

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

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November 6, 2020

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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 older adults, health is an important determinant of working decisions. In this paper, I introduce heterogeneity in health dynamics with age and argue that uncertainty about health dynamics affects the working decisions of older adults. Using the Health and Retirement Study, I first show evidence of heterogeneity in health profiles with age. Second, I use subjective survival expectations to infer health beliefs in a Bayesian-learning framework. Third, I 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 look at a policy that could affect beliefs: the provision of information on blood glucose and cholesterol levels. I take advantage of the randomization on the collection and provision of such information. The results show the 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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\*I would like to thank Stéphane Bonhomme, Alessandra Voena, Derek Neal, and David Meltzer for serving on my thesis committee and providing invaluable guidance and support. I am also grateful for the discussions and feedback of many people, including Siying Cao, Kai-Wei Hsu, Cristhian Seminario-Amez, the Labor Party student group, and the participants of the Econometrics working group and the public-labor seminar at the University of Chicago. I gratefully acknowledge financial support from the University of Chicago Social Sciences Division and the University of Chicago Kenneth C. Griffin Department of Economics

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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. And though participation of older adults in the labor market has also been recently increasing, 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. 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.<sup>1</sup> 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 and expectations.<sup>2</sup> 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 working decisions implied by an economic model that incorporates heterogeneous and uncertain health dynamics. I focus on the effects that health beliefs have on working decisions of older adults. Instead of following a structural estimation approach, I use machine learning tools. A big limitation of this approach is that I can not run counterfactual analysis. However, the tools do not require to specify the primitives of the model or to add almost any functional-form assumption. Thus, the results are robust to misspecification of those elements.

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

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

<sup>2</sup> For health effects on retirement choices, see, for example, [Bound et al. \(1999\)](#) and [Maurer et al. \(2011\)](#). For health effects on retirement expectations, see [Dwyer and Mitchell \(1999\)](#) and [McGarry \(2004\)](#).

forms of heterogeneity.<sup>3</sup> 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 levels and in changes. Furthermore, the heterogeneity in changes helps explain the increasing variance of health with age, a pattern observed in the population but mostly ignored by traditional models of health.<sup>4</sup>

The panel estimates in 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<sup>5</sup> with initial beliefs that allow for bias (through the mean) and uncertainty (through the variance). Data on subjective survival expectations,<sup>6</sup> 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. Average survival expectations speak to bias in beliefs. 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.<sup>7</sup>

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

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<sup>3</sup> Most of the literature allows only for individual heterogeneity in health levels. See, for example, [Contoyannis et al. \(2004\)](#) and [Heiss \(2011\)](#).

<sup>4</sup> See, for example, [Heiss \(2011\)](#) and [Heiss et al. \(2014\)](#).

<sup>5</sup> 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.

<sup>6</sup> 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. \(2001\)](#).

<sup>7</sup> As discussed section 5, this result of negative bias in initial beliefs is consistent with the literature. See [Elder \(2013\)](#) and [Ludwig and Zimper \(2013\)](#).

the moment they make those decisions, including their beliefs about their health profiles. Under the Bayesian assumptions of the learning model, including normality of beliefs, those beliefs are summarized by their mean and variance. This section is similar in spirit to [Arellano et al. \(2017\)](#) who estimate a nonlinear policy rule for consumption nonparametrically, without specifying a full structural model. As in their case, I provide estimates of marginal quantities, here, marginal changes in the probability of work. One of the drawbacks of this approach is that, by not fully specifying the structure of the model, both in terms of primitives and functional-form assumptions, we can not perform policy counterfactuals. However, at the same time, the results on marginal effects are robust to misspecification of those elements. Besides robustness to misspecification, another attractive feature of this framework is that it 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.

To estimate the policy rule for working decisions flexibly, I use neural networks. Neural networks are a tool within the machine learning toolkit that, in the present context, generalize logit with a non-linear index (see [Farrell et al. \(2020\)](#), [Hornik et al. \(1989\)](#), [Goodfellow et al. \(2016\)](#)). 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 ([Dempster et al. \(1977\)](#)).

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 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 this result is not a consequence of any assumption on the structure of the economic model. As mentioned by [Arellano et al. \(2017\)](#), economic structure could be added to this framework to conduct policy evaluation exercises. This result suggests that when adding such structure, adjustment costs of returning to labor market should be included. Hence, the two approaches complement each other.

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 through changes in information about health profiles. 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 result, I simulate the impact of changing beliefs, by applying machine learning tools to predict not only work but also assets and health insurance. I use those results to compare baseline working probabilities over time with probabilities after eliminating initial overall bias in beliefs. I find that eliminating initial bias increases participation by 2 percentage points, an 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, 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<sup>8</sup> shows small and insignificant effects of this additional information on survival expectations and working decisions. I then analyze these data through the lens of the model. That is, I modify the learning model to include blood glucose and cholesterol results as additional signals of health profiles. Consistently, this model-based analysis also shows small and insignificant results. The model, however, provides us with an interpretation for the results: the magnitude of this blood-based signal is too small.

**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

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<sup>8</sup> As discussed in section 8, the design needs to control also for changes in interview mode.

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 measures 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.<sup>9</sup> 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 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 Zimmer (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 (Siddiqui (1997), McClellan (1998), Bound et al. (1999), French (2005), Disney et al. (2006), Zucchelli et al. (2010), 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

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<sup>9</sup> 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)).

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.

**Organization.** The paper proceeds as follows. Section 2 presents the framework, that is, an economic model of working decisions that incorporates heterogeneous and uncertain health dynamics. This framework underlies and gives context to the analysis in the rest of the paper. 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 health is scalar and follows,

$$h_{it} = \rho h_{it-1} + \alpha_i + \delta_i \cdot t + \epsilon_{it}. \quad (1)$$

The parameter  $\rho \in (0, 1)$  captures persistence in health,  $\alpha_i$  captures heterogeneous levels in health,  $\delta_i$  captures heterogeneous changes of health with age, and  $\epsilon_{it}$  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,  $\delta_i$ . Larger values of  $h_{it}$  represent better health, and health decreases with age.

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.<sup>10</sup>

## 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 they do not observe their health shocks  $\epsilon_{it}$  nor they observe their individual heterogeneity  $(\alpha_i, \delta_i)$ . Given that health deteriorates in old age, I assume 50-years old individuals do not know  $\delta_i$ , which has not affected them before.<sup>11</sup> I assume they know their heterogeneous level  $\alpha_i$ ,<sup>12</sup> as they have observed their health for several decades.

Under uncertainty, rational individuals form beliefs about their health slopes  $\delta_i$  (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  $\delta_i$  equal to  $N(\hat{\delta}_{i0}, \hat{\sigma}_0^2)$ .<sup>13</sup> By further assuming that health shocks  $\epsilon_{it}$  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 by

<sup>10</sup> The assumption is also relevant for the identification of beliefs, as discussed in section 5.

<sup>11</sup> 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.

<sup>12</sup> 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.

<sup>13</sup> 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.



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

$$\frac{1}{\hat{\sigma}_t^2} = \frac{1}{\hat{\sigma}_{t-1}^2} + \frac{t^2}{\sigma_\epsilon^2}. \quad (3)$$

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  $\sigma_\epsilon^2$ ) 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  $\sigma_\epsilon^2$ ) and when individuals are older.

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

$$b = \mathbb{E}(\hat{\delta}_{i0} - \delta_i) \quad (4)$$

$$\lambda^2 = \frac{\hat{\sigma}_0^2}{\text{Var}(\delta_i)}. \quad (5)$$

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  $\lambda$  measures the degree of initial uncertainty individuals face regarding  $\delta_i$ , 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  $\lambda$  the more uncertain individuals are and the more weight they give to new information. The Bayesian learning and normality assumptions allow 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 about 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 uncertainty about health profiles with age, specifically  $\delta_i$ , and study 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  $\epsilon_{it}$ , and in part because they don't know their health slopes  $\delta_i$ . They form beliefs about their slopes  $\delta_i$  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  $\alpha_i$  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

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

Slope uncertainty implies  $\delta_i$  does not belong to  $\Omega_{it-1}$ , but beliefs about  $\delta_i$  do, with those beliefs summarized by  $\hat{\delta}_{it-1}$  and  $\hat{\sigma}_{it-1}^2$ . Note that I am assuming only heterogeneity in health; thus, no other individual-level heterogeneity is stated in  $\Omega_{it-1}$ .

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  $\theta$  (including the discount factor and parameters 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,

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

Similarly, policy rules for other decisions, including consumption and assets, can be written as functions of the state variables  $\Omega_{it-1}$ . In the spirit of [Arellano and Bonhomme \(2016\)](#) and [Arellano et al. \(2017\)](#), the objective is to estimate this relation between participation decisions and its inputs flexibly, without adding the full structure required by structural models.

Equation (6) assumes these decisions are stochastic. Implicitly, I am assuming there are random taste shifters affecting individuals preferences. These taste shifters are part of the state variables, but they are unobserved by the econometrician. Hence, from the econometrician's point of view, the decision is stochastic, corresponding to a conditional choice probability problem.

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, particularly heterogeneity in  $\delta_i$ .
- (ii) To study older adults' beliefs about their health dynamics, in particular, to estimate their initial bias  $b$  and their initial uncertainty  $\lambda$ .
- (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,<sup>14</sup>

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

The 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 suggest 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 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 a 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  $\epsilon_{it-1}$  in working decisions. On the one hand, a health shock  $\epsilon_{it-1}$  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  $\epsilon_{it-1}$  and  $\delta_i$  within  $h_{it-1}$ . Hence, the effect of a shock  $\epsilon_{it-1}$  on  $h_{it-1}$  is partly interpreted as new information regarding  $\delta_i$ , affecting beliefs  $\hat{\delta}_{it-1}$ . This information channel disappears if  $\lambda = 0$ . Using Bayes' rule, we can write,

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

<sup>14</sup> I focus on the marginal effect of the posterior mean  $\hat{\delta}_{it-1}$  and not of the posterior variance  $\hat{\sigma}_t^2$ . The reason for this choice is that the posterior variance  $\hat{\sigma}_{t-1}^2$  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.

where the *factor* term corresponds to the change in the posterior mean  $\hat{\delta}_{it-1}$  given a marginal change in  $\epsilon_{it-1}$ , 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  $\delta_i$  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),<sup>15</sup> 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.<sup>16</sup> For most of the analysis, I use the RAND version of these data.<sup>17</sup> 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 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 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. Furthermore, as it is mention later, the heterogeneity in health dynamics is

<sup>15</sup> The HRS (Health and Retirement Study) is sponsored by the National Institute on Aging (grant number NIA U01AG009740) and is conducted by the University of Michigan.

<sup>16</sup> I exclude proxy interviews because questions on survival expectations are not asked in these interviews.

<sup>17</sup> The RAND HRS Longitudinal File is an easy-to-use dataset based on the HRS core data. This file was developed at RAND with funding from the National Institute on Aging and the Social Security Administration.

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-assessed 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

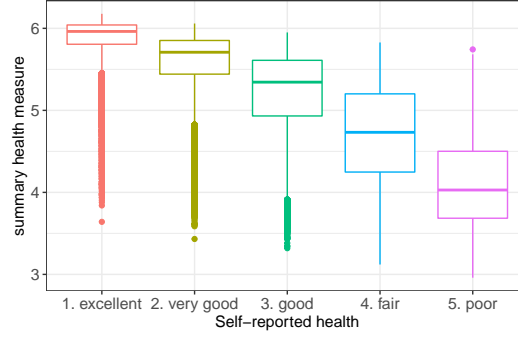
*Note:* Summary statistics for the health measures including the summary health measure. The sample comprises 30,657 individuals interviewed in-person, in wave 4 or later, that are 50 years old or older. Chronic conditions include: high blood pressure, heart attack, diabetes, stroke, lung disease, arthritis, cancer. The categories for self-assessed 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. mild 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.

robust to the use of self-assessed health instead of the summary measure.

Figure 2 shows the mean and variance of health  $h_{it}$  by age.<sup>18</sup> 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. The pattern in these plots suggests a process with heterogeneous slopes with age, which I empirically investigate in section 4. Finally, Figure 4 shows the mean of health for groups of individuals surviving to different ages. The figure suggests survival bias, because cohorts of individuals surviving to older ages have better health than cohorts

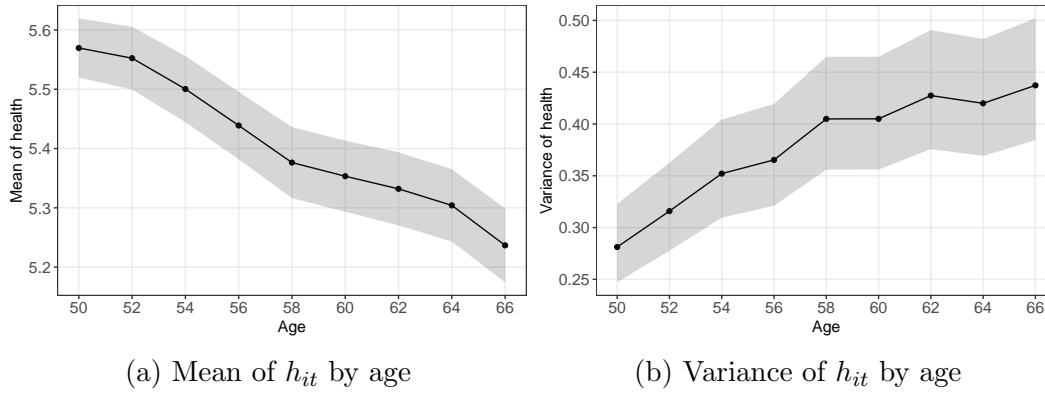
<sup>18</sup> The standard errors in this figure, as well as the following results in this paper, need yet to be adjusted for the estimation of the summary health measure, something that I am working on.

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



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

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 I address it also, as explained in the section 4.

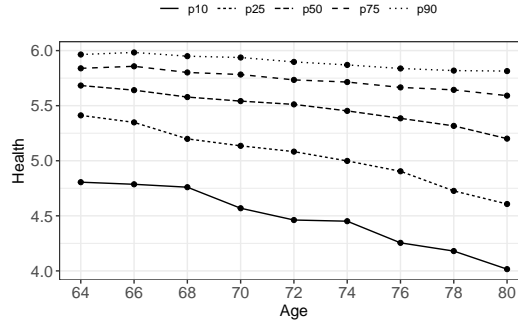
### 3.2 Data on subjective survival expectations

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.<sup>19</sup> Survival expectations have been shown to have predictive power for individuals'

<sup>19</sup> 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.

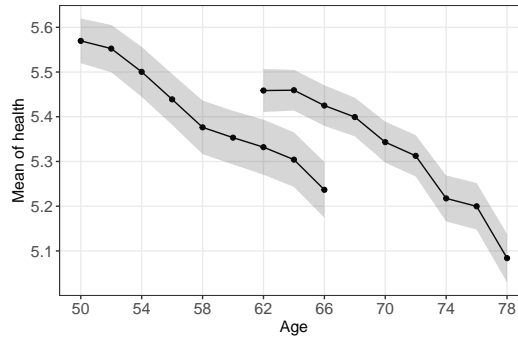


Figure 3: Health percentiles by age



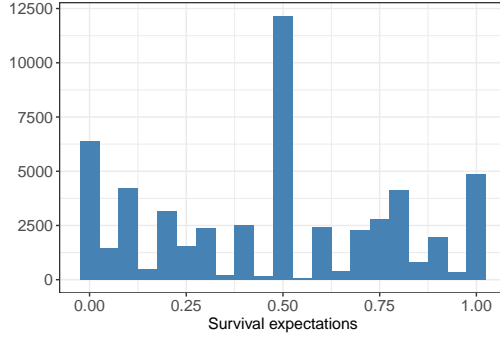
*Note:* Results from a balanced sample of 414 individuals observed at age 64 with at least 9 consecutive waves.

Figure 4: Mean of health with age for individuals with different survival ages



*Note:* Results from two balanced samples of individuals with at least 9 consecutive waves: 433 individuals observed from age 50, and 509 individuals observed from age 62. The bands represent 95% confidence intervals.

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.

survival (Hurd et al. (2001), Hurd and McGarry (1995)) and to be consistently updated with new health information (Hurd and McGarry (2002), Smith et al. (2001)). Furthermore, survival expectations are correlated with several outcomes for older individuals. A histogram of the variable is shown in Figure 5. The figure shows this variable suffers from measurement error, including rounding and focal point issues (Manski and Molinari (2010), Kleinjans and Van Soest (2014)). The model in this paper takes those issues into account.

### 3.3 Data on other variables related to 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  $\alpha_i$ , beliefs regarding health profiles  $(\hat{\delta}_{it}, \hat{\sigma}_t^2)$ , as well as other variables in the information set  $\Omega_{it-1}$ , including assets  $a_{it-1}$  and labor income  $w_{it-1}$ . Table 2 presents summary statistics for these other variables in  $\Omega_{it-1}$  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.

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

Variable	Mean	SD	Min	Max
<i>Panel (a)</i>				
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 divorced	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
<i>Panel (b)</i>				
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.

## 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

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

$$S_{it} = \mathbb{1}\{\gamma h_{it-1} + \theta_0 + \theta_1 \cdot t + \theta'_2 x_i + \eta_{it}\} S_{it-1}, \quad \eta_{it} \text{ iid } N(0, 1) \quad (10)$$

with individual-level heterogeneity  $(\alpha_i, \delta_i)$ ,

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

The health process is persistent, measured by the parameter  $\rho$ , and it has heterogeneous levels  $\alpha_i$  and heterogeneous slopes with age  $\delta_i$ . The survival process depends on age through the parameter  $\theta_1$ , and it depends on health through the parameter  $\gamma_1$ . This dependence of survival on health allows us to take into account the survival bias observed in the data (see figure 4). The health and survival shocks,  $\epsilon_{it}$  and  $\eta_{it}$ , are assumed independent. The appendix includes a specification allowing for survival to depend directly on individual-level heterogeneity,  $\alpha_i$  and  $\delta_i$ . However, those results indicate there is no such dependence. 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  $\alpha_i$  and  $\delta_i$ . Let  $\Theta$  be the set of parameters of this random-coefficients model.<sup>20</sup> I estimate these parameters by maximizing the likelihood:

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

## 4.2 Results

I use a sample of 8,901 correlative observations from 1,671 individuals observed since they were 50 years old ( $t = 0$ ).<sup>21</sup> 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

<sup>20</sup>  $\Theta = \{\rho, \tau, \sigma_\epsilon^2, \gamma, \theta_0, \theta_1, \theta_2, \mu_\alpha, \mu_\delta, \nu_\alpha, \nu_\delta, \omega_\alpha, \omega_\delta, \sigma_\alpha^2, \sigma_\delta^2, \phi\}$

<sup>21</sup> I approximate the double integral by using one thousand draws from a bivariate normal distribution.

Table 3: MLE results on health and survival

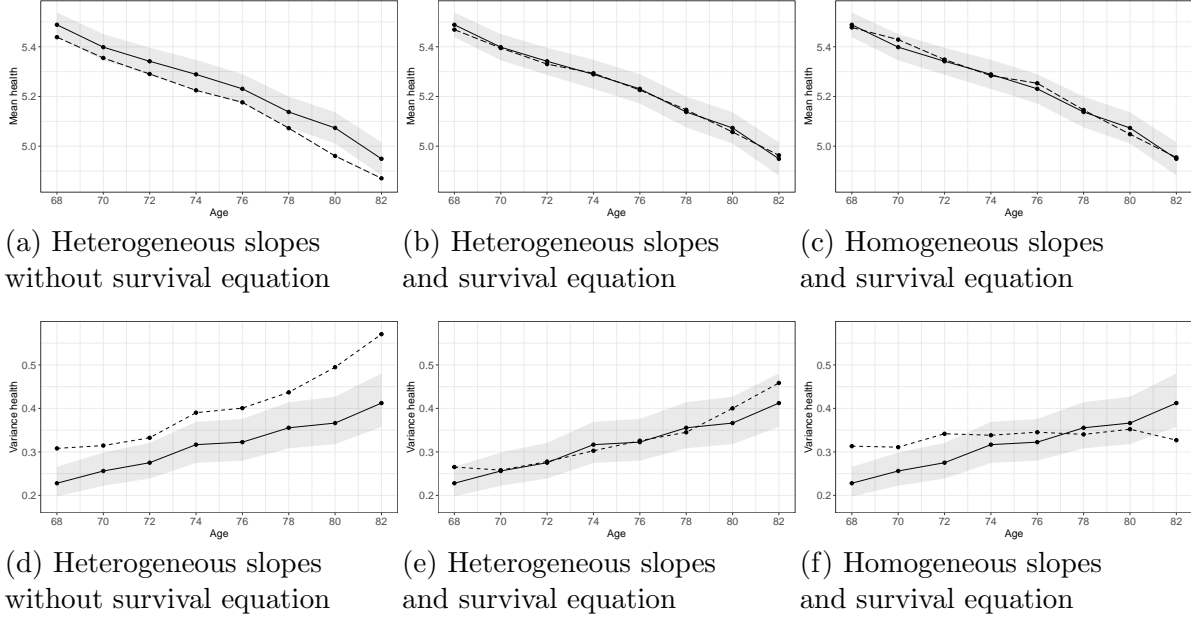
	Symbol	Coefficient	Pvalue
Persistence	$\rho$	0.222	0.000
Mean* of $\alpha_i$	$\mu_\alpha$	0.967	0.000
Mean* of $\delta_i$	$\mu_\delta$	-0.059	0.006
SD of $\alpha_i$	$\sigma_\alpha$	0.236	0.000
SD of $\delta_i$	$\sigma_\delta$	0.043	0.000
$Corr(\alpha_i, \delta_i)$	$\phi$	-0.034	0.605
SD of health shocks	$\sigma_\epsilon$	0.266	0.000
Survival dependence on health	$\gamma_1$	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.

significant  $\sigma_\alpha^2$  and  $\sigma_\delta^2$ . Second, these two sources of heterogeneity are uncorrelated, which implies knowing  $\alpha_i$  does not provide additional information on  $\delta_i$ . 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  $\alpha_i$ , but it does not provide information on  $\delta_i$ .

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  $\rho$  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 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

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



*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 figure plots data from 354 individuals with health in all 9 waves. The solid lines plot the health data and the dotted lines plot the predicted values of health in each model.

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, included in the appendix, I estimate a version with heteroskedastic error  $\epsilon_{it}$  allowing for its variance to depend on age. The results show increasing variance of health shocks do not explain away the heterogeneity in slopes  $\delta_i$ .

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  $(\alpha_i, \delta_i)$  directly to the survival equation. The results show  $\alpha_i$  and  $\delta_i$  are not (jointly) significant, that is, there are no direct effect of heterogeneity in survival, once we condition on lagged health  $h_{it-1}$ . The lack of significance of  $\delta_i$  has an additional advantage. It implies survival is not another signal for the unknown  $\delta_i$ . If that were not the case, then, as in the case of health, survival would provide individuals with additional information. In that case, by being alive, individuals would learn something more about their heterogeneous slopes, and the Bayesian updating equations (2) and (3) would not be

valid. The results in this exercise, with the lack of significance of  $\delta_i$  on survival, say this is not the case.

Overall, these results show novel evidence of heterogeneity in health profiles, in particular, in health slopes with age. To study the effects of this heterogeneity on individuals' working decisions, we need to know how much individuals know about their own slope  $\delta_i$ , which I address next.

## 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  $\lambda$ . These parameters are defined by

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

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 question follows:

[*plive10<sub>it</sub>*] *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  $\Omega_{it}$ , 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  $\lambda$  and  $b$ . Therefore,  $plive10_{it}$  are complex non-linear functions of slope beliefs,

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

The exact function is given in the appendix. Each period, individuals observe their health and update their beliefs regarding their unknown  $\delta_i$ . 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  $\lambda$ .

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  $\delta_i$  contained in  $\alpha_i$  is already incorporated in initial beliefs  $\hat{\delta}_{i0}$ .

## Identification using subjective expectations about survival rates (ideal data)

The relation between survival expectations  $plive10_{it}$  and the parameters governing beliefs,  $b$  and  $\lambda$ , is a complex one. To provide intuition, I start by discussing identification using ideal data, which I do not actually observe. This intuition carries out to the data available in the HRS, which I show numerically next. Let  $\Omega_{it}$  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  $\lambda$ )** *Let health and survival process be given by equations (9) and (10), and assume individuals are Bayesian learners with prior beliefs about  $\delta_i$  following*

$N(\hat{\delta}_{i0}, \hat{\sigma}_0^2)$ . Consider the subjective expectations about survival rates:

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

Then,

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

where the time-varying constant  $C_t$  is increasing in  $\lambda$ .

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

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

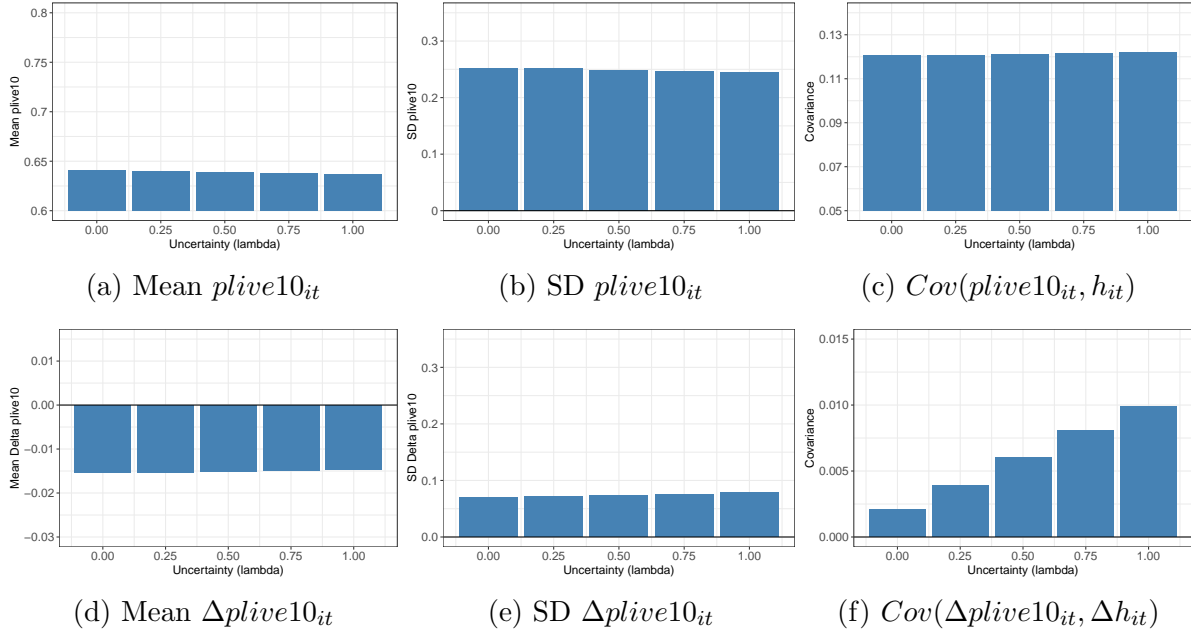
shows individuals update their survival expectations for two reasons. The first reason is that health is a persistent process; thus, any change in health will have future repercussions on health and therefore on survival. Note that if  $\rho = 0$ , this channel disappears. The second reason is that learning 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 (HRS 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  $\lambda$ , 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

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



*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  $\lambda$  used in the data-generating process. In all cases, the bias parameter  $b$  is set to zero.

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 or sufficient signal available to individuals. This assumption is partly address in the last section of the paper, where I look at another source of information that may shift beliefs.

Under these assumptions,  $plive10_{it}$  is a function of initial beliefs  $N(\hat{\delta}_{i0}, \hat{\sigma}_0^2)$ , heterogeneous intercept  $\alpha_i$ , and health history up to  $t$ ,  $(h_{i0}, \dots, h_{it})$ . Hence, for any value of  $b$  and  $\lambda$ , I can use the estimated health process to simulate draws  $\alpha_i$  and  $\hat{\delta}_{i0}$ , and then use those variables to simulate  $plive10_{it}$ .<sup>22</sup> I estimate the parameters governing initial beliefs,  $b$  and  $\lambda$ , 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  $h_{it}$ .<sup>23</sup> Details of the implementation are given in the appendix.

Subjective survival expectations are measured with substantive error, which is well estab-

<sup>22</sup> The distribution of  $\hat{\delta}_{i0}$  depends on  $b$  and  $\lambda$ . Hence, I first simulate  $\alpha_i$  and  $\delta_i$  conditional on health history  $h_{i0}, \dots, h_{iT_i}$ , and then for a given value of  $b$  and  $\lambda$ , I draw  $\hat{\delta}_{i0}$  conditional on  $\alpha_i$ ,  $\delta_i$ , and  $h_{i0}$ .

<sup>23</sup> 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.

lished 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  $\nu_{it} \sim N(\mu_{\text{error}}, \sigma_{\text{error}}^2)$ , such that the observed survival expectations are given by

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

Note the measurement error shifts *observed survival expectations* by  $\mu_{\text{error}}$  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.

## 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 (included in the appendix). 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  $\text{plive10}_{it}$ , while panel *b* shows the fit of similar un-targeted moments using survival expectations to age 75.<sup>[24](#)</sup>

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.

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<sup>24</sup> The HRS includes two questions on survival expectations every wave:  $\text{plive10}_{it}$  asks for a reference age approximately 10 years ahead, and  $\text{plive75}_{it}$  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 4: Estimated parameters of prior beliefs

	Symbol	Coefficient	Lower bound	Upper bound
Uncertainty	$\lambda$	0.338	0.336	0.340
Bias	$b$	-0.061	-0.061	-0.060
Mean of measurement error	$\mu_{error}$	0.121	0.118	0.123
SD of measurement error	$\sigma_{error}$	0.177	0.176	0.177

*Note:* Prior beliefs about slopes are unobserved  $N(\delta_i + b, \lambda^2 \sigma_\delta^2)$ , depending on the bias  $b$  and uncertainty  $\lambda$  parameters, 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.

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

<i>a. Targeted moments</i>			
	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
<i>b. Other moments (not targeted)</i>			
	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,

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

*st.*    budget constraint,  
           health (9) and survival (10) processes,  
           and beliefs updating equations (2) and (3),

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,

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

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 beliefs 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. 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. Note also that, conditional on states variables in  $\Omega_{it-1}$ , survival expectations  $plive10_{it}$  do not play an additional role in working decisions  $p_{it}$ .

### 6.1 Probit results on working decisions

To explore the relation between health beliefs and working decisions of older adults, I first estimate equation (13) using a probit approach, i.e. assuming that  $\mathbb{P}(p_{it} = 1 | \Omega_{it-1}) = \Phi(\beta' \Omega_{it-1})$ . Note that some of the input variables are unobserved by the econometrician; namely, heterogeneity

in health level  $\alpha_i$  and beliefs about slope heterogeneity,  $\hat{\delta}_{it}$  and  $\hat{\sigma}_t^2$ . 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.

Table 6 presents the results of the probit estimation. As expected, the probability of work decreases with age and increases with better lagged health. Lagged work has a significant effect; the probability of work is larger for individuals that were working the previous period. This result confirms the dynamic aspect of the working decisions. Furthermore, the table 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.<sup>25</sup> The table also shows that *survival expectations*  $plive10_{it}$  are significant predictors in the probability of work, but that significance holds only while slope beliefs are not accounted for. This is line with survival expectations reflecting individuals' beliefs about slope heterogeneity. Thus, once those beliefs are considered, survival expectations do not provide additional information.

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	$\alpha_i$	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	$\hat{\sigma}_{t-1}^2/\sigma_\delta^2$	-13.85***	(2.048)			-13.33***	(2.102)
survival expectations	$plive10_{it}$			0.11***	(0.031)	0.01	(0.043)
Controls	other vars $\Omega_{it-1}$	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. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

Though interesting, these results assume a linear index for the probability of work, which is a strong assumption, not justified by assumptions on the fundamentals of the model. Hence, the results may be inconsistent with the policy rule derived from the economic model. Thus, in what follows, I estimate the probability of work flexibly, without imposing this index linearity. I achieve

<sup>25</sup> The assumptions of the learning model imply the posterior variance  $\hat{\sigma}_t^2$  is constant across individuals of the same age  $t$ . Given that age is also a relevant determinant of working decisions, I don't have enough variation to disentangle these 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.



that flexibility by using instead a neural network approach.

## 6.2 Neural-network approach

A neural network provides a 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 (Hornik et al. (1989), Goodfellow et al. (2016)). 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 ( $\hat{\delta}_{it-1}, \hat{\sigma}_t^2$ ) and heterogeneous health levels  $\alpha_i$ . 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.<sup>26</sup> 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 (Dempster et al. (1977)).

Let  $\theta$  be the parameters governing an outcome variable, in this case, working decisions. When there is underlying heterogeneity, we estimate  $\theta$  by maximizing a likelihood that integrates out that heterogeneity. In this context, EM-type algorithms provide us with two key insights. First, the parameter  $\theta$  that maximizes the integrated log-likelihood also maximizes an alternative specification using the posterior distribution given the outcome variable. Formally, let  $\eta_i$  denote the vector of unobserved heterogeneity,  $f(\eta_i)$  its prior distribution and  $f(\eta_i|p_i; \theta)$  its posterior distribution given the outcomes  $p_i$ . The first insight of EM-type algorithms is to note that,

$$\arg \max_{\theta} \log \int \mathbb{P}(p_i|\eta_i; \theta) f(\eta_i) d\eta_i = \arg \max_{\theta} \int \log(\mathbb{P}(p_i|\eta_i; \theta)) f(\eta_i|p_i; \theta) d\eta_i \quad (14)$$

The expression on the right-hand side is simpler to use. However, because this posterior distribution depends on  $\theta$ , it is unknown. Thus, the second insight of EM-type algorithms is to solve the problem for  $\theta$  iteratively: in iteration  $k$ , the E step uses  $\theta_{k-1}$  to update the posterior distribution of the heterogeneity, and the M step estimates  $\theta_k$  by maximizing the right-hand side of equation (14), using that posterior.

I use this same iterative logic as a convenient implementation for maximizing the integrated

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<sup>26</sup> This relationship depends also on the parameters of the health process ( $\rho, \sigma_{\epsilon}^2$ ) and the parameters of beliefs ( $b$  and  $\lambda$ ), but it does not depend on the parameters defining the relation between working decisions and state variables.

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  $p_i$ .<sup>27</sup> 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  $\theta$  by using a neural network on the expanded data.<sup>28</sup> 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,<sup>29</sup> I estimate the probability of work conditional on the state variables  $\Omega_{it-1}$ . This set includes past participation  $p_{it-1}$ , past health  $h_{it-1}$ , heterogeneous health levels  $\alpha_i$  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.*

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, 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.

*(2) For individuals in their 50s who are not working, there is an interaction between beliefs and health in their future participation decisions.*

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<sup>27</sup> MCMC uses the likelihood of  $p_i$  given  $(\alpha_i, \hat{\delta}_{i0})$  from the previous-iteration M step and the prior distribution of  $(\alpha_i, \hat{\delta}_{i0})$ .

<sup>28</sup> 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 solution. Therefore, the approach is not aimed at getting at the unique solution, but as a convenient implementation. See the appendix for more details.

<sup>29</sup> The results presented here use the incomplete posterior mentioned before. The iterative process is underway.

This result can be seen in Figure 8. The figure shows beliefs have larger marginal effects on working probabilities for individuals with worse health. At the same time, health has larger marginal effects on working probabilities for individuals who believe their health will deteriorate relatively slowly. These results suggest that adjustment costs of going back to work are important for the decisions of this group. These adjustments costs could be due to difficulties in finding jobs, or to adapting to new work environments. The framework and data-driven approach used in this paper have the advantage of letting the data suggest mechanisms that may be otherwise overlooked. Overlooking important mechanisms is a source of misspecification in structural models. Hence, the approach in this paper complements structural models, by providing a flexible way of identifying patterns in the data that suggest mechanisms to incorporate in such models.

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

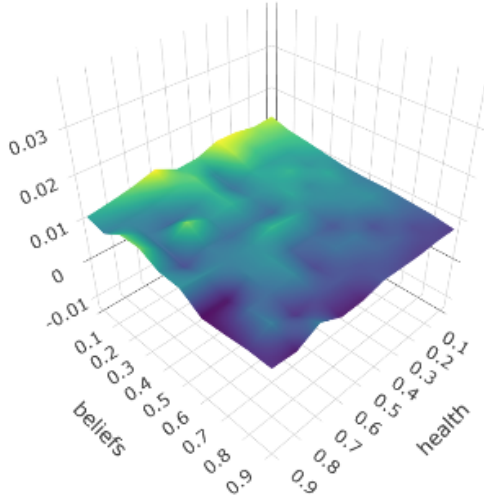
This result is shown in Table 7, which includes the decomposition of the effects of a health shock into a persistence channel and an information channel, according to equation (8). The persistence channel refers to the effect that a health shock  $\epsilon_{it-1}$  has on  $h_{it}$  through  $h_{it-1}$  and the persistence of the health process. The information channel refers to the effect that a health shock  $\epsilon_{it-1}$  has on beliefs  $\hat{\delta}_{it-1}$ , as individuals interpret  $h_{it-1}$  (and hence this health shock) as a health signal. According to equation (8), the total effect of a health shock is a weighted sum of the effects through these two channels. Note the small values on the column Factor in Table 7, 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.

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

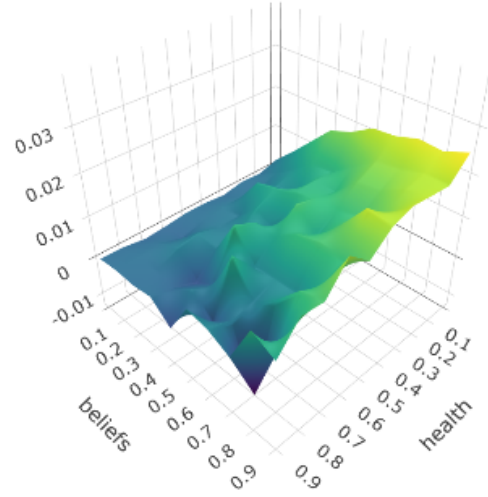
Age	Average marginal effects			Decomposition of a health shock		
	Health $h_{it-1}$	Beliefs $\hat{\delta}_{it-1}$	Assets $a_{it-1}$	Factor	Persistence channel	Information channel
$p_{it-1} = 0$						
52	0.055	0.011	-0.043	0.003	1.00	0.00
54	0.046	0.011	-0.037	0.006	1.00	0.00
56	0.040	0.012	-0.033	0.008	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.

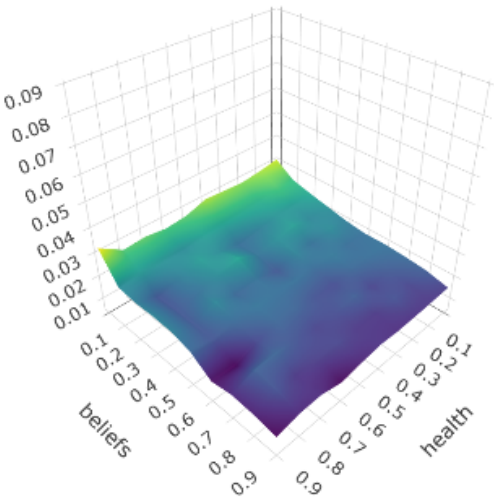
Figure 8: Average marginal effect of expected beliefs  $\hat{\delta}_{it-1}$ , and health  $h_{it-1}$  on the probability of work  $p_{it}$  for adults in their 50s



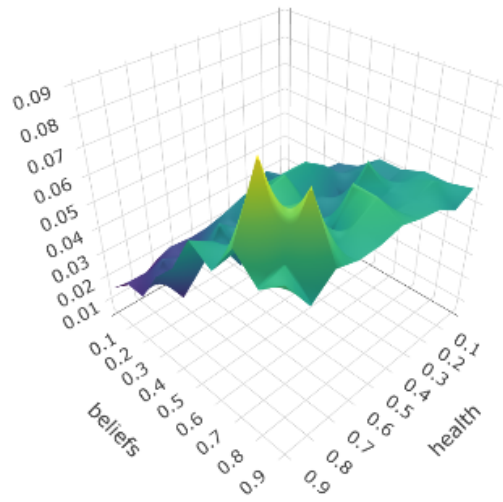
(a) Marginal change in  $\hat{\delta}_{it-1}$  conditional on  $p_{it-1} = 1$



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



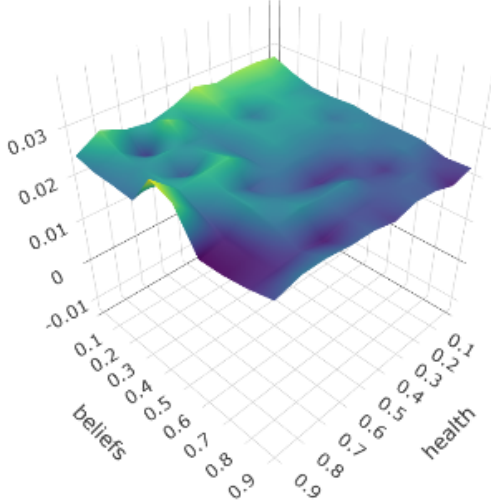
(c) Marginal change in  $h_{it-1}$  conditional on  $p_{it-1} = 1$



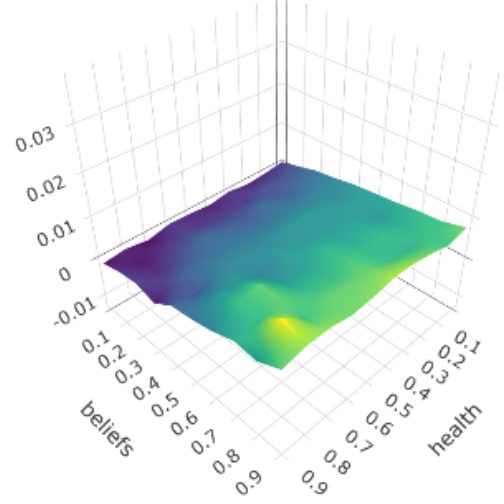
(d) Marginal change in  $h_{it-1}$  conditional on  $p_{it-1} = 0$

*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. The z-axis corresponds to the work response (probability). Note the range of z-axis changes in each row.

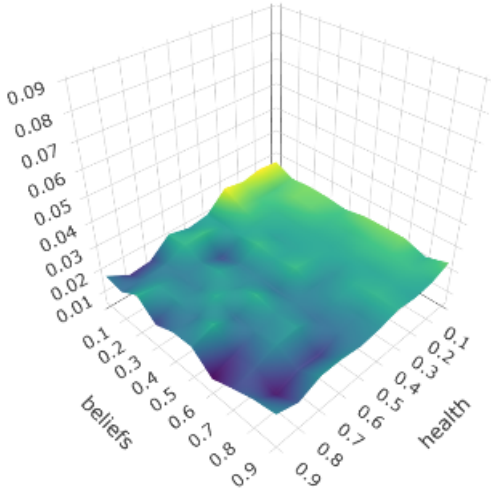
Figure 9: Average marginal effect of expected beliefs  $\hat{\delta}_{it-1}$  and health  $h_{it-1}$  on the probability of work  $p_{it}$  for adults between 66 and 75 years old



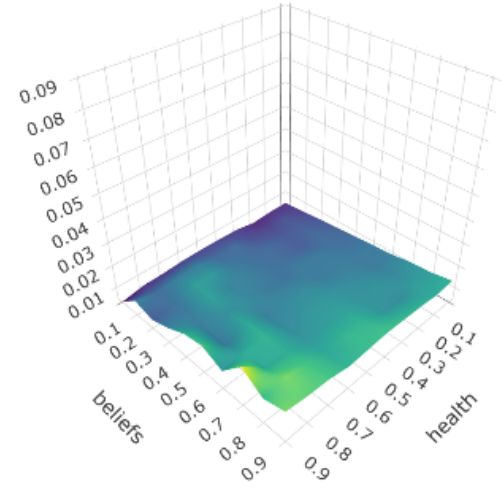
(a) Marginal change in  $\hat{\delta}_{it-1}$  conditional on  $p_{it-1} = 1$



(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 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. The z-axis corresponds to the work response (probability). Note the range of 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  $\delta_i$ ?

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 counterfactual analysis, but is a interesting exercise as long we are capturing the main choices.

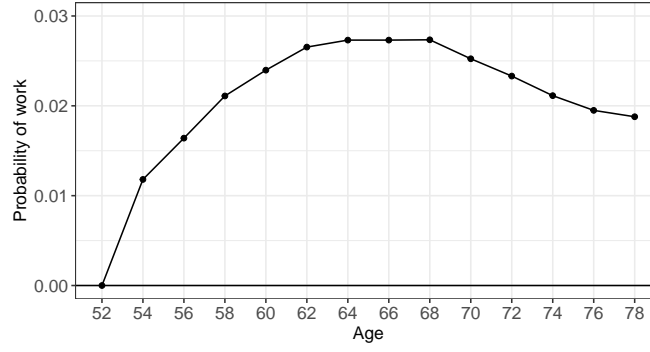
*(1) Eliminating the bias in prior beliefs  $b$  would increase participation by more than 2 percentage points around the formal retirement age (66-67).*

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.*



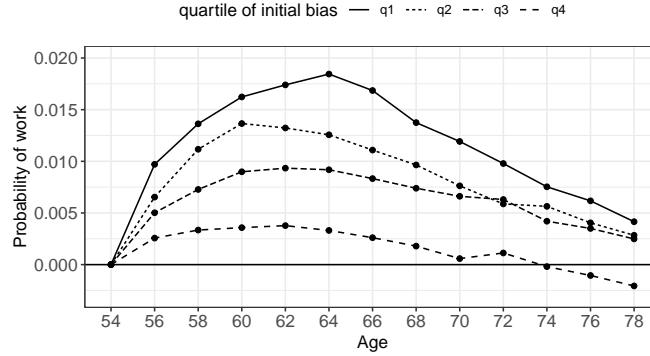
Figure 10: Impulse response function to a shift in prior beliefs eliminating overall bias  $b$



*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 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 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

### 8.1 Setup

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 exploit a feature of the HRS and study the effects on individuals' decisions of an information shock: information on blood-based biomarkers. In 2006, the HRS introduced the collection of a blood sample for measuring biomarkers. 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<sup>30</sup> (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 diagnoses through the surveys increase 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. \(2017\)](#)).

A key aspect in the introduction of these measures in the HRS is that, 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<sup>31</sup> and to use additional sources of variation when estimating the effects of beliefs on working decisions of older adults.<sup>32</sup> However, the counterpart of using this

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<sup>30</sup> 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 provide additional information to individuals.

<sup>31</sup> 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.

<sup>32</sup> 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

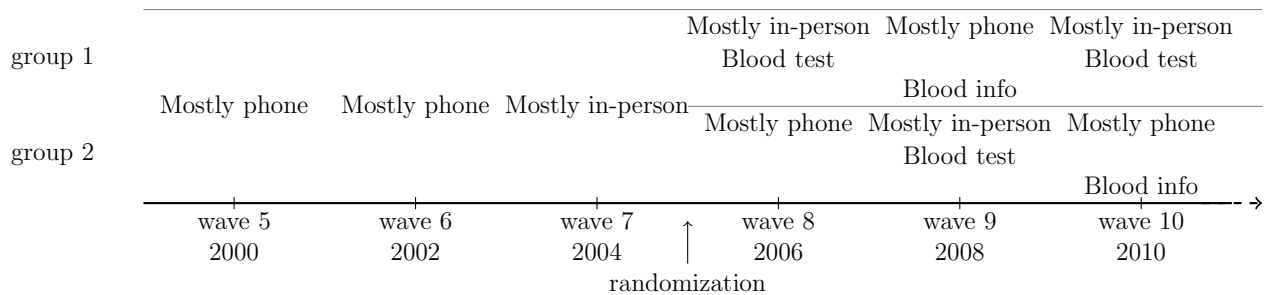
experiment is that the information provided in the experiment is very small.

## 8.2 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.<sup>33</sup> 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. Note, first, that a difference-in-differences analysis using waves 7 and 8 returns the interview-mode effect. Second, 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



survival-expectations histories.

<sup>33</sup> 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.

Therefore, I estimate the following equation:

$$y_{iw} = \beta_0 + \beta_1 d_{g_i} + \beta_{2w} d_w + \beta_{3w} d_{g_i} \cdot d_w + \epsilon_{iw}, \quad (15)$$

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.<sup>34</sup>  $d_{g_i}$  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  $\beta_{3w_8}$ , 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 (15) 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<sup>35</sup> 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.<sup>36</sup>

<sup>34</sup> I use only up to wave 9, because from wave 10 onward, the groups are no longer comparable, given that they have been provided information with different timing.

<sup>35</sup> The lack of an interview-mode effect on working decisions is expected, given the more objective nature of working outcomes versus survival expectations.

<sup>36</sup> 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

Table 8: Information and interview mode effects of biomarker experiment

		Survival expectation ( $plive10_{iw}$ )			Work decision ( $p_{iw}$ )		
		All	Less college	College	All	Less college	College
Group 1	$\beta_1$	-0.47	-0.24	-1.38	0.00	0.01	-0.01
Wave 6	$\beta_{2w6}$	-1.42***	-1.21**	-2.09**	-0.07***	-0.07***	-0.09***
Wave 7	$\beta_{2w7}$	-1.50***	-1.44***	-1.72**	-0.12***	-0.12***	-0.12***
Wave 8	$\beta_{2w8}$	-6.41***	-6.12***	-7.37***	-0.16***	-0.16***	-0.19***
Wave 9	$\beta_{2w9}$	-3.57***	-3.22***	-4.70***	-0.20***	-0.20***	-0.22***
Group 1, wave 6	$\beta_{3w6}$	0.28	-0.06	1.37	0.01	0.00	0.02
Group 1, wave 7	$\beta_{3w7}$	-0.27	-0.24	-0.33	0.01	0.01	0.01
Group 1, wave 8	$\beta_{3w8}$ (a)	1.77**	1.29	3.31***	0.01	0.00	0.03
Group 1, wave 9	$\beta_{3w9}$ (b)	-0.42	-1.12	1.82	0.01	0.01	0.00
Constant	$\beta_0$	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 (15). 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. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

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,<sup>37</sup> 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.

### 8.3 Model-based approach

In this section, I use the learning model to re-assess the information experiment. I estimate survival expectations allowing for the biomarker information to be a second signal for health profiles. For these biomarkers to be a valid signal, being correlated with health is not enough; they must be correlated with  $\delta_i$ . 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  $\alpha_i$  and heterogeneous slopes  $\delta_i$  are correlated with these particular biomarkers.

Hence, some individuals have two signals of  $\delta_i$ : health  $h_{it}$ , and biomarker results  $l_{it}$ . Let  $l_{it}$  be the blood-glucose level of individual  $i$  at age  $t$ ,<sup>38</sup> and the two signals be given by

$$\begin{aligned} h_{it} &= \rho h_{it-1} + \alpha_i + \delta_i \cdot t + \epsilon_{it} \\ l_{it} &= \tau_0 + \tau_1 h_{it-1} + \tau_2 \alpha_i + \tau_3 \delta_i \cdot t + \tau_4 \cdot t + \tau_5 \cdot x_i + \omega_{it}, \end{aligned}$$

were  $\omega_{it}$  are i.i.d. and independent of health shocks  $\epsilon_{it}$ . Bayes' rule implies that the updating equations for the posterior mean and variance of beliefs are given by

$$\frac{\hat{\delta}_{it}}{\hat{\sigma}_t^2} = \frac{\hat{\delta}_{it-1}}{\hat{\sigma}_{t-1}^2} + \frac{(h_{it} - \rho h_{it-1} - \alpha_i)t}{\sigma_\epsilon^2} + \frac{(l_{it} - \tau_0 - \tau_1 h_{it-1} - \tau_2 \alpha_i - \tau_4 t - \tau_5 x_i)t \cdot \tau_3}{\sigma_\omega^2} \quad (16)$$

$$\frac{1}{\hat{\sigma}_t^2} = \frac{1}{\hat{\sigma}_{t-1}^2} + \frac{t^2}{\sigma_\epsilon^2} + \frac{\tau_3^2 t^2}{\sigma_\omega^2}. \quad (17)$$

Equation (17) shows the posterior variance includes the information provided by health and

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with the help of their physicians, even if the number of doctor visits remains the same.

<sup>37</sup> 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.

<sup>38</sup> I focus on blood glucose because it is the biomarker more consistently related to slopes  $\delta_i$ .

by the biomarker results. As long as the biomarkers provide information about  $\delta_i$ , that is, as long as  $\tau_3 \neq 0$ , having this additional signal increases precision of posterior beliefs. Furthermore, the overall gain in precision depends on both  $\tau_3$  and  $\sigma_\omega$ , as they determine the biomarkers' signal-to-noise ratio. Equation (16) shows the posterior mean of  $\delta_i$  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  $\hat{\delta}_{it}$  and survival expectations  $plive10_{it}$ , a key issue is to measure the precision of the additional signal.

To measure that precision, I use the biomarker experiment in the spirit of [Todd and Wolpin \(2006\)](#). That is, to predict beliefs of group 1, I use parameters estimated using data from future waves of group 2. Specifically, I want to predict beliefs when biomarker information was first introduced between waves 8 and 9. By wave 8, only group 1 had their blood collected and by wave 9 only them had their biomarker information available as a second signal. I estimate the parameters governing the precision of that second signal, using individuals from group 2. They had their blood collected for the first time in wave 9, and they received their biomarker 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.<sup>39</sup> Using those parameters, I predict beliefs and survival expectations for group 1 in wave 9 (no second signal was available yet in wave 8). 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.

The overall results on survival expectations by group are presented in [Table 9](#). According to these results, 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 percentage points more than the control group. This change in survival expectations is positive but negligible, consistent with the results in [Table 8](#). Thus, though a valid signal for health profiles, biomarker results are only a small signal, not enough to shift beliefs and affects decisions in a considerable way.

## 9 Conclusion

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. In the first part of the paper, I show evidence that health dynamics are indeed heterogeneous. In

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<sup>39</sup> In an alternative version, I use a maximum likelihood approach to jointly estimate health and biomarker results as a function of slope heterogeneity  $\delta_i$ . 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.

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<sub>iw</sub>* 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  $\delta_i$  come from an estimation using future values of the control group (waves 9 and 10)

particular, I show health is heterogeneous in the way it changes with age and that this heterogeneity helps explain the increasing variance of health with age, a pattern observed in the population but mostly ignored by traditional models of health. Motivated by this evidence, I turn to the question of how much individuals know about their own health profiles. I develop 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. Leveraging data on subjective survival expectations, I find individuals are uncertain and they are negatively biased, that is, on average, they believe their health will deteriorate faster than the average rate on the population.

Using the results from the learning model, I infer individuals' beliefs about their own health profiles. In an economic model with heterogeneous and uncertain health dynamics, those beliefs are inputs in the policy rule for labor participation. I estimate this policy rule flexibly, using a neural-networks approach. I find that beliefs matter for 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, suggesting that adjustment costs of finding a job are important in individuals' decisions of going back to work. The framework and data-driven estimation approach imply this result is not a consequence of any additional structure imposed to the economic model. In an additional exercise, applying machine learning tools to predict also assets and health insurance, I simulate the effects on participation over time of eliminating the initial bias in beliefs. I find that labor-force participation would increase by up to 2 percentage points, an effect that lasts beyond traditional retirement ages. Taken together, these results suggests that there is room for policies to affect



labor-participation decisions by shifting individuals beliefs about their future health.

Thus, in the last part of the paper, I look at one such policy: the provision of information on blood glucose and cholesterol levels. I take advantage of the randomization done on the collection and provision of such information, and analyze the results using a reduced-form approach and a model-based approach. The results show the additional information has negligible effects on survival expectations and working decision. This negligible result is due to a small effect of the information on beliefs, as shown by the model. Nevertheless, 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.<sup>40</sup> 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. As final note of caution, note this paper assumes no endogenous acquisition of health information (for example, through preventive care), an interesting question that is left for future research.

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<sup>40</sup> Information policies have been studied in other settings; for example, [Delavande and Kohler \(2015\)](#) and [Bates \(2020\)](#). Information policies have also been studied in the context of surveys; for example, [Armona et al. \(2018\)](#) and [Wiswall and Zafar \(2014\)](#).

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