results presented in Table 4 show individuals face a sizable amount of uncertainty and a large amount of negative initial bias; that is, individuals believe their health will decay with age at a faster rate than what is actually true on average. In line with previous literature, subjective survival expectations are subject to large amounts of measurement error. Following Manski and Molinari (2010), I also estimate a version including rounding and find similar results (not shown). These results are consistent with previous evidence that finds that, on average, older adults up to 65 years old underestimate their chances of survival (Elder (2013), Ludwig and Zimper (2013)). Those papers also find that adults 80 years and older overestimate their survival changes. This is also the case according to my results, which say that overestimation is caused by measurement error. The fit of the results is shown in Table 5. Panel *a* shows the fit of the targeted moments using $plive10_{it}$, while panel *b* shows the fit of similar un-targeted moments using survival expectations to age 75.[26]

With these estimated parameters, I can simulate slope beliefs, which I use in the next section to study their effect on working decisions of older adults.

[26] The HRS includes two questions on survival expectations every wave: $plive10_{it}$ asks for a reference age approximately 10 years ahead, and $plive75_{it}$ asks for a reference age equal to 75 years. However, this last question is only asked to individuals 65 or younger, limiting the sample, hence I use it only here as a check.

Table 5: Estimation results of initial beliefs by simulated method of moments: Moments' fit

a. Targeted moments			
	Data moment	SE	Simulated moment
$\mathbb{E}(plive10)$	0.531	(0.00011)	0.538
$\mathbb{E}(plive10^2)$	0.371	(0.00012)	0.357
$\mathbb{E}(plive10 \cdot h)$	2.890	(0.00065)	2.957
$\mathbb{E}(\Delta plive10)$	-0.013	(0.00002)	-0.014
$\mathbb{E}((\Delta plive10)^2)$	0.070	(0.00003)	0.066
$\mathbb{E}(\Delta plive10 \Delta h)$	0.007	(0.00002)	0.007
b. Other moments (not targeted)			
	Data moment	SE	Simulated moment
$\mathbb{E}(plive75)$	0.702	(0.00017)	0.806
$\mathbb{E}(plive75^2)$	0.556	(0.00021)	0.687
$\mathbb{E}(plive75 \cdot h)$	3.886	(0.00101)	4.469
$\mathbb{E}(\Delta plive75)$	-0.001	(0.00010)	0.018
$\mathbb{E}((\Delta plive75)^2)$	0.054	(0.00008)	0.042
$\mathbb{E}(\Delta plive75 \Delta h)$	0.006	(0.00005)	0.003

Note: Panel a. uses the same sample used for estimation. Panel b. uses a subsample of $1,247$ individuals up to 65 years old for whom $plive75_{it}$ (*the percentage chance you will live to be 75*) is asked.

6 Working decisions as functions of beliefs about health

In the life-cycle model of labor participation p_{it} and consumption c_{it} outlined in section 2, an individual's dynamic problem is,

$$V_t(\Omega_{it-1}) = \max_{p_{it}, c_{it}} \left\{ \mathbb{E}\left(U(p_{it}, c_{it}, h_{it}, p_{it-1}) \middle| \Omega_{it-1} \right) + \beta \mathbb{E}\left(S_{it+1} V_{it+1}(\Omega_{it}) + (1 - S_{it+1}) B(a_{it}) \middle| \Omega_{it-1}, p_{it}, h_{it} \right) \right\}$$

$$\begin{aligned} st. \quad & \text{budget constraint,} \\ & \text{health (9) and survival (10) processes,} \\ & \text{and beliefs updating equations (2) and (3),} \end{aligned}$$

where $B(a_{it})$ is the utility perceived by leaving bequest a_{it}. In this problem, the policy rule for labor participation is a function of the state variables in the model. The novelty in this paper is that those state variables include individuals' beliefs about their future health. These beliefs are the result of two key elements: heterogeneity in health dynamics and uncertainty about that heterogeneity. These elements imply beliefs about that heterogeneity -instead of just a common parameter- enter individuals' choices. In this section, I estimate the probability of work as a function of those state variables,

$$\mathbb{P}(p_{it} = 1 | \Omega_{it-1}) \quad = \quad \mathbb{P}(p_{it} = 1 | p_{it-1}, a_{it-1}, w_{it-1}, h_{it-1}, \hat{\delta}_{it-1}, \hat{\sigma}^2_{t-1}, \alpha_i). \tag{13}$$

By using the results from the previous section, we can simulate all of the state variables, and hence identify their effect on working decision. Furthermore, by using *survival expectations* to identify and simulate beliefs, no additional assumption on the relation between belieds and working decisions has been made. In particular, there is no restriction on the sign of the effect of $\hat{\delta}_{it-1}$ on working decisions.[27] Note also that, conditional on states variables in Ω_{it-1}, survival expectations $plive10_{it}$ do not play an additional role in working decisions p_{it}.

6.1 Probit results on working decisions

I first estimate equation (13) using a probit approach, i.e. assuming that $\mathbb{P}(p_{it} = 1|\Omega_{it-1}) = \Phi\big(\beta'\Omega_{it-1}\big)$ and integrating out the unobserved underlying heterogeneity α_i, δ_{i0}.[28]

Table 6 presents these results. It shows that beliefs do matter for working decisions, with a positive and significant coefficient for $\hat{\delta}_{it-1}$. This positive sign implies that expecting better health, that is, expecting health to deteriorate more slowly with age, is associated with larger probabilities of work.[29]

[27] If individuals expecting better future health want to work longer, the sign would be positive. This could happen if the dominant effect were the desire to save more given the longer life expectancy implied by better health. If individuals expecting worse future health want to work longer, the sign would be negative. This could happen if the dominant effect were the desire to save more given the higher cost of future healthcare implied by worse health.

[28] Some of the input variables are unobserved by the econometrician; namely, heterogeneity in health level α_i and beliefs about slope heterogeneity, $\hat{\delta}_{it}$ and $\hat{\sigma}^2_t$. Conditional on health history, these unobserved variables depend on individual-level heterogeneity, which is integrated out. See the appendix for details on the likelihood specification.

[29] The assumptions of the learning model imply the posterior variance $\hat{\sigma}^2_t$ is constant across individuals of the same age t. Given that age is a also a relevant determinant of working decisions, I don't have enough variation to disentangle these

On the other hand, *survival expectations* $plive10_{it}$ are also significant predictors in the probability of work, but that significance holds only while slope beliefs are not accounted for. Though interesting, these results assume a linear index for the probability of work, which is a very strong assumption, that is not justified by assumptions on the fundamentals of the model. Thus, in what follows, I estimate the probability of work flexibly, using instead a neural network approach.

Table 6: Probit results on probability of work

		(1)		(2)		(3)	
		Coefficient	SE	Coefficient	SE	Coefficient	SE
age	t	-0.20***	(0.016)	-0.08***	(0.003)	-0.19***	(0.016)
lagged work	p_{it-1}	2.03***	(0.018)	2.03***	(0.019)	2.03***	(0.019)
lagged health	h_{it-1}	0.17***	(0.024)	0.26***	(0.033)	0.18***	(0.046)
heterogeneous intercept	α_i	0.24***	(0.036)	0.07	(0.046)	0.24***	(0.075)
beliefs mean	$\hat{\delta}_{it-1}$	1.93***	(0.249)			1.90***	(0.499)
beliefs var	$\hat{\sigma}^2_{t-1}/\sigma^2_{\delta}$	-13.85***	(2.048)			-13.33***	(2.102)
survival expectations	$plive10_{it}$			0.11***	(0.031)	0.01	(0.043)
Controls	other vars Ω_{it-1}	Yes		Yes		Yes	
N individuals		14,969		14,718		14,718	
N observations		58,040		55,592		55,592	

Note: Results of estimating equation (13) using a probit approach. Standard errors are clustered at the individual level.*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

6.2 Neural-network approach

A neural network provides a very flexible tool for estimation. In the case of a binary outcome, and under some particular specifications, a neural network corresponds to a maximum likelihood estimation with logistic errors, where the probability of success is a complex non-linear index of the inputs. As mentioned by Farrell et al. (2020), we can think of neural networks as a type of non-parametric or sieve estimation whereby the basis functions are learned from the data, hence allowing for greater flexibility.

In this case, I also need to account for the fact that some of the input variables are unobserved by the econometrician. These unobserved variables are slopes beliefs $(\hat{\delta}_{it-1}, \hat{\sigma}^2_t)$ and heterogeneous health levels α_i. Though they are time-varying variables, they can be written as functions of time-invariant unobserved variables $(\hat{\delta}_{i0}, \alpha_i)$ and the observed health path $(h_{i1}, \dots h_{iT_i})$ of each individual.[30] Thus, following a standard likelihood approach, I want to maximize the log of the likelihood integrating out this time-invariant unobserved heterogeneity. To do so, I follow the insight of EM-type algorithms.

Let θ be the parameters governing an outcome variable, in this case, working decisions. When there

two effects separately; any results would be based on functional form assumptions alone. Therefore, I focus instead on interpreting the effects of the posterior mean.

[30] This relationship depends also on the parameters of the health process (ρ, σ^2_ϵ) and the parameters of beliefs (b and λ), but it does not depend on the parameters defining the relation between working decisions and state variables.

is underlying heterogeneity, we estimate θ by maximizing a likelihood that integrates out that heterogeneity. In this context, EM-type algorithms provide us with two key insights. First, the parameter θ that maximizes the *log of the integral* also maximizes the *integral of the log* if instead of using the prior distribution of the heterogeneity, we use its posterior distribution given the outcome variable. However, because this posterior distribution depends on θ, it is unknown. Thus, the second insight of EM-type algorithms is to solve the problem for θ iteratively: in iteration k, the E step uses θ_{k-1} to update the posterior distribution of the heterogeneity, and the M step estimates θ_k by maximizing the integral of the log using that posterior.

I use this same iterative logic as a convenient implementation for maximizing the integrated likelihood under a neural network approach. In this case, the E step is done by Markov chain Monte Carlo (MCMC) and provides draws from the posterior distribution of $(\alpha_i, \hat{\delta}_{i0})$ given working decisions p_i.[31] Then, the M step uses those draws to expand the data, simulate the inputs $(\hat{\delta}_{it}, \hat{\sigma}_t^2, \alpha_i)$ using health, and estimates θ by using a neural network on the expanded data.[32] I start this iterative process at an M step using an incomplete posterior: the distribution of $(\alpha_i, \hat{\delta}_{i0})$ conditional on the health history $(h_{i1}, \dots h_{iT_i})$ and the history of survival expectations $(plive10_{i1}, \dots plive10_{iT_i})$. This distribution is incomplete because it does not condition on the working decisions, but it does already include the heterogeneity information contained in the health and expectations variables.

6.3 Neural-network results on working decisions

Following this strategy,[33] I estimate the probability of work conditional on the state variables Ω_{it-1}. This set includes past participation p_{it-1}, past health h_{it-1}, heterogeneous health levels α_i and slope beliefs $\hat{\delta}_{it}, \hat{\sigma}_t^2$, which are the main interest in this paper. It also includes more traditional variables, listed in Table 2, including demographic variables, income, wealth, health insurance, and job characteristics. I restrict the analysis to a sample of individuals who are attached to the labor market, defined as individuals with at least 20 years of working experience. The loss and fit of the model is given in the appendix.

> ***(1)*** *Beliefs play a role in the participation decisions of older adults, with positive average marginal effects that are similar in orders of magnitude to the average marginal effects of health and assets. Furthermore, there is an interaction between beliefs and health for individuals in their 50s that are not working.*

Table 7 presents the effects on the probability of work of a marginal change in expected beliefs $\hat{\delta}_{it-1}$, health h_{it-1}, and assets a_{it-1}, respectively, conditional on age and past participation p_{it-1}, averaged across individuals. The table shows that, even though the effects are of different magnitudes and signs,

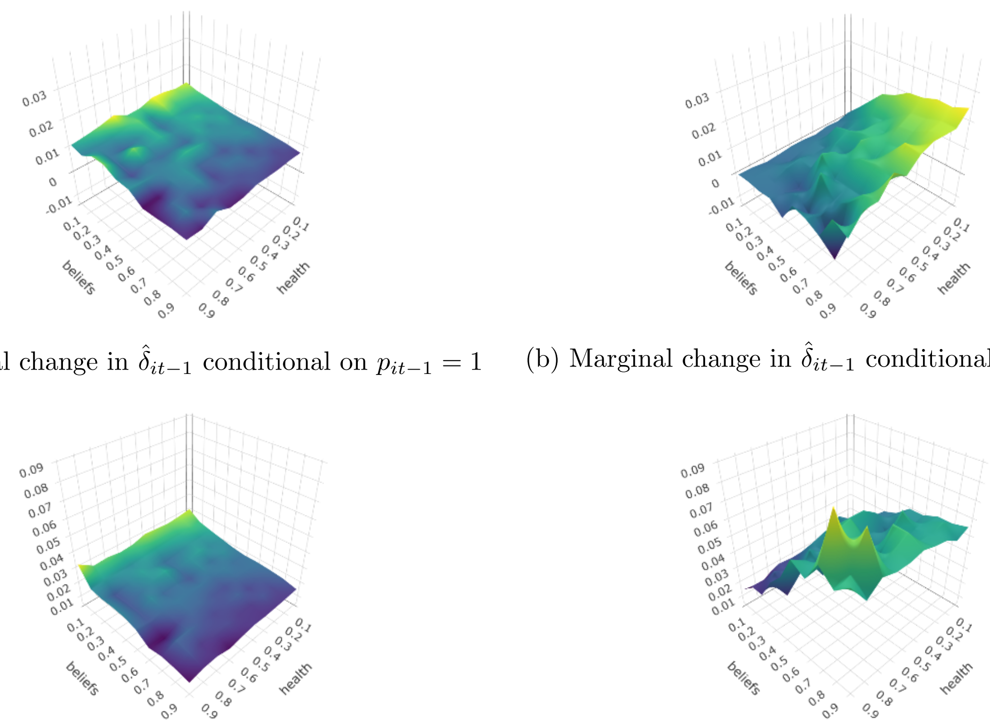
[31] MCMC uses the likelihood of p_i given $(\alpha_i, \hat{\delta}_{i0})$ from the previous-iteration M step and the prior distribution of $(\alpha_i, \hat{\delta}_{i0})$.

[32] The standard EM algorithm is known to converge, as the likelihood increases in each step of the sequence. This convergence does not hold in this case, given the lack of uniqueness of the estimation in each step. First, the E step does not return a closed-form solution for the posterior, but it returns draws from MCMC. Second, the non-convexity of the neural network's optimization problem implies non-uniqueness of the solution of the M step. Therefore, the approach is not aimed at getting at the unique solution, which does not necessarily exists, but as a convenient implementation.

[33] The results presented here use the incomplete posterior mentioned before. The iterative process is underway.

they are similar in orders of magnitude. The same result holds in Figures 8 and 9, which show the marginal effects of beliefs $\hat{\delta}_{it-1}$ by deciles of health and beliefs for adults aged 52-59 and 66-75, respectively. More interestingly, Figure 8 shows an interaction between health and beliefs for individuals in their 50s not working. The figure shows marginal effect of increasing beliefs on working probabilities are larger for individuals with worse health. At the same time, marginal effects of health on working probabilities are larger for individuals who believe their health will deteriorate relatively slowly. These results suggest that adjustment costs of finding a job are important in the working decisions of this group. This adjustments cost could be due to difficulties in finding jobs, or to adapting to a new work environment. The data-driven approach used in this paper has the advantage of letting the data suggest mechanisms that may be otherwise overlooked, and hence, the approach complements structural models.

Figure 8: Average marginal effect of expected beliefs $\hat{\delta}_{it-1}$, and health h_{it-1}on the probability of work p_{it} for adults in their 50s



(a) Marginal change in $\hat{\delta}_{it-1}$ conditional on $p_{it-1} = 1$

(b) Marginal change in $\hat{\delta}_{it-1}$ conditional on $p_{it-1} = 0$

(c) Marginal change in h_{it-1} conditional on $p_{it-1} = 1$

(d) Marginal change in h_{it-1} conditional on $p_{it-1} = 0$

Note: Each row corresponds to the average marginal effects with respect to $\hat{\delta}_{it-1}$ and h_{it-1}, respectively. The left column conditions on individuals who were working, $p_{it-1} = 1$, and the right column conditions on individuals who were not working, p_{it-1}=0, in the previous period. In each plot, the x- and y-axis correspond to deciles of health h_{it-1} and expected beliefs $\hat{\delta}_{it-1}$ for the corresponding subsample of the plot. Note the z-axis changes in each row.

> ***(2)** The total effect of a health shock ϵ_{it-1} on working decisions goes mostly through the persistence channel, with negligible effects through the information channel.*

This result is shown in Table 7, which includes the decomposition of the effects of a health shock into a persistence channel and an information channel, according to equation (8). Note the small values on

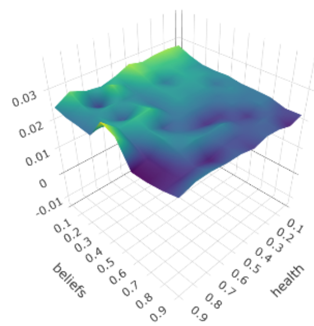
Table 7: Average marginal effects on the probability of work and decomposition of the effects of a health shock

Age	Average marginal effects			Decomposition of a health shock		
	Health h_{it-1}	Beliefs $\hat{\delta}_{it-1}$	Assets a_{it-1}	Factor	Persistence channel	Information channel
$p_{it-1} = 0$						
52	0.055	0.011	-0.043	0.003	1.00	0.00
54	0.046	0.011	-0.037	0.006	1.00	0.00
56	0.040	0.012	-0.033	0.008	1.00	0.00
58	0.034	0.012	-0.028	0.011	1.00	0.00
60	0.027	0.011	-0.023	0.012	0.99	0.01
62	0.021	0.010	-0.018	0.014	0.99	0.01
64	0.016	0.010	-0.013	0.014	0.99	0.01
66	0.014	0.009	-0.010	0.015	0.99	0.01
68	0.013	0.006	-0.010	0.014	0.99	0.01
70	0.011	0.004	-0.008	0.014	1.00	0.00
72	0.009	0.002	-0.007	0.013	1.00	0.00
74	0.007	0.001	-0.005	0.012	1.00	0.00
$p_{it-1} = 1$						
52	0.015	0.007	-0.012	0.003	1.00	0.00
54	0.018	0.009	-0.014	0.006	1.00	0.00
56	0.021	0.010	-0.016	0.008	1.00	0.00
58	0.024	0.013	-0.017	0.011	0.99	0.01
60	0.026	0.015	-0.018	0.012	0.99	0.01
62	0.028	0.018	-0.016	0.014	0.99	0.01
64	0.027	0.021	-0.010	0.014	0.99	0.01
66	0.024	0.023	-0.004	0.015	0.99	0.01
68	0.023	0.024	-0.001	0.014	0.98	0.02
70	0.021	0.025	0.002	0.014	0.98	0.02
72	0.020	0.026	0.004	0.013	0.98	0.02
74	0.019	0.027	0.007	0.012	0.98	0.02

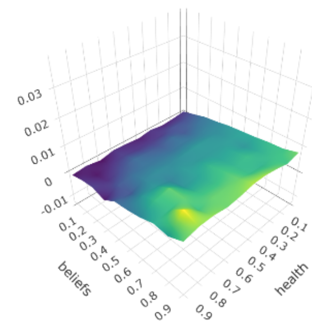
Note: The columns on persistence and information channels correspond to the terms in equation (8), expressed as a proportion of the total partial effect.

the column Factor, which imply that a health shock has only a small effect on beliefs $\hat{\delta}_{it-1}$ and, therefore, only a small effect through the information channel. This result highlights that, even though individuals are uncertain and biased, to significantly affect their decisions, we need large enough signals. Section 8 looks at one possible such policy: health information regarding blood glucose and cholesterol levels.

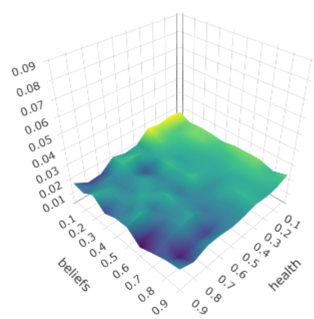
Figure 9: Average marginal effect of expected beliefs $\hat{\delta}_{it-1}$ and health h_{it-1}on the probability of work p_{it} for adults between 66 and 75 years old



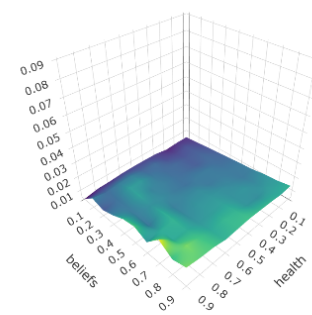
(a) Marginal change in $\hat{\delta}_{it-1}$ conditional on $p_{it-1} = 1$



(b) Marginal change in $\hat{\delta}_{it-1}$ conditional on $p_{it-1} = 0$



(c) Marginal change in h_{it-1} conditional on $p_{it-1} = 1$



(d) Marginal change in h_{it-1} conditional on $p_{it-1} = 0$

Note: Each row corresponds to the average marginal effects with respect to $\hat{\delta}_{it-1}$ and h_{it-1}, respectively. The left column conditions on individuals who were working, $p_{it-1} = 1$, and the right column conditions on individuals who were not not working, p_{it-1}=0, in the previous period. In each plot, the x- and y-axis correspond to deciles of health h_{it-1} and expected beliefs $\hat{\delta}_{it-1}$ for the corresponding subsample of the plot. Note the z-axis changes in each row.

7 Reducing bias in initial beliefs

In this section, I study how labor participation would change if we could eliminate bias in initial beliefs. In particular, I look at two questions:

1. How much would labor participation change if initial beliefs were unbiased at the population level, that is, $\mathbb{E}(\hat{\delta}_{i0}) = \mathbb{E}(\delta_i)$?

2. How much would labor participation change if we could reduce each individual's bias in half, by closing the distance between $\hat{\delta}_{i0}$ and δ_i?

To look at these questions, I use an impulse-response function approach, using the results of the previous section. That is, I simulate working decisions under a sample's baseline scenario, and compare those predictions against the predictions simulated under each of these two potential changes in initial beliefs. The figures in this section present the response in terms of labor-participation decisions by age, given a change in initial beliefs. Over time, this change in initial beliefs translates into changes in posterior beliefs, labor-participation decisions, as well as decisions regarding assets and health-insurance. The effects on these last two variables were also predicted using a neural-network approach. Note this exercise assumes no other variable change in response to the change in initial beliefs or to the subsequent changes in participation, assets or health insurance. Therefore, the exercise presented here are not exactly a conterfactual analysis, but is a interesting exercise as long we are capturing the main choices.

> ***(1)*** *Eliminating the bias in prior beliefs b would increase participation by more than 2 percentage points around the formal retirement age (66-67).*

Figure 10 shows the average change in the probability of work after eliminating the initial bias in prior beliefs, b. Note this effect has an inverted-U shape. In the early 50s, the effect is small given that individuals are still mostly working. But as people start to retire, the new beliefs imply larger probabilities of work that do not vanish completely over time and remain above 2 percentage points for individuals in their early seventies. Note that, in this sample, the average probability of work prior the change in beliefs is 34% at age 66 and 17% at age 78; hence, the increment in the figure is not trivial. Furthermore, as this effect results from eliminating a misconception at the population level, it is an easier target policy that could be addressed by information campaigns, without the need of providing individual-specific information.

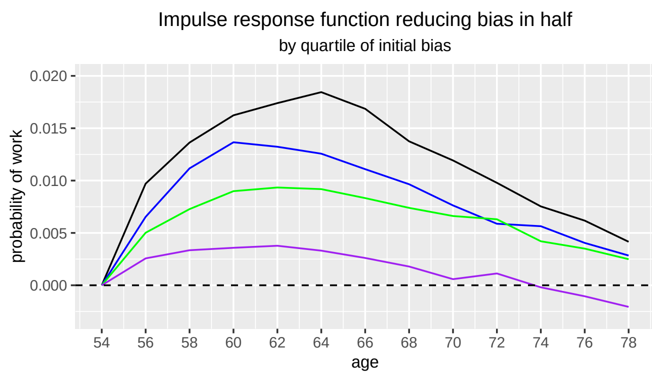
> ***(2)*** *Reducing the initial bias of each individual in half has a heterogeneous effect, with larger gains in the probability of work for individuals who are initially more biased.*

Figure 11 shows this results, distinguishing by quartile of initial bias, $\hat{\delta}_{i0} - \delta_i$. Given that the overall initial bias $b < 0$, most individuals are initially downward biased. Thus, reducing bias in half per each individual means increasing initial beliefs for most of them, which translates into the effects being positive, as shown in the figure.

Figure 10: Impulse response function to a shift in prior beliefs eliminating overall bias b

Note: Impulse response function using the subsample of individuals used in estimation that are observed at 52 years old, corresponding to 1,184 individuals.

Figure 11: Impulse response function to reducing individuals' initial bias by half



Note: Impulse response function using the subsample of individuals used in estimation that are observed at 52 years old, corresponding to 1,184 individuals.

As a reference, using a structural model, French and Jones (2011) find that raising the 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 work force by 0.076 years.

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

The results on working decisions of older adults show beliefs matter, and expecting health to deteriorate more slowly is associated with larger probabilities of work. Furthermore, beliefs are initially biased and eliminating that bias has non-trivial effects. Information campaigns providing better information can be a way of eliminating that bias. In this section, I look at one additional signal of health slopes with age δ_i: blood-based biomarkers. By providing information about health, blood-based biomarkers can signal individuals' slopes. In 2006, the HRS introduced the collection of a blood sample for measuring biomarkers.[34] With the blood sample, three biomarkers are measured and individuals are informed of their levels: HDL cholesterol (known as the *good cholesterol*), total cholesterol, and blood glucose hbA1c. The results are provided around a month after the survey has ended[35] (see Edwards (2018) for more details). These biomarkers are also included in other health surveys, including the REasons for Geographic and Racial Differences in Stroke study (REGARDS) and the National Health and Nutrition Examination Survey (NHANES), where the information is also provided to individuals. Studies using those biomarkers have found that new diagnosis through the surveys increases the number of doctor visits for Medicare beneficiaries (Myerson et al. (2018)), but they increase the fraction of patients with low uptake of ex-post medical treatment (Myerson et al. (2017)).

In this section, I study whether receiving this information provides individuals with an additional signal about their health, in particular, about their slopes δ_i, and study whether they change their survival expectations and working behavior accordingly. To achieve that goal, I make use of a key aspect in the introduction of these measures in the HRS: to control costs associated with their collection, the HRS randomly split the sample into two halves, and in each wave, the HRS collects these biomarkers in only one of those halves. Hence, this collection scheme provides us with an information experiment, that is, with exogenous variation in who receives this additional information. Note, however, that this was not the intended goal of the HRS, and as such this is not an ideal experiment. An ideal experiment would include a control arm of individuals who get their blood taken but are not informed on their results. Still, the HRS collection scheme of biomarkers does provide us with exogenous variation that I use in this section. Another advantage of looking at this additional source of information is that it allows me to relax the assumption of health as the only (or sufficient) signal[36] and to use additional sources of variation when estimating the effects of beliefs on the working decisions of older adults.[37]

For these biomarkers to be a valid slope signal, being correlated with health is not enough; they must be correlated with δ_i. The appendix shows this is in fact the case. It presents the results of estimating an equation for health, similar to the equation of section 4, allowing for the distribution of the heterogeneity to depend on blood glucose and cholesterol levels. The results show both the heterogeneous intercepts α_i and heterogeneous slopes δ_i are correlated with these particular biomarkers.

[34] The collection introduced more detailed measures of health, including physical measures, a saliva sample for DNA analysis, and a blood sample for measuring biomarkers. The physical measures include blood pressure and pulse, lung function, hand grip strength, balance test, timed walk test, height, weight, and waist circumference. These variables are valuable measures of health, but I do not include them in this paper, given that they are measured only every two waves. Furthermore, their value as signals of health is limited given that, on one hand, they reflect aspects of health already experienced by individuals in their everyday life, and on the other, the results of the measures are immediately communicated to individuals before asking them about their survival expectations.

[35] 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 levels on these two biomarkers; hence, these results do not play a role as health signals.

[36] The signal analyzed here is provided exogenously to individuals. Hence, this paper does not address endogenous acquisition of information, which is left for future work.

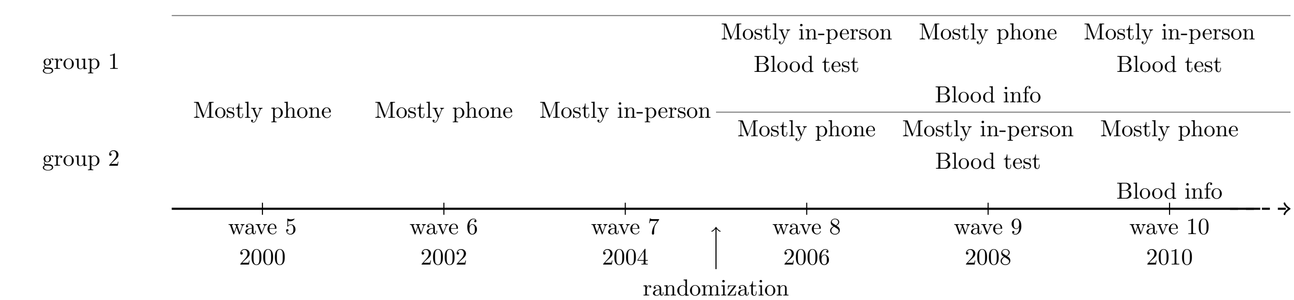
[37] In inferring slope beliefs and using them to study their effect on labor-participation decisions in the previous sections, I only use cross-sectional variation given by differences in initial beliefs, conditional on health and survival-expectations histories.

8.1 Reduced-form approach

I then turn to estimate the overall effect of receiving this information on individuals' survival expectations and working decisions. To that end, I use the experiment introduced with the biomarker collection in 2006 (wave 8), when the sample was randomly divided into two. To be able to generate this information, the experiment also introduces a difference in interview mode between the two groups, because an in-person interview is required to collect the blood sample.[38] The interview mode could have an effect on individuals' answers, in particular, to questions regarding opinions and expectations. Though potentially problematic, the timing of the information provision allows me to separately identify the interview-mode effect from the information effect of the biomarker results, because that information is only provided to individuals after the fieldwork has ended. Hence, individuals do not have the information in the wave when the blood is collected, but in the following wave.

Figure 12 presents the structure of the biomarker collection and the information experiment, and it helps us visualize the identification strategy. On the one hand, a difference-in-differences analysis using waves 7 and 8 returns the interview-mode effect. On the other hand, a difference-in-differences analysis using waves 7 and 9 returns the interview-mode effect (with the opposite sign) plus the information effect of receiving the additional signal. Hence, we can identify the information effect by adding these two terms. Under the parallel-trends assumption, the same idea holds if we construct these terms using wave 5 instead of wave 7.

Figure 12: Timing of the biomarker collection and information experiment



Therefore, I estimate the following equation:

$$y_{iw} \quad = \quad \beta_0 + \beta_1 d_{g_i} + \beta_{2w} d_w + \beta_{3w} d_{g_i} \cdot d_w + \epsilon_{iw}, \tag{14}$$

where i denotes an individual and w denotes a wave. I use w instead of t, because in this paper, t denotes age. I consider two dependent variables separately, survival expectations $plive10_{iw}$ and a binary of work p_{iw}. I estimate these equations using a balanced sample of individuals observed from waves 5 to 9.[39]

[38] The HRS survey is usually conducted by phone, except for first interviews of new cohorts, people who request in-person interviews, and individuals residing in nursing homes. A shift to in-person interviews in 2004 also occurred in an attempt by the HRS to increase individuals' consent to link their survey responses with administrative data. These differences in interview mode are unimportant for the analysis as long as they are applied in the same way across the two groups.

[39] I use only up to wave 9, because from wave 10 onward, the groups are no longer comparable, given that they have been

d_{g_i} is a dummy for the group of individuals set for blood collection in wave 8 (group 1 in Figure 12, with group 2 as the reference category), and d_w are dummies for waves 6 to 9 (wave 5 is the reference category). Hence, the interview-mode effect is given by β_{3w_8}, and the information effect of the signal is given by $\beta_{3w_8} + \beta_{3w_9}$, where the interview-mode effects in each group cancel each other out. Trends are parallel before the randomization happens if $\beta_{3w_6} = \beta_{3w_7} = 0$, and randomization in the selection of the two groups implies $\beta_1 = 0$.

Table 8 presents the estimation results of equation (14) for both $plive10_{iw}$ and p_{iw}. When looking at the results for survival expectation, $plive10_{iw}$, the table shows the two groups are similar and that pre-trends are parallel. The table also shows a positive and significant interview-mode effect of 1.77 percentage points and a similar but insignificant information effect of 1.36 percentage points. Though insignificant, this positive sign is aligned with what we already know about beliefs; on average, individuals' beliefs about health and survival are downward biased. Therefore, providing more information moves those expectations up. When looking at the results for working decisions, p_{iw}, the two groups are similar to begin with and have parallel pre-trends, but we find no significant effect of interview mode[40] or information. Overall, these results suggest the signal is not large enough to have a significant effect on expectations and decisions.

The table also presents the results separately by education level. It shows that for adults with a college degree, both the interview-mode and information effects are larger and significant when looking at survival expectations. For adults with less than a college degree, only the interview-mode effect is significant. When looking at working decisions, no significant effects -interview-mode or information effects- for either group are seen. These differences by education level suggest the ability to process the information matters, with more educated adults internalizing the provided information better. The effect on their working decisions is also larger though still not significant.[41]

The appendix further decomposes group 1 into adults who receive a bad biomarker result versus those who do not. However, because we cannot make the same distinction in group 2,[42] we cannot identify information effects by the type of signal received (good or bad biomarker results). Still, this analysis is interesting because it shows older adults who receive bad results have lower survival expectations to begin with, suggesting they already knew at least some of this information. Consistently, by wave 7, people who later receive bad biomarker results also work less on average than those who receive good results.

provided information with different timing.

[40] The lack of an interview-mode effect on working decisions is expected, given the more objective nature of working outcomes versus survival expectations.

[41] I run a similar regression with the number of doctor visits since the last interview as a dependent variable and find no effects (results not shown), neither interview-mode nor information effects, for either group. This result suggests the difference in survival expectations between these two groups is not explained by a different number of doctor visits. However, more educated individuals may still be better able to incorporate the new information with the help of their physicians, even if the number of doctor visits remains the same.

[42] One possibility would be to use the biomarker results in wave 9 to attempt the same distinction for group 2. However, an analysis using repeated biomarker results from future waves shows these results change over time, introducing noise when using results from wave 9 to assign wave 8 status for the second group.

Table 8: Interview mode and information effects of biomarker experiment

		Survival expectation ($plive10_{iw}$)			Work decision (p_{iw})		
		All	Less college	College	All	Less college	College
Group 1	β_1	-0.47	-0.24	-1.38	0.00	0.01	-0.01
Wave 6	β_{2w_6}	-1.42***	-1.21**	-2.09**	-0.07***	-0.07***	-0.09***
Wave 7	β_{2w_7}	-1.50***	-1.44***	-1.72**	-0.12***	-0.12***	-0.12***
Wave 8	β_{2w_8}	-6.41***	-6.12***	-7.37***	-0.16***	-0.16***	-0.19***
Wave 9	β_{2w_9}	-3.57***	-3.22***	-4.70***	-0.20***	-0.20***	-0.22***
Group 1, wave 6	β_{3w_6}	0.28	-0.06	1.37	0.01	0.00	0.02
Group 1, wave 7	β_{3w_7}	-0.27	-0.24	-0.33	0.01	0.01	0.01
Group 1, wave 8	β_{3w_8} (a)	1.77**	1.29	3.31***	0.01	0.00	0.03
Group 1, wave 9	β_{3w_9} (b)	-0.42	-1.12	1.82	0.01	0.01	0.00
Constant	β_0	53.97***	52.42***	58.96***	0.49***	0.45***	0.61***
Observations		41,930	31,815	10,115	41,923	31,810	10,113
R-squared		0.004	0.004	0.005	0.021	0.021	0.022
Interview mode effect (a)		1.77**	1.29	3.31**	0.01	0.00	0.03
Information effect (a)+(b)		1.36	1.65	5.12**	0.02	0.01	0.04

Note: Estimation results are from equation (14). The sample consists of $N = 8,386$ 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. Seven of these observations do not have information on p_{iw}. Standard errors are clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1

Table 9: Predicted survival expectations in a model with health and blood glucose as signals

	Number of observations	Predicted survival expectations		
		wave 8	wave 9	wave 9 - wave 8
Control (group 2)	4,852	45.8	45.4	-0.3
Treated (group 1)	5,357	44.8	44.9	0.1
Treated with bad blood glucose result	552	39.1	38.5	-0.5
Treated with good blood glucose result	3,649	46.0	46.3	0.3
Treated no blood glucose result	1,156	43.8	43.7	-0.2

Note: The sample consists of $N = 10,209$ individuals with non-proxy interviews who are at least 50 years old in wave 8 and who give a valid answer to $plive10_{iw}$ in waves 8 and 9. Survival expectations are predicted from a model with one signal for the control group (health) and two signals for the treated group (health and blood glucose results). These two signals are assumed to be independent conditional on individual heterogeneity. The parameters determining the strength of blood glucose as a signal of δ_i come from an estimation using future values of the control group (waves 9 and 10)

8.2 Model-based approach

These reduced-form results are also consistent with the predictions of a learning model. For illustration, I estimate survival expectations allowing for the biomarker information to be a second signal for group 1 in wave 9.[43] Bayes' rule implies that in this case, the posterior mean of δ_i is a weighted average of the prior at that period, the signal provided by health and the signal provided by the biomarker information. The weights depend on how uncertain individuals are to begin with, and on how precise is the information provided by each signal. Thus, to predict beliefs $\hat{\delta}_{it}$, a key issue is to predict the precision of the additional signal. To measure that precision, I use future biomarker results from group 2. These individuals were tested in wave 9 and received the information before wave 10. Hence, I use their biomarker information and their survival expectations in waves 9 and 10 to estimate the parameters of the additional signal using simulated method of moments.[44] The randomness in the selection of the groups implies the parameters recovered by looking at group 2 must also represent the parameters governing the biomarker signal for group 1.

Hence, using those parameters, I go back to group 1 and predict their survival expectations at wave 9. As shown in Table 9, the learning model suggests that by having the additional signal on health, group 1 increases their survival expectations between waves 8 and 9 by 0.4 percentages points more than the control group. This change in survival expectations is positive but negligible, consistent with the results in Table 8. In that sense, the reduced-form evidence supports the predictions of the learning model.

[43] I consider in this analysis only blood glucose because it is the biomarker more consistently related to slopes δ_i.

[44] In an alternative version, I use a maximum likelihood approach to jointly estimate health and lab results as a function of slope heterogeneity. I then use those parameters to predict slope beliefs and survival expectations. Under this alternative approach, I get qualitatively the same results as the ones from using SMM.

9 Conclusion

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10 Appendix

10.1 Estimation of summary measure of health

All coefficients significant at 1%.

Measure of health		Coefficient
Chronic conditions	loading	1
	intercept	0
Self reported health	loading	-1.027
	intercept	8.188
Body mass index	loading	-1.812
	intercept	37.278
Eyesight in general	loading	-0.549
	intercept	5.710
Eyesight at a distance	loading	-0.502
	intercept	5.177
Eyesight up close	loading	-0.523
	intercept	5.465
Hearing	loading	-0.424
	intercept	4.830
Pain	loading	-0.802
	intercept	4.792
ADLs regarding mobility	loading	-1.598
	intercept	9.398
ADLs of large muscles	loading	-1.475
	intercept	8.964
Other ADLs	loading	-0.654
	intercept	3.812
mean(health)		5.226
var(health)		0.511

Measure	R-squared
Chronic conditions	0.29
Self reported health	0.44
Body mass index	0.05
Eyesight in general	0.15
Eyesight at a distance	0.13
Eyesight up close	0.13
Hearing	0.08
Pain	0.36
ADLs regarding mobility	0.64
ADLs of large muscles	0.63
Other ADLs	0.50

10.2 MLE results on health and survival under different assumptions

	Heterogeneous slopes without mortality eq		Heterogeneous slopes with mortality eq		Homogeneous slopes with mortality eq	
	Coefficient	Pvalue	Coefficient	Pvalue	Coefficient	Pvalue
ρ	0.205	0.000	0.222	0.000	0.367	0.000
γ	0.002	0.042	0.001	0.056	0.002	0.014
μ_α	0.983	0.000	0.967	0.000	0.836	0.000
$\nu_{\alpha female}$	-0.029	0.104	-0.027	0.134	-0.021	0.216
$\nu_{\alpha white}$	0.009	0.653	0.025	0.239	0.017	0.359
$\nu_{\alpha hispanic}$	-0.010	0.740	0.004	0.888	0.002	0.943
$\nu_{\alpha less\_HS}$	-0.122	0.000	-0.135	0.000	-0.118	0.000
$\nu_{\alpha EBB\_coh}$	-0.020	0.252	-0.019	0.280	-0.016	0.350
ω_α	0.625	0.000	0.605	0.000	0.484	0.000
μ_δ	-0.069	0.001	-0.059	0.006	-0.056	0.000
$\nu_{\delta female}$	0.006	0.194	0.005	0.223	0.004	0.233
$\nu_{\delta white}$	0.016	0.003	0.015	0.004	0.013	0.000
$\nu_{\delta hispanic}$	0.008	0.257	0.010	0.198	0.006	0.366
$\nu_{\delta less\_HS}$	-0.004	0.517	-0.003	0.627	0.001	0.880
$\nu_{\delta EBB\_coh}$	0.006	0.163	0.006	0.188	0.005	0.176
ω_δ	0.001	0.881	-0.001	0.835		
σ_α	0.231	0.000	0.236	0.000	0.213	0.000
σ_δ	0.041	0.000	0.043	0.000		
ϕ	-0.060	0.429	-0.034	0.605		
σ_ϵ	0.264	0.000	0.266	0.000	0.285	0.000
γ_1			0.656	0.002	0.647	0.000
γ_2			-0.253	0.491	-0.288	0.417
γ_3			-0.023	0.997	-0.025	
γ_4			0.005	0.903	0.005	0.918
γ_5			0.033	0.970	0.005	0.999
θ_0			0.539	0.510	0.497	
θ_1			-0.279	0.116	-0.269	0.239
θ_2			0.020	0.059	0.018	0.067
$\theta_{3female}$			0.286	0.001	0.285	
θ_{3white}			0.023	0.830	0.033	
$\theta_{3hispanic}$			0.336	0.050	0.327	
θ_{3less_HS}			-0.094	0.354	-0.092	0.339
θ_{3EBB_coh}			-0.211	0.017	-0.223	
N alive observations	8,901		8,901		8,901	
N dead observations	0		112		112	
N individuals	1,671		1,671		1,671	
-LL	3,620.2		3,021.1		3,055.7	

10.3 MLE results for *self-assessed health*

Let h_{it}^{SAH} be the 1 to 5 *self-assessed health* measure and h_{it}^{*} the corresponding latent health variable. Consider the following model

$$\begin{aligned} h_{it}^{*} &= \rho h_{it-1} + \alpha_i + \delta_i \cdot t + \gamma \cdot t^2 + \epsilon_{it}, \quad \epsilon_{it} \sim N(0,1), \quad t \geq 1 \\ h_{it}^{SAH} &= \begin{cases} 1 & \text{if} \quad h_{it}^{*} \leq 0 \\ 2 & \text{if} \quad 0 < h_{it}^{*} \leq O_2 \\ 3 & \text{if} \quad O_2 < h_{it}^{*} \leq O_3 \\ 4 & \text{if} \quad O_3 < h_{it}^{*} \leq O_4 \\ 5 & \text{if} \quad O_4 < h_{it}^{*} \end{cases} \end{aligned}$$

Table 10 present the results. They show that in this case too there is evidence of slope heterogeneity, suggesting that heterogeneity in health dynamics is robust to using this measure instead of the summary measure of health used in the main analysis.

10.4 Identification of λ with ideal data

10.5 Strategy for simulating survival expectations

To estimate the bias b and uncertainty λ parameters, I use that survival expectations $plive10_{it}$ are a function of those parameters, $plive10(\alpha_i, \hat{\delta}_{i0}, h_{i0}, \ldots h_{it}, b, \lambda)$. In this expression, α_i and $\hat{\delta}_{i0}$ are unobserved by the econometrician, but with a know distribution. In particular, the distribution of $\hat{\delta}_{i0}$ depends on λ and b. Hence, to estimate b and λ, I follow these steps:

- Draw (α_i, δ_i) conditional on $h_{i0}, \ldots h_{iT}$
- For a given b and λ,
  - Draw $\hat{\delta}_{i0}$ conditional in $\alpha_i, \delta_i, h_{i0}$
  - Use α_i and $\hat{\delta}_{i0}$ to simulate $plive10_{it}$
  - Compare the distance between the empirical moments and the simulated ones

These steps are possible when $t_0 = 0$, i.e. when we observe the health history of individual i starting at age 50. When $t_0 > 0$, we observe $h_{it_0}, \ldots h_{iT}$. In this case, the prior mean $\hat{\delta}_{it_0}$ at that point is not random conditional on b and λ. Instead, it satisfies,

$$\begin{aligned} \hat{\delta}_{it_0} = K_{t_0}(\lambda)\Big[&-\rho^{t_0} h_{i0} - \alpha_i \sum_{k=0}^{t_0-1} \rho^k + \delta_i \Big(\frac{1}{t_0} \sum_{l=1}^{t_0-1} l^2 - \sum_{k=1}^{t_0-1} (t_0 - k)\rho^k \Big) \\ &-\rho T_{i1} + T_{i2} \frac{1}{t_0} + \Big(h_{it_0} - \gamma \sum_{k=0}^{t_0-1} (t_0-k)^2 \rho^k \Big) \Big] + \hat{\delta}_{i0} \frac{\sigma_\epsilon^2}{\lambda^2 \sigma_\delta^2} \frac{K_{t_0}(\lambda)}{t_0} \end{aligned}$$

Table 10: MLE results for SAH with and without a survival equation

	Without survival eq		With survival eq	
	Coefficient	Pvalue	Coefficient	Pvalue
ρ	0.230	0.000	0.230	0.000
γ	0.012	0.000	0.012	0.000
μ_α	-1.168	0.000	-1.185	0.000
$\nu_{\alpha female}$	-0.006	0.939	-0.005	0.951
$\nu_{\alpha white}$	0.236	0.010	0.242	0.009
$\nu_{\alpha hispanic}$	-0.265	0.048	-0.266	0.047
$\nu_{\alpha less\_HS}$	-0.612	0.000	-0.603	0.000
ω_α	1.148	0.000	1.151	0.000
μ_δ	-0.057	0.158	-0.054	0.182
$\nu_{\delta female}$	0.030	0.085	0.029	0.089
$\nu_{\delta white}$	-0.008	0.696	-0.009	0.647
$\nu_{\delta hispanic}$	0.060	0.040	0.060	0.040
$\nu_{\delta less\_HS}$	0.020	0.378	0.019	0.406
ω_δ	-0.043	0.000	-0.043	0.000
σ_α	0.970	0.000	0.970	0.000
σ_δ	0.137	0.000	0.137	0.000
ϕ	-0.258	0.004	-0.257	0.004
γ_1			0.402	0.000
θ_0			1.371	0.000
θ_1			-0.101	0.000
$\theta_{3female}$			0.164	0.043
θ_{3white}			0.034	0.711
$\theta_{3hispanic}$			0.404	0.018
θ_{3less_HS}			-0.076	0.457
O_2	1.713	0.000	1.712	0.000
$O_3 - O_2$	1.711	0.000	1.711	0.000
$O_4 - O_3$	2.062	0.000	2.063	0.000
N alive observations	8,901		8,901	
N dead observations	0		112	
N individuals	1,671		1,671	
-LL	8,985.2		9,502.0	

where

$$T_{i1} = \sum_{l=1}^{t_0-1} \rho^{t_0-1-l} \epsilon_{il}, \qquad\qquad T_{i2} = \sum_{l=1}^{t_0-1} l\epsilon_{il}$$

and K_{t_0} is constant across individuals depending on both λ and t_0. According to this expression, $\hat{\delta}_{it_0} = \hat{\delta}_{it_0}(h_{i0}, \alpha_i, \delta_i, T_{i1}, T_{i2}, \hat{\delta}_{i0}, h_{it0}; \lambda)$. Hence, we can simulate $\hat{\delta}_{it_0}$ by simulating $(h_{i0}, \alpha_i, \delta_i, T_{i1}, T_{i2}, \hat{\delta}_{i0})$. However, being alive at t_0 further restricts the distribution of $(h_{i0}, \alpha_i, \delta_i, T_{i1}, T_{i2})$. Given that there is no closed-form solution for the distribution of this vector conditional on observed health, I use MCMC to get these conditional draws. Then, for given values of b and λ, I follow the next steps,

- Draw $\hat{\delta}_{i0}$ conditional on $\alpha_i, \delta_i, h_{i0}$
- Use $\hat{\delta}_{i0}$ and $(h_{i0}, \alpha_i, \delta_i, T_{i1}, T_{i2})$ to construct $\hat{\delta}_{it_0}$
- Use α_i and $\hat{\delta}_{it_0}$ to simulate $plive10_{it}$
- Compare the distance between the empirical moments and the simulated ones

Overall, I target moments of averages across time for sub samples of individuals with different values of t_0.

10.6 Details of probit implementation and results

10.7 Additional neural-network results

10.8 Correlation of biomarkers with health slopes δ_i

10.9 Biomarkers results distinguishing by good or bad result