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The Dynamic Effects of Health on the Employment of Older Workers

Abstract

Using data from the Health and Retirement Study (HRS) and the English Longitudinal Study of Ageing (ELSA), we estimate a dynamic model of health and employment. We estimate how transitory and persistent health shocks affect employment over time. In a first step, we formulate and estimate a dynamic model of health. The procedure accounts for measurement error and the possibility that people might justify their employment status by reporting bad health. We find that health is well represented by the sum of a transitory white noise process and a persistent AR(1) process. Next, we use the method of simulated moments to estimate the employment response to these shocks. We find that persistent shocks have much bigger effects on employment than transitory shocks, and that these persistent shocks are long lived. For this reason employment is strongly correlated with lagged health, a fact that the usual cross-sectional estimates do not account for. We also show that accounting for the dynamics of health and employment leads to larger estimates of health's effects on employment than what simple OLS estimates of health on employment would imply. We argue that the dynamic effect of health on employment could be generated by a model with human capital accumulation, where negative health shocks slowly reduce the human capital stock, and thus, gradually cause people to exit the labor market.

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1 Introduction

This paper investigates the dynamic effects of health on the employment of older workers. Specifically, we estimate how transitory and permanent health shocks affect employment over time. Most research on the effect of health on employment does not distinguish between the short and the long run effects and yet these are likely to be very different, and both are important. A transitory health shock, such as a broken bone, may lead some to drop out of work for a short period of time, but many of these workers will be back into employment as their condition improves. However, poor health may have effects on employment that outlive the health condition for a myriad of reasons. For instance, by keeping individuals out of work, poor health may erode the individual competencies that are valued in the labor market, hence reducing productivity. Furthermore, individuals driven off employment because of a bad health shock may have a difficult time returning to the labor force, even if their health improves. The longer poor health conditions persist, the larger the productivity and long-term employment effects are expected to be.

Understanding the dynamic relationship between health and employment is key to informing the effective design and evaluation of public policy. For instance, disability policy aims to protect individuals against risks that are not insurable through the market. In the health context, uninsurable risks are likely related to shocks that persistently impair employment and earnings capacity. In turn, the institutional setting is likely to have a strong influence on the impact of health shocks on employment. Conceivably, more generous health insurance, sickness/incapacity benefits and off-work payments may promote both time off paid work *and* health investments in response to poor health. These benefits may affect employment in two opposite directions: positively, by leading to a fast recovery and a swift return to work, and negatively, by promoting time out of the labor market in the short run along with the consequent skill depreciation.

The dynamic interactions between health and labor supply are expected to change with age, particularly around retirement age as health problems become increasingly more frequent and serious, and out-of-work benefits change rapidly (Disney et al. (2006), Casanova (2013)). We focus on individuals in the years leading to retirement, aged 50-66, and estimate the overall impact of health on their employment by explicitly taking into account that these effects may build over time. We do this both for England and the US, two countries that share much in terms of culture and values while differing markedly in the institutional context in which older workers frame their decisions, including health policy, working and retirement incentives.

We develop a dynamic model of health and labor supply that allows for rich interactions between the two variables in order to capture the different paths leading to the long-term effects of health. To do so, our model extends those existing in the literature in several directions.[1] *First*, we distinguish between transitory and persistent shocks and allow their effects to differ. We believe that separating persistent shocks is crucial for two main reasons: they are a better indicator of the serious health conditions that are likely to limit current working capacity and productivity, and their persistency may lead to magnified consequences inflicted by permanent losses in productivity and labor market attachment. *Second*, we consider that past health may affect current labor supply, even after conditioning on current health. This may happen because health reduces opportunities for human capital investment, for example. As for current shocks, we allow for the effects of past shocks to differ by the nature of the shock, whether persistent or transitory. *Third*, we allow for the health effects to be reinforced through additional persistency of the employment

[1] E.g. Au et al., 2005, Disney et al. (2006), Bound et al. (1999), Bound et al. (2010), Bound et al. (1999).

process. And *fourth*, we control for person specific heterogeneity in health, allowing for the possibility that health and labor supply are correlated partly because more motivated people tend to be healthier. Put differently, we relax the assumption that the correlation between health and labor supply is exclusively driven by the effects that health may have on labor supply.

We find that health is well represented by the sum of a transitory white noise process and also a permanent AR(1) process. Next, we use the method of simulated moments to estimate the employment response to these shocks. We find that permanent shocks have much bigger effects on employment than transitory shocks, and that these permanent shocks are long lived. For this reason, employment is strongly correlated with lagged health, a fact that the usual cross sectional estimates do not account for. We also show that accounting for the dynamics of health and employment leads to larger estimates of the effect of health on employment than what simple OLS estimates of health on employment would imply. We argue that the dynamic effect of health on employment could be generated by a model with human capital accumulation, where negative health shocks slowly reduce the human capital stock, and thus slowly cause people to exit the labor market.

2 Model

We consider the health and employment processes of a single cohort, so time is age and is denoted by a. All parts of the model are education- and gender-specific, with three education groups: less than High School Dropouts, High School Graduates and University Graduates. In what follows, the gender and education dependencies are omitted to simplify the notation.

The health of individual i at age a follows the process

$$\begin{aligned} h_{ia} &= \beta_0 + x_{ia}\beta_x + \pi_{ia} + \epsilon_{ia} && (1)\\ \pi_{ia} &= \rho\pi_{ia-1} + \omega_{ia} && (2)\\ \omega_{ia}, \epsilon_{ia} &\sim iid && (3) \end{aligned}$$

where h is health, x includes an age polynomial and health outcomes of the individual as a child, π_{ia} is the persistent health shock, assumed to follow an AR(1) process with innovation ω_{ia}, and ϵ_{ia} is a transitory health shock, specified as a white noise. We assume that ω_{ia} and ϵ_{ia} are iid.[2]

Our model of employment allows for rich dynamic effects of health on employment. First, we consider that persistent and transitory shocks (π and ϵ) may have different effects on employment as they may stand for health conditions that limit work and productivity in very different ways. Second, we allow for health shocks to affect current employment, through a direct effect on productivity and preferences, and future employment, through lagged effects on earnings capacity or the ability to move back into work. And third, the persistency of employment may in itself help propagating the impact of health shocks over time. Formally, we specify the dynamic labor supply decision at the extensive margin by the latent variable model:

$$\begin{aligned} E^*_{ia} &= \alpha_0 + \alpha_{E1}E_{ia-1} + \alpha_{E2}(E_{ia-1} * a) + x_{ia}\alpha_x + \delta_0\pi_{ia} + \delta_1\pi_{ia-1} + \gamma_0\epsilon_{ia} + \gamma_1\epsilon_{ia-1} + u_{ia} && (4)\\ E_{ia} &= \mathbf{1}(E^*_{ia} > 0) && (5) \end{aligned}$$

[2]We considered alternative specifications of unobserved health, including an MA(1) process for the transitory component ϵ and age-dependent distributions. These did not significantly improve the fit of the health process.

where E^* is the latent process for employment and E is the employment indicator. We allow for the effect of lagged employment to vary with age to capture the rapidly changing incentives to work that workers face before retirement. The shock to employment, u, is assumed to be iid and independent of the health shocks. We further assume that (π, ϵ, u) are (independently) normally distributed and standardise the variance of u to 1.

3 Data

Our estimates are based on two longitudinal datasets: the US Health and Retirement Study (HRS) and the English Longitudinal Survey of Aging (ELSA). The ELSA data was based upon the design of the US Health and Retirement Study (HRS) data. For this reason, the timing of the interviews, their structure and the information collected are all very similar.

ELSA is designed to be a representative sample of non-institutionalized individuals living in England and aged 50 or older. Interviews were held bi-annually from 2002/03 onwards, with the six currently available waves covering the period up to 2012/13. The sample was drawn from respondents to the Health Survey for England (HSE) in 1998, 1999 or 2001, with refreshment samples added in waves 3 and 6 also drawn from the HSE. Both the selected members of the panel and their partners were interviewed in each wave, resulting in some respondents being younger than 50 at the time of the interview.

HRS began in 1992, with a representative sample of individuals living in the United States aged 50 to 61. These individuals were interviewed again biennially and refreshment samples were added every 6 years. A self-completion workbook was also left behind for respondents starting in 2004. Respondents were initially selected from the non-institutionalized population but efforts were made to include them in later waves even if they were admitted into nursing homes. We further augment the HRS dataset with the RAND HRS Data File which contains minor imputations of the core HRS variables and, in general, cleaner data. Similar to ELSA, if an individual is included in the HRS, so too is their partner, regardless of age.

In both cases, our estimates are based on the sub-sample of main respondents and their partners aged 50 to 66. We use the entire collection of waves for ELSA and the HRS, covering the years up to 2012.

In total, there are 11,217 individuals in ELSA aged 50-66, of whom 54% are women. 12% of our ELSA sample respondents are observed for all 6 waves, and more than half are observed for at least 3 waves. In the HRS there are 24,804 individuals, with the same sex ratio as in ELSA. almost 8% of the respondents are observed over the 8 waves that cover our age-window, and almost 70% are observed for at least 3 waves. The education and gender distribution of both samples is detailed in Table 1. We consider three education levels, the lowest corresponding to high-school dropouts in the US and GCSE qualitfications in England, the medium being high-school graduates and the highest level being 3+ years college degrees. The sample sizes per wave are outlined in Table 3.

A critical issue for our analysis is how to measure health. The literature on the effects of health has raised concerns that estimates of these impacts may be biased due to measurement error in health.[3] One problem is that only limited health measures are generally available, and

[3]Bound (1991) and Stern (1989).

Table 1: ELSA and HRS sample sizes by education and gender

	ELSA		HRS	
	Men	Women	Men	Women
High School dropouts	1653	2362	2437	2839
High school	2312	2687	6309	8065
College	1193	1010	2635	2519

Table 2: ELSA and HRS years and sample sizes

	ELSA		HRS	
Year	Wave	Sample Size	Wave	Sample Size
1992	-	-	1	10,857
1994	-	-	2	9,989
1996	-	-	3	9,480
1998	-	-	4	10,311
2000	-	-	5	8,763
2002	1	8,008	6	7,422
2004	2	6,104	7	8,733
2006	3	6,403	8	7,146
2008	4	7,426	9	5,913
2010	5	6,620	10	10,544
2012	6	6,834	11	9,597

Sample sizes for 50-70 year olds only.

Table 3: ELSA data - observations in selected sample, by wave

Wave	Year	Sample Size
1	2002	6,339
2	2004	4,781
3	2006	5,185
4	2008	5,955
5	2010	5,139
6	2012	5,208

those available may capture only one dimension of health. This issue is especially relevant when estimating the effect of objective measures on labour supply. For example, whether an individual has diabetes may or may not have a sizeable effect on labour supply depending, amongst other things, on her other health conditions. Furthermore, people may errantly misreport their health status because they misinterpret a question, or interpret the question differently than others.[4] Most likely, this type of measurement error leads to an understatement of the effect of health on labour supply. Another problem is that estimates of the effect of health status and labour supply potentially suffer from "justification bias", as those who are not working might claim to be

[4]For example Kapteyn et al. (2007) show that differences in reported work disability between the Dutch and Americans largely stem from the fact that Dutch respondents have a lower threshold in reporting whether they have a work disability than American respondents.

unhealthy in order to justify their working status. [5] This would likely lead to an overstatement of the effect of health on labour supply. In most of these studies, the estimated effect of health on labour supply is found to be larger when using subjective measures than objective measures (Blundell et al. (2016)). These differences in estimates could be attributable to either of these mechanisms.

We deal with measurement error in health by building a composite index using all the objective and subjective self-reported measures of health that are observed in all waves. The objective health measures consist of questions relating to whether the respondent has a given chronic illness (such as cancer or diabetes) and measures on mobility and Activities of Daily Living (ADL). All these are listed in Table 4, together with some brief descriptive statistics.[6] Similarly, Table 5 describes all subjective health measures in our index. The two tables clearly demonstrate the similarities in the measurement of health in the two surveys.

We construct the health index using a two step procedure. First, we extract the first factor from a principal component analysis of the set of subjective health measures; this should deal with the first problem mentioned above. Second, we instrument this subjective health factor with objective measures of health, which should take care of justification bias as objective measures are less likely to be sensitive to it. We describe our principal components analysis more carefully in appendix A.

[5] See, for example Butler et al. (1987).

[6] The objective health measures are all dichotomous variables about specific conditions, mostly aiming to assess whether the respondent has recently received or is currently receiving treatment for each condition. The subjective health measures aim to assess overall wellbeing and working capacity.

Table 4: Objective health variables

Variable	Description	N	Min	Max	Mean	SD
ELSA Data						
Cancer	Received cancer treatment in past 2 years	41361	0	1	0.02	0.15
Diabetes	Taking medication for diabetes	41356	0	1	0.05	0.22
Sight	Reported poor eyesight	41358	0	1	0.02	0.14
Hearing	Reported poor hearing	41360	0	1	0.03	0.17
Blood pressure	Taking medication for high blood pressure	41389	0	1	0.24	0.42
Arthritis	Reported arthritis this wave	41154	0	1	0.28	0.45
Psychiatric	Reported psychiatric problem this wave	41391	0	1	0.07	0.25
Difficulty Walking One Block	Mobility: Does not (0), does (1)	41297	0	1	0.09	0.28
Difficulty Sitting for Two Hours	Mobility: Does not (0), does (1)	41297	0	1	0.13	0.34
Difficulty Getting Up from a Chair	Mobility: Does not (0), does (1)	41297	0	1	0.21	0.41
Difficulty Climbing Several Flights of Stairs	Mobility: Does not (0), does (1)	41297	0	1	0.28	0.45
Difficulty Climbing One Flight of Stairs	Mobility: Does not (0), does (1)	41297	0	1	0.10	0.30
Difficulty Stooping, Kneeling, or Crouching	Mobility: Does not (0), does (1)	41297	0	1	0.30	0.46
Difficulty Lifting or Carrying 10 pounds	Mobility: Does not (0), does (1)	41297	0	1	0.18	0.38
Difficulty Picking Up a Dime	Mobility: Does not (0), does (1)	41297	0	1	0.04	0.20
Difficulty Extending Arms	Mobility: Does not (0), does (1)	41297	0	1	0.09	0.29
Difficulty Pushing or Pulling Large Object	Mobility: Does not (0), does (1)	41297	0	1	0.13	0.34
Difficulty Walking across Room	ADL: Does not (0), does (1)	41299	0	1	0.02	0.15
Difficulty Getting Dressed	ADL: Does not (0), does (1)	41299	0	1	0.10	0.30
Difficulty Bathing or Showering	ADL: Does not (0), does (1)	41299	0	1	0.07	0.26
Difficulty Eating	ADL: Does not (0), does (1)	41299	0	1	0.02	0.12
Difficulty Getting In or Out of Bed	ADL: Does not (0), does (1)	41299	0	1	0.05	0.23
Difficulty Using the Toilet	ADL: Does not (0), does (1)	41299	0	1	0.03	0.16
HRS Data						
Cancer	Reported cancer this wave	103139	0	1	0.10	0.30
Diabetes	Reported diabetes this wave	103006	0	1	0.18	0.38
Sight	Reported poor eyesight	103253	0	1	0.04	0.21
Hearing	Wears hearing aid	103263	0	1	0.04	0.19
Blood pressure	Reported high blood pressure this wave	102672	0	1	0.50	0.50
Arthritis	Reported arthritis this wave	102652	0	1	0.52	0.50
Psychiatric	Reported psychiatric problem this wave	102793	0	1	0.17	0.38
Difficulty Walking One Block	Mobility: Does not (0), does (1)	103052	0	1	0.01	0.08
Difficulty Sitting for Two Hours	Mobility: Does not (0), does (1)	103036	0	1	0.00	0.06
Difficulty Getting Up from a Chair	Mobility: Does not (0), does (1)	103026	0	1	0.00	0.05
Difficulty Climbing Several Flights of Stairs	Mobility: Does not (0), does (1)	102950	0	1	0.03	0.18
Difficulty Climbing One Flight of Stairs	Mobility: Does not (0), does (1)	103009	0	1	0.02	0.13
Difficulty Stooping, Kneeling, or Crouching	Mobility: Does not (0), does (1)	103012	0	1	0.02	0.15
Difficulty Lifting or Carrying 10 pounds	Mobility: Does not (0), does (1)	103032	0	1	0.02	0.12
Difficulty Picking Up a Dime	Mobility: Does not (0), does (1)	103039	0	1	0.00	0.04
Difficulty Extending Arms	Mobility: Does not (0), does (1)	103032	0	1	0.00	0.07
Difficulty Pushing or Pulling Large Object	Mobility: Does not (0), does (1)	103022	0	1	0.02	0.14
Difficulty Walking across Room	ADL: Does not (0), does (1)	103065	0	1	0.00	0.05
Difficulty Getting Dressed	ADL: Does not (0), does (1)	103073	0	1	0.00	0.05
Difficulty Bathing or Showering	ADL: Does not (0), does (1)	103070	0	1	0.00	0.04
Difficulty Eating	ADL: Does not (0), does (1)	103078	0	1	0.00	0.03
Difficulty Getting In or Out of Bed	ADL: Does not (0), does (1)	103067	0	1	0.00	0.03
Difficulty Using the Toilet	ADL: Does not (0), does (1)	103070	0	1	0.00	0.03

Table 5: Subjective health variables

Variable	Description	N	Min	Max	Mean	SD
ELSA Data						
Health limits activities	Does not (0), does (1)	39421	0	1	0.53	0.50
General health	Excellent (1), very good (2), good (3), fair (4), poor (5)	36231	1	5	2.59	1.11
Health limits work	Does not (0), does (1)	33341	0	1	0.25	0.43
HRS Data						
Health limits activities	Does not (0), does (1)	103273	0	1	0.13	0.33
General health	Excellent (1), very good (2), good (3), fair (4), poor (5)	103219	1	5	2.77	1.13
Health limits work	Does not (0), does (1)	99649	0	1	0.26	0.44

Our choice to synthesise all health information in a single index is simple and parsimonious, but is only adequate for our purpose of measuring the impact of health on employment if it is capable of summarising the relevant health information for employment. We have investigated this by estimating regression models controlling for more detailed health information and found that adding more detailed information produces results similar to the ones we get with our single index. In particular, we have tried the following.[7]

First, we tried using not just the first principle component but the second principle component of the subjective measures in the employment equation. The regression coefficient on the second principle component was not statistically significant and was small in magnitude. This holds whether or not we just regressed employment on the first and second principle components or instrumented for these two principle components using the objective health measures. Thus we decided that little would be gained by adding the second principle component.

Second, we tried regressing employment on all the objective health measures. This procedure produced similar but less stable and usually smaller estimated effects of health on employment than our preferred method of regressing employment on our single health index.[8] We attribute our more stable and slightly larger estimates using our procedure to the fact that our procedure handles measurement error in the objective health measures. See also Blundell et al. (2016) for more details on the data, and the robustness of estimates to alternative measures of health.

4 Estimation

For simplicity, we denote by 0 the youngest age group in our sample, aged 50-51. The parameters of interest are those characterising the dynamics of health, $(\rho, \sigma_\omega, \sigma_{\pi_0}, \sigma_\epsilon)$, its effect on employment $(\eta_0, \eta - 1, \delta_0, \delta_1, \gamma)$, the effects of lagged employment on current employment $(\alpha_{E1}, \alpha_{E2})$, and the initial (at age 0) correlation between employment and the health error components $(\sigma_{E_0\pi_0}, \sigma_{E_0\epsilon_0})$.

We estimate the model in two steps. First, the parameters in the health process $(\rho, \sigma_\omega, \sigma_{\pi_0}, \sigma_\epsilon)$ can be estimated in a first stage by using an error components model. We estimate the parameter

[7] Detailed results available from the authors upon request.

[8] For example, we calculated the share of the employment decline between ages 52 and 69 that can be explained by declining health as implied by our health index or by the entire set of objective measures. Using our our preferred approach and averaging over our education groups, we can explain 12% of the decline in employment among men in both the ELSA and HRS data. The similar measures using the collection of objective measures is 5% and 12% for the ELSA and HRS data, respectively.

vector that best matches the empirical auto-covariance matrix of health residuals, where the health residuals are constructed using a regression of health on an age polynomial only. The time correlations in individual residuals separate the structure of the persistent and transitory health shocks. Since health is pre-determined in our model, the parameters of the health model can be estimated without any reference to the employment decision.

In the second step we estimate the other model parameters using the Method of Simulated Moments conditional on the structure of the health process.[9] The estimation procedure at this stage is conditional on the parameters driving the health shocks. We assume all health and employment residuals are normally distributed and independent, so the employment regression is a probit. Lagged employment is endogenous in this regression given its relationship with health residuals. We explicitly account for this dependence by simulating employment conditional on health shocks, using simulated lagged employment in predicting future employment status, and by matching employment rates by age and the autocovariances of employment calculated on this simulated series with their data counterparts. Furthermore, endogeneity of initial employment is dealt with by starting the simulations 4 periods (8 years) prior to the start of the age interval observed in the data.

For any set of parameters, $(\delta_0, \delta_1, \gamma_0, \gamma_1, \alpha_{E1}, \alpha_{E2})$, we simulate the health residuals and the employment process over the entire observation period for every individual and select the parameter vector that minimizes the GMM criterion:

$$\left(\hat{M}^d - M^m(\Theta)\right)' \hat{\Omega}^{-1} \left(\hat{M}^d - M^m(\Theta)\right) \tag{6}$$

where $(\hat{M}^d, M^m)$ are the data and model simulated moments, respectively, and $\hat{\Omega}$ is the estimated variance-covariance matrix of the data moments estimates. We then select the set of parameters for which the moments calculated from the simulated data best match moments estimated with ELSA or HRS data. We chose to match 3 sets of moments: the auto-covariance matrix of employment, the matrix of cross-correlations between employment and health residuals, and a set of moments describing employment probabilities by age. Since the dynamic structure of the health process is known at this stage, the cross-correlations between employment and health help identifying the coefficients driving the effects of health on employment (the δ's and γ's). Then the other moments capture the employment rates, how they change with age and the coefficients on lagged employment.[10]

The following describes our procedure to estimate $\Theta = (\delta_0, \delta_1, \gamma_0, \gamma_1, \alpha_{E1}, \alpha_{E2})$ conditional on the parameters characterising the residual health process and estimated in step 1, $(\hat{\rho}, \hat{\sigma}_\omega, \hat{\sigma}_{\pi_0}, \hat{\sigma}_\epsilon)$.

1. Estimate all moments and the variance-covariance matrix of these estimates on survey data (ELSA or HRS) for 50-65 year olds.

2. Using the estimated parameters from step 1, simulate the health residuals process from the age of 42 to 65.

3. Choose initial values of the parameters being estimated in the second stage and get employment at age 42 from historical data.

4. Simulate the employment process from age 42 to 65.

[9] Original references are McFadden (1989) and Pakes and Pollard (1989).
[10] Further details of our identification strategy can be found in the appendix B.

5. Calculate the model generated moments using simulations for the age group 50-65.
6. Compare model generated moments to the moments in the data. Calculate the GMM criterion.
7. Take a new set of parameters (where the new set is taken using a Nelder-Mead/Amoeba algorithm) and repeat steps 4-6 until a global minimum is found.

5 Results

Our key findings are as follows:

1. The dynamic properties of health are well described by the sum of a highly persistent AR(1) component, plus a transitory component.
2. Transitory health shocks have little impact on employment.
3. Permanent health shocks have much bigger effects on employment.
4. Employment is highly persistent. Lagged employment strongly predicts current employment, even after accounting for the persistence in health.
5. Model estimates suggest a larger impact of health on employment than what OLS estimates imply.

This section describes these findings in greater depth.

5.1 The health process

5.1.1 Estimates

Table 6 presents estimates of the parameters of the health process using ELSA and HRS data. Estimates are by gender for the three educational groups we consider, corresponding to high-school dropouts (Ed 1), high-school graduates (Ed 2) and college graduates (Ed 3).

The figures in Table 6 show show remarkable similarities between the health processes estimated for the two countries. In both cases, the dynamic properties of health are well described by the sum of a highly persistent AR(1) component plus a transitory component. Moreover, the autocorrelation parameter (ρ) is close to 0.9 for all groups. However, the dispersions in the initial permanent health component ($\sigma_{\pi 0}$) and in persistent health shocks (σ_{ω}) are generally higher in England than in the US. These differences are partly compensated amongst low and medium educated men, who face an higher dispersion in the transitory health shocks (ϵ) in the US than in England. More generally, the variability of both the transitory and the permanent health shocks vary a great deal from group to group.

	Health parameters			
	Var pers. shock (σ^2_ω)	Var initial π ($\sigma^2_{\pi 0}$)	Autocorr coeff (ρ)	Var trans. shock (σ^2_ϵ)
	Estimates for England			
Men, Ed 1	0.325	0.988	0.903	0.047
Men, Ed 2	0.171	1.045	0.914	0.123
Men, Ed 3	0.100	0.705	0.920	0.166
Women, Ed 1	0.137	0.622	0.934	0.108
Women, Ed 2	0.024	0.121	1.058	0.120
Women, Ed 3	0.059	0.475	0.984	0.118
	Estimates for the US			
Men, Ed 1	0.097	0.604	0.893	0.254
Men, Ed 2	0.051	0.679	0.951	0.219
Men, Ed 3	0.073	0.368	0.907	0.133
Women, Ed 1	0.051	0.395	0.940	0.133
Women, Ed 2	0.020	0.159	0.956	0.070
Women, Ed 3	0.036	0.174	0.907	0.041

Table 6: Parameter estimates for the health process 50-66 (diagonal weights). Ed 1, 2, 3 is high-school dropouts, high school graduates and college graduates respectively.

5.1.2 Model Fit

Figures 1 and 2 show how the model fits the variance of health across the different age groups. Unsurprisingly, those with the lowest education have the most variable health for both genders, and for both England and the US. Moreover, the health measure is more disperse among men than it is among women. This is consistent with low educated men being especially at risk of serious negative health shocks and with the high disability rates among them.

The results for England show, as expected, that the variability of health rises with age as some people remain healthy while others accumulate health problems or are hit by large negative health shocks. However, this pattern is not clear in the US, where indeed the variability of the health process is mostly flat or even mildly decreasing with age among low and medium educated men. Moreover, in line with estimates in Table 6, these figures show that the dispersion of health in England is higher than that in the US for all groups at all ages. In future work, we will investigate the connections between our health indexes and the specific health conditions underlying them to shed light on these cross-country differences in levels and age patterns.

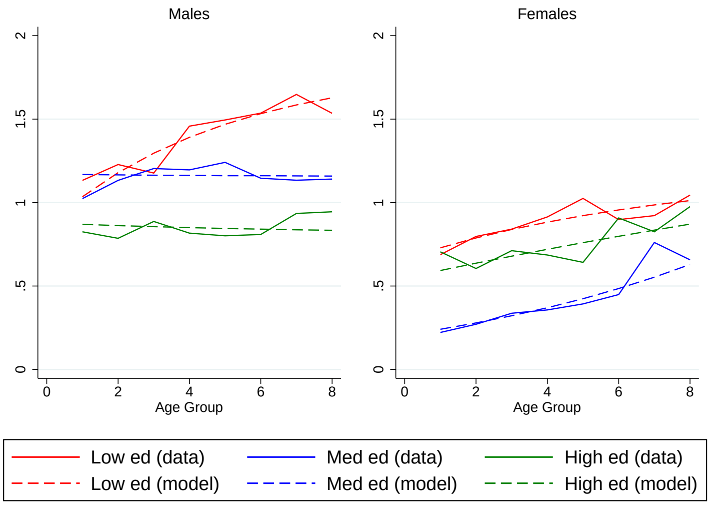


Figure 1: England - model fit for the variance of health on age, by gender and education. Low, Med and High Ed stad for high-school dropouts, high school graduates and college graduates respectively.

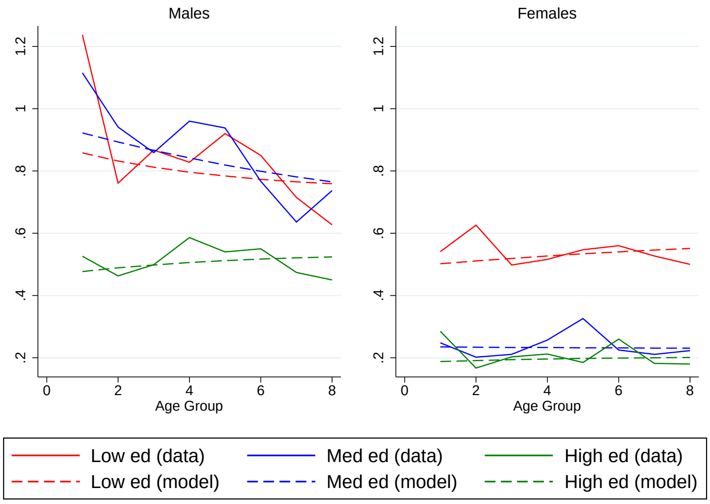


Figure 2: US - model fit for the variance of health on age, by gender and education. Low, Med and High Ed stad for high-school dropouts, high school graduates and college graduates respectively.

Figures 1 and 2 show that the model captures well the age patterns in the variance of health. These variances are a subset of the moments we use in estimation, corresponding to the diagonal elements of the auto-covariance matrix of the health residuals. The fit of the remaining moments are shown in Tables 7 and 8 for high-school dropout men. Similar figures are available from the authors for the other groups.

Tables 7 and 8 show that the model also captures the covariances well. For both datasets, there is a big drop between the variance and first autocovariance. For example, the variance of the health index for 50-51 years old in England is 1.133, but the first auto-covariance (between age 50-51 and 52-53) is 0.878. A similar pattern can be seen for all other groups. This drop is consistent with the view that there is a non-trivial transitory component to health. Subsequent covariances remain high, however. For example, the covariance between health at age 50-51 and 60-61 is 0.623, which is consistent with the view that there is an important persistent component of health. As we show below, the employment responses to the transitory and persistent components of health are very different.

	Age groups							
Age groups	50-51	52-53	54-55	56-57	58-59	60-61	62-63	64-65
	Data							
50-51	1.133							
52-53	0.878	1.228						
54-55	0.857	0.964	1.177					
56-57	0.803	0.946	1.071	1.458				
58-59	0.731	0.774	1.076	1.321	1.495			
60-61	0.623	0.783	0.777	1.195	1.198	1.536		
62-63		0.641	0.682	0.983	1.241	1.330	1.648	
64-65			0.633	0.953	1.254	1.229	1.374	1.535
	Model							
50-51	1.035							
52-53	0.893	1.179						
54-55	0.806	1.022	1.296					
56-57	0.728	0.923	1.128	1.391				
58-59	0.658	0.834	1.019	1.214	1.469			
60-61	0.595	0.754	0.921	1.097	1.285	1.533		
62-63		0.681	0.832	0.991	1.161	1.342	1.585	
64-65			0.751	0.895	1.049	1.213	1.389	1.628

Table 7: England - Health variance covariance matrix for men, high-school dropouts, data vs model

	Age groups							
Age groups	50-51	52-53	54-55	56-57	58-59	60-61	62-63	64-65
	Data							
50-51	1.237							
52-53	0.424	0.761						
54-55	0.528	0.422	0.867					
56-57	0.569	0.436	0.538	0.828				
58-59	0.514	0.382	0.462	0.467	0.920			
60-61	0.477	0.345	0.409	0.451	0.505	0.850		
62-63	0.243	0.321	0.354	0.419	0.456	0.483	0.715	
64-65	0.197	0.341	0.277	0.286	0.410	0.391	0.470	0.627
	Model							
50-51	0.858							
52-53	0.539	0.832						
54-55	0.481	0.516	0.812					
56-57	0.429	0.461	0.498	0.796				
58-59	0.383	0.412	0.445	0.484	0.784			
60-61	0.342	0.367	0.397	0.432	0.473	0.773		
62-63	0.306	0.328	0.355	0.386	0.422	0.464	0.765	
64-65	0.273	0.293	0.317	0.345	0.377	0.414	0.457	0.759

Table 8: US - Health variance covariance matrix for men, high-school dropouts, data vs model

5.2 The employment process

5.2.1 Estimates

The coefficient estimates for the employment process are given in Table 9. The coefficients α_{E1} and α_{E2} suggest a high degree of persistence in employment. For instance, estimates imply that the index E^* raises by 1.256 for a 50 year old, high-school dropout man in England if they worked in the previous period, and it raises by 1.256+5*0.419=3.351 at the age of 60. To put these values in perspective, take the values of $(var(\pi_0), var(\epsilon))$ to be (1,0.05), similar to the figures in Table 6, and the value of all other coefficients in the employment index (except the effect of lagged employment) to be zero. Then the predicted probability of employment at age 50 would be .5 if not working in the previous period and .79 if working the previous period.[11] Lagged employment is also a main driver of current employment in the US, with estimates very close to those obtained for England.

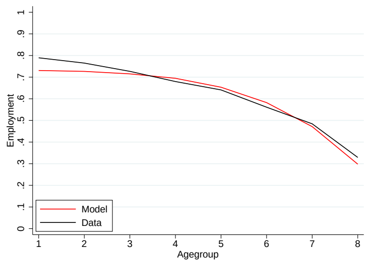
The estimates of the impact of persistent shocks are very similar in both countries, generally larger for men than for women and decreasing in education attainment (coefficients on π and its lag). The effects of the transitory shocks show no clear patterns, varying widely by education, gender and country, which suggests they are not important drivers of employment.

[11]The variance of the residual in the equation is 1+1*0.687-0.05*2.649=1.55. So $\Phi(0) = .5$ if not working in the previous period and $\Phi(1.256/1.55) = .79$ if working the previous period.

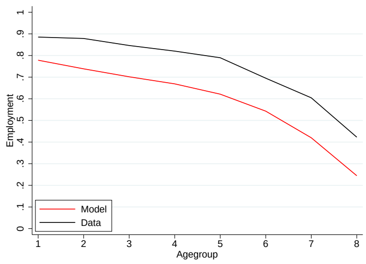
	Coefficients in employment process							
	constant (α_0)	E_{t-1} (α_{E1})	$E_{t-1}\times$age (α_{E2})	age (α_2)	age^2 (α_3)	age^3 (α_4)	coeffs on (π_t, π_{t-1}) ($\sum\delta$)	coeffs on $(\epsilon_t, \epsilon_{t-1})$ ($\sum\gamma$)
	Estimates for England							
Men, Ed 1	0.025	1.256	0.419	-.249	0.022	-.008	0.687	-2.649
Men, Ed 2	-1.155	2.951	0.042	-.167	0.052	-.008	0.465	-1.424
Men, Ed 3	-.279	2.258	0.413	-.274	-.023	-.002	0.463	-.397
Women, Ed 1	-.436	1.998	0.090	-.003	-.066	0.005	0.271	0.532
Women, Ed 2	-.036	1.786	0.027	0.333	-.197	0.017	0.389	-.517
Women, Ed 3	-.357	2.362	0.046	0.120	-.102	0.007	0.205	0.158
	Estimates for the US							
Men, Ed 1	-1.140	3.023	-.043	0.244	-.062	0.001	1.113	-1.970
Men, Ed 2	-1.528	2.696	-.061	0.153	0.034	-.007	0.354	-.207
Men, Ed 3	-.653	2.444	0.052	0.000	-.018	-.001	0.501	-.568
Women, Ed 1	-1.582	2.264	0.042	0.099	0.018	-.005	0.410	-1.245
Women, Ed 2	0.292	0.456	0.168	0.077	-.073	0.005	0.374	0.013
Women, Ed 3	-1.049	2.983	-.059	-.021	-.004	-.001	0.161	-.197

Table 9: Estimates of parameters in dynamic employment process. Ed 1, 2, 3 stand for high-school dropouts, high school graduates and college graduates respectively. Parameters correspond to coefficients in equation 10, where $\alpha_2, \alpha_3, \alpha_4$ are the coefficients on the age cubic.

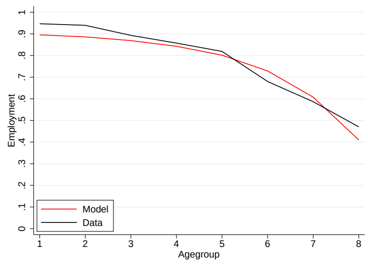
5.2.2 Model Fit



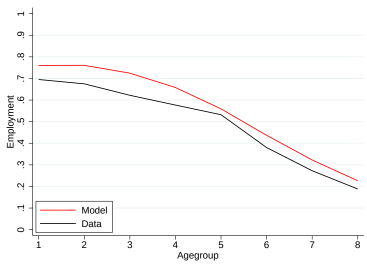
Men, high-school dropouts



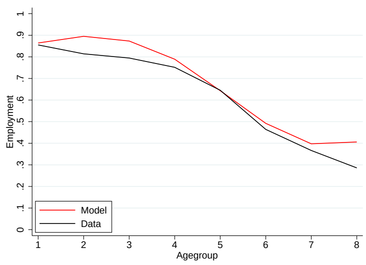
Men, high-school graduates



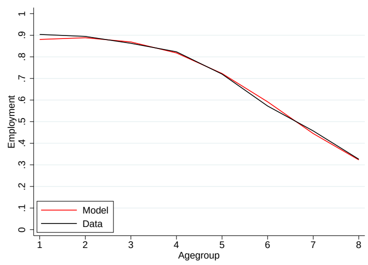
Men, college dropouts



Women, high-school dropouts

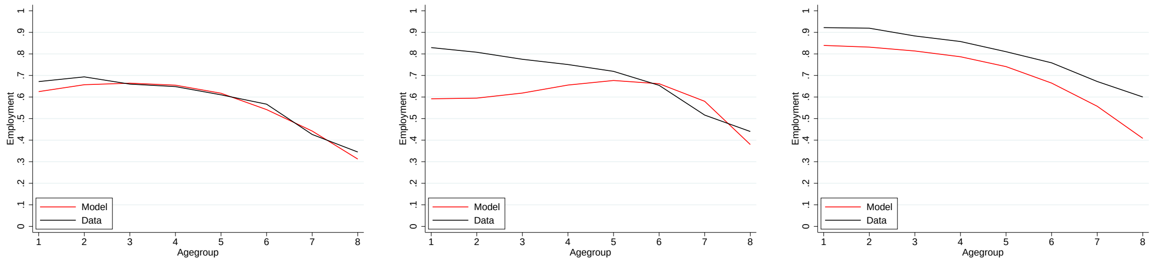


Women, high-school graduates

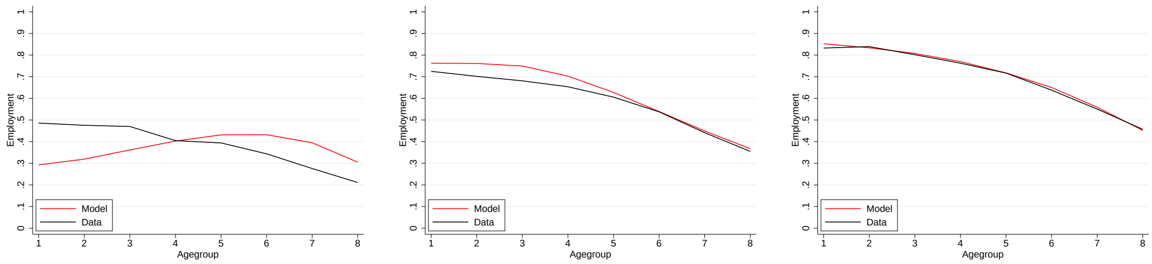


Women, college graduates

Figure 3: England - Mean employment, actual (black) vs model (red) by gender and education.



Men, high-school dropouts | Men, high-school graduates | Men, college dropouts



Women, high-school dropouts | Women, high-school graduates | Women, college graduates

Figure 4: US - Mean employment, actual (black) vs model (red) by gender and education.

Figures 4 and 3 contrast survey employment profiles by age with those predicted by the model. The fit is generally good but not equally so for all groups. For England, the model does worse in capturing the employment level of high-school graduated men, while for the US it fails to capture the employment profile of high-school graduated men and high-school dropout women, as well as the employment level of college graduated men.

Other moments are closely fit. Tables 10 and 11 show the variance-covariance matrix of employment for high-school dropout men estimated on survey data and predicted by the model, for England and the US respectively.[12] Employment is highly serially correlated. This serial correlation in employment is captured both through the lagged employment parameter and through the persistent component of health.

[12]Similar figures for other groups available from the authors.

	Age groups							
Age groups	50-51	52-53	54-55	56-57	58-59	60-61	62-63	64-65
	Data							
50-51	0.1672							
52-53	0.1344	0.1803						
54-55	0.1203	0.1491	0.1990					
56-57	0.1057	0.1452	0.1542	0.2181				
58-59	0.0687	0.1146	0.1364	0.1699	0.2305			
60-61	0.0092	0.0884	0.1245	0.1522	0.1639	0.2466		
62-63		0.0538	0.1101	0.1269	0.1466	0.1822	0.2501	
64-65			0.0943	0.0850	0.1041	0.1143	0.1425	0.2211
	Model							
50-51	0.1967							
52-53	0.1322	0.1986						
54-55	0.1001	0.1490	0.2037					
56-57	0.0840	0.1212	0.1644	0.2121				
58-59	0.0758	0.1064	0.1424	0.1834	0.2265			
60-61	0.0671	0.0914	0.1224	0.1569	0.1947	0.2432		
62-63		0.0738	0.0987	0.1263	0.1564	0.1952	0.2492	
64-65			0.0638	0.0814	0.0990	0.1232	0.1572	0.2092

Table 10: England - Employment variance covariance matrix for men, high-school dropouts, data vs model

	Age groups							
Age groups	50-51	52-53	54-55	56-57	58-59	60-61	62-63	64-65
	Data							
50-51	0.2212							
52-53	0.1532	0.2128						
54-55	0.1251	0.1548	0.2246					
56-57	0.1332	0.1315	0.1637	0.2281				
58-59	0.1323	0.1188	0.1491	0.1703	0.2380			
60-61	0.0726	0.0922	0.1154	0.1377	0.1655	0.2457		
62-63	0.0672	0.0705	0.0910	0.0997	0.1181	0.1536	0.2448	
64-65	0.0457	0.0682	0.0847	0.0818	0.0865	0.1145	0.1539	0.2262
	Model							
50-51	0.2344							
52-53	0.1776	0.2254						
54-55	0.1376	0.1737	0.2230					
56-57	0.1081	0.1334	0.1713	0.2260				
58-59	0.0907	0.1091	0.1355	0.1779	0.2362			
60-61	0.0733	0.0864	0.1053	0.1344	0.1783	0.2483		
62-63	0.0567	0.0663	0.0804	0.1007	0.1302	0.1792	0.2467	
64-65	0.0410	0.0471	0.0557	0.0677	0.0857	0.1146	0.1581	0.2148

Table 11: England - Employment variance covariance matrix for men, high-school dropouts, data vs model

Tables 12 and 13 show the covariance matrix of health and employment for men who are high-school dropouts in England and the US, respectively.[13] Interestingly, employment correlation with lagged health is similar the employment correlation with current health. For example,

[13] Again, similar moments for the other education and gender groups can be obtained from the authors.

in England the covariance between employment and health at ages 58-59 is 0.3384, whereas covariance between employment at ages 58-59 and health at ages 56-57 is 0.3427.

Lagged health is likely to be highly correlated with employment through two channels within the model. First, health itself is persistent. Second, health impacts employment, which in turn affects future employment. To get a better sense of the importance of these mechanisms, we simulate the impact of health shocks on employment below.

Health by	Employment by age group							
age groups	50-51	52-53	54-55	56-57	58-59	60-61	62-63	64-65
				Data				
50-51	0.2813	0.2640	0.2368	0.2029	0.1716	0.1253		
52-53	0.2828	0.2758	0.2854	0.2996	0.2569	0.1771	0.1789	
54-55	0.2702	0.2717	0.2991	0.3014	0.3212	0.2035	0.2504	0.2278
56-57	0.2566	0.2769	0.3048	0.3111	0.3427	0.2854	0.2828	0.2807
58-59	0.2239	0.1934	0.2795	0.3426	0.3384	0.2983	0.3131	0.3121
60-61	0.1357	0.1749	0.1894	0.2892	0.2762	0.3186	0.3169	0.2751
62-63		0.1302	0.1897	0.2476	0.2554	0.3093	0.3231	0.2748
64-65			0.1636	0.1844	0.1955	0.2221	0.2045	0.1884
				Model				
50-51	0.2131	0.1935	0.1888	0.1850	0.1835	0.1784		
52-53	0.2034	0.2362	0.2295	0.2284	0.2283	0.2225	0.2086	
54-55	0.1823	0.2233	0.2593	0.2579	0.2632	0.2626	0.2473	0.1882
56-57	0.1655	0.2007	0.2424	0.2809	0.2887	0.2926	0.2801	0.2161
58-59	0.1476	0.1813	0.2191	0.2616	0.3037	0.3113	0.3051	0.2365
60-61	0.1323	0.1623	0.1948	0.2347	0.2816	0.3267	0.3219	0.2609
62-63		0.1470	0.1756	0.2123	0.2553	0.3028	0.3397	0.2765
64-65			0.1613	0.1960	0.2343	0.2785	0.3222	0.3071

Table 12: England - Health employment covariance matrix for men, high-school dropouts, data vs model

Health by age groups	Employment by age group							
	50-51	52-53	54-55	56-57	58-59	60-61	62-63	64-65
	Data							
50-51	0.2202	0.1590	0.1475	0.1639	0.1538	0.1465	0.1069	0.0563
52-53	0.2199	0.1810	0.1544	0.1562	0.1380	0.1214	0.1054	0.0654
54-55	0.2589	0.1861	0.2217	0.1875	0.1629	0.1498	0.1260	0.0848
56-57	0.2521	0.2133	0.2257	0.1993	0.1583	0.1388	0.1151	0.0773
58-59	0.2588	0.2124	0.2122	0.2046	0.2064	0.1477	0.1259	0.0966
60-61	0.2161	0.1832	0.1829	0.1882	0.1858	0.1882	0.1365	0.1064
62-63	0.1438	0.1458	0.1390	0.1295	0.1382	0.1446	0.1166	0.0948
64-65	0.1285	0.1179	0.1106	0.0893	0.1005	0.0915	0.1018	0.0961
	Model							
50-51	0.1812	0.1331	0.1462	0.1498	0.1527	0.1491	0.1355	0.1080
52-53	0.1718	0.1743	0.1319	0.1461	0.1518	0.1530	0.1406	0.1122
54-55	0.1528	0.1680	0.1733	0.1307	0.1448	0.1518	0.1452	0.1218
56-57	0.1390	0.1501	0.1665	0.1718	0.1314	0.1484	0.1462	0.1262
58-59	0.1212	0.1356	0.1493	0.1665	0.1763	0.1255	0.1401	0.1251
60-61	0.1104	0.1191	0.1323	0.1481	0.1682	0.1764	0.1203	0.1204
62-63	0.0990	0.1099	0.1212	0.1322	0.1495	0.1699	0.1708	0.0997
64-65	0.0875	0.0971	0.1072	0.1188	0.1365	0.1547	0.1694	0.1546

Table 13: US - Health employment covariance matrix for men, high-school dropouts, data vs model

5.2.3 Simulating health shocks

To give a sense of the importance of the dynamic model, we compare the predicted employment decline from a one standard deviation negative shock to health as predicted by the estimated dynamic model relative to what would be predicted using OLS estimates of the effect of health on employment. Results are displayed in figures 5 and 6. Our estimated dynamic model has a predicted employment response that is similar to the OLS estimates although the employment response is slightly longer lived. This is true for both England and the US. The reason why our estimates from the dynamic mode persist for longer is the strong correlation between lagged and current employment and also because lagged health appears to impact current employment, even after accounting for lagged employment and current health. However, the predictions from the OLS regression model combined with the dynamic model of health capture a very similar pattern.

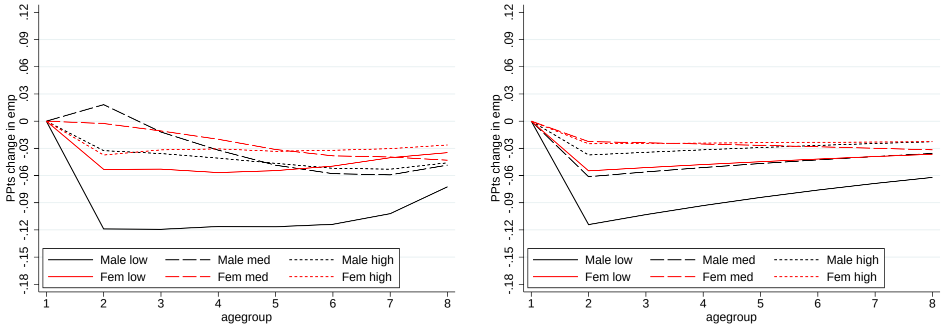


Figure 5: England - Model predictions (left) and OLS predictions (right) of employment response to a 1 standard deviation shock to the permanent component of health at age 50-51. Low, med and high are for high-school dropouts, high-school graduates and college graduates. Age groups 1 to 8 are for 50-51 to 64-65.

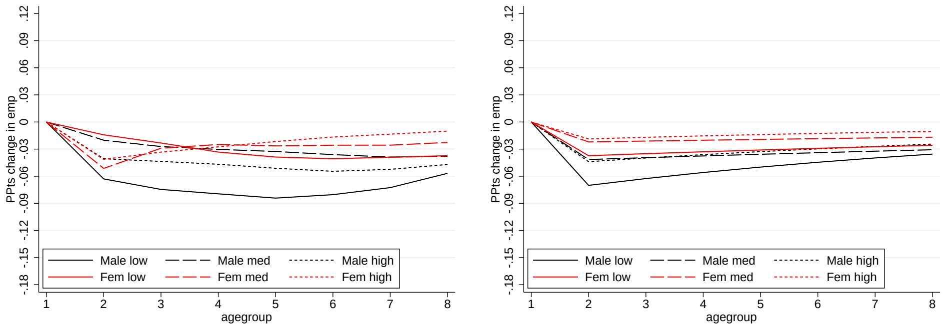


Figure 6: US - Model predictions (left) and OLS predictions (right) of employment response to a 1 standard deviation shock to the permanent component of health at age 50-51. Low, med and high are for high-school dropouts, high-school graduates and college graduates. Age groups 1 to 8 are for 50-51 to 64-65.

6 Conclusions

We estimate the effect of health on employment using a dynamic model. Our key findings are as follows:

1. The dynamic properties of health are well described by the sum of a highly persistent AR(1) component, plus a transitory component.

2. Transitory health shocks have little impact on employment.

3. Permanent health shocks have much bigger effects on employment.

4. Employment is highly persistent. Lagged employment strongly predicts current employment, even after accounting for the persistence in health.

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Appendix A: Using Principal Components Analysis to construct the health index

In this appendix we describe our Principal Components Analysis approach.

We are concerned that a health measure we look at to investigate the effect on employment and earnings will be subject to both measurement error - individuals may just be having a bad day, for example - and justification bias, where individuals report ill health as a consequence of having lower earnings or being unemployed. We attempt to deal with these problems by creating a health measure using a two-stage process. First, we attempt to deal with measurement error by taking a weighted average of the three subjective health measures, with the weights determined using principle components analysis. Second, to deal with justification bias, we regress this on all of the objective health measures, age, age squared, and a set of wave dummies (separately by gender and education) and use the estimated coefficients of the model to predict subjective health.

Specifically we take the first principal component of the data matrix of the three health subjective health measures, which we define as $H^S_{i,t,1}, H^S_{i,t,2}, H^S_{i,t,3}$, which will give us weights $\hat{\psi}_1, \hat{\psi}_2, \hat{\psi}_3$, to construct the subjective health index

$$\tilde{H}_{i,t} = \hat{\psi}_1 H^S_{i,t,1} + \hat{\psi}_2 H^S_{i,t,2} + \hat{\psi}_3 H^S_{i,t,3} \tag{7}$$

We then take this index and estimate

$$\tilde{H}_{i,t} = \alpha + X'_{i,t}\delta + \sum_{k=1}^{7} \rho_k H^O_{i,t,k} + \epsilon_{i,t} \tag{8}$$

where X is vector including an age polynomial and a full set of wave dummies, and $H^O_{i,t,1}...H^O_{i,t,7}$ are the objective health measures. Our measure of health that we use throughout the paper is then given by equation 9

$$H_{i,t} = \hat{\alpha} + X'_{i,t}\hat{\delta} + \sum_{k=1}^{7} \hat{\rho}_k H^O_{i,t,k} \tag{9}$$

Appendix B: Identification

In this appendix we discuss the identification of the parameters driving health and employment.

Identifying the parameters of the health process

The structure of the health residual is simply identified from the auto-correlation moments in health, conditional on a polynomial in age. The health of process is described in equations (1) and (2) in the main text, which we reproduce here for convenience

$$\begin{aligned} h_{ia} &= \beta_0 + x_{ia}\beta_x + \pi_{ia} + \epsilon_{ia} \\ \pi_{ia} &= \rho\pi_{ia-1} + \omega_{ia} \end{aligned}$$

where the indexes i and a stand for individual and age, h is health measured as described in Section 3 and appendix A, x is a polynomial in age, π is the persistent health shock, assumed to follow an AR(1) process with innovation ω and ϵ is the transitory health shock. We assume that (ω, ϵ) are iid and and mutually independent. All equations are education and gender specific and we omit dependence on these characteristics for simplicity.

We start by regressing h on x simply by OLS and predict the residuals from this regression, which we denote by $\hat{R}_{ia}$. Then

$$\hat{R}_{ia} = \hat{\pi}_{ia} + \hat{\epsilon}_{ia}$$

To identify the parameters characterizing the residual process we use the autocovariance moments for the residual $R = \pi + \epsilon$:

$$\begin{aligned}
Var\left(R_{i0}\right) &= \sigma_{\pi 0}^{2} + \sigma_{\psi}^{2} \\
Var\left(R_{ia}\right) &= \rho^{2a}\sigma_{\pi 0}^{2} + \frac{1-\rho^{2a}}{1-\rho^{2}}\sigma_{\omega}^{2} + \sigma_{\psi}^{2} \text{ for } a = 1, \ldots \\
E\left(R_{ia}R_{ia-1}\right) &= E\left(\rho\pi_{ia-1} + \omega_{ia} + \psi_{ia}\right)\left(\pi_{ia-1} + \psi_{ia-1}\right) \\
&= \rho\left(\rho^{2(a-1)}\sigma_{\pi 0}^{2} + \frac{1-\rho^{2(a-1)}}{1-\rho^{2}}\sigma_{\omega}^{2}\right)
\end{aligned}$$

and in general, for $l > 1$

$$\begin{aligned}
E\left(R_{ia}R_{ia-l}\right) &= E\left(\pi_{ia} + \psi_{ia}\right)\left(\pi_{ia-l} + \psi_{ia-l}\right) \\
&= \rho^{l}\sigma_{\pi a-l}^{2} \\
&= \rho^{l}\left(\rho^{2(a-l)}\sigma_{\pi 0}^{2} + \frac{1-\rho^{2(a-l)}}{1-\rho^{2}}\sigma_{\omega}^{2}\right)
\end{aligned}$$

From these expressions it is clear that identification of $(\sigma_{\pi 0},\, \rho,\, \sigma_{\omega},\, \sigma_{\psi})$ requires at least 3 periods. Taking periods $a = 0, 1, 2$, it is easy to show:

$$\begin{aligned}
\rho &= \frac{E\left(R_{i2}R_{i0}\right)}{E\left(R_{i1}R_{i0}\right)} \\
\sigma_{\pi 0}^{2} &= \frac{E\left(R_{i1}R_{i0}\right)^{2}}{E\left(R_{i2}R_{i0}\right)} \\
\sigma_{\omega}^{2} &= \frac{E\left(R_{i1}R_{i0}\right)^{2} - E\left(R_{i2}R_{i0}\right)^{2}}{E\left(R_{i2}R_{i0}\right)} + Var\left(R_{i1}\right) - Var\left(R_{i0}\right) \\
\sigma_{\psi}^{2} &= Var\left(R_{i0}\right) - \frac{E\left(R_{i1}R_{i0}\right)^{2}}{E\left(R_{i2}R_{i0}\right)}
\end{aligned}$$

Identifying the parameters of the employment process

The employment process is formalised in equations (4) and (5), which we reproduce here for convenience:

$$\begin{aligned}
E_{ia}^{*} &= \alpha_{0} + \alpha_{E1}E_{ia-1} + \alpha_{E2}(E_{ia-1} * a) + x_{ia}\alpha_{x} + \delta_{0}\pi_{ia} + \delta_{1}\pi_{ia-1} + \gamma_{0}\epsilon_{ia} + \gamma_{1}\epsilon_{ia-1} + u_{ia} \\
E_{ia} &= \mathbf{1}\left(E_{ia}^{*} > 0\right)
\end{aligned}$$

where employment E is a discrete variable with latent process E^{*}. The latter is a function of observed variables x, which include an cubic polynomial in age, health residuals (π, ϵ) and employment residual u. All equations are education and gender specific and we omit dependence on these characteristics for simplicity.

We assume all health and employment residuals are normally distributed and independent. Hence, the employment regression is a probit. Lagged employment is endogenous in this regression given its mechanical relationship with health residuals. We explicitly take this into account by simulating the employment and health residual processes jointly – thus formally accounting for the links between the two processes – and then matching conditional (on observed x's) employment rates, employment rates conditional on past employment and the current and lagged correlations between employment and health calculated on the model simulations with their data counterparts. Furthermore, endogeneity of initial employment is dealt with by starting the simulations 2 years prior to the start of the age interval we are considering. After this "burn in" phase, the structure of the relationship between employment and the health residual will have created the correlation between lagged employment and the overall residual in the employment equation that is consistent with the data moments.

Demonstrating identification in a linear probability model based on the set of moments we use is similar (although more laborious and tedious) to what we have done above for the health residuals. Suppose we know $(\alpha_0, \alpha_x, \alpha_{E1}, \alpha_{E2})$. We can then predict the employment residuals $(\delta_0 \pi_{ia} + \delta_1 \pi_{ia-1} + \gamma_0 \epsilon_{ia} + \gamma_1 \epsilon_{ia-1} + u_{ia})$ and use these to calculate their autocovariances and correlations with health residuals (current and lagged). Since we know all parameters in the health process, this procedure identifies $(\delta_0, \delta_1, \gamma_0, \gamma_1)$.[14] The parameters $(\alpha_0, \alpha_x, \alpha_{E1}, \alpha_{E2})$ can be identified from the employment rates and the correlations between employment, lagged employment and x. Estimating $(\alpha_0, \alpha_x, \alpha_{E1}, \alpha_{E2}, \delta_0, \delta_1, \gamma_0, \gamma_1)$ together ensures that the mechanical endogeneity of lagged employment is fully accounted for and the estimates are consistent. Finally, since imposing normality does not affect identification, a similar procedure can be used to identify the parameters in our non-linear model.

[14] Calculations are available from the authors upon request.