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Abstract

Using data from the Health and Retirement Study (HRS) and the English Longitudinal Study of Ageing (ELSA), we estimate the impact of health on employment. Estimating the model separately by race and gender, we find that racial differences in employment can be partly explained by the worse health of minorities and the larger impact of health on employment for these groups.

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1 Introduction

This paper investigates the effect of health on the employment of those aged 50-70, by race, gender, and country. Understanding the 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 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.

The dynamic interactions between health and labor supply are expected to change with age, particularly near retirement age as health problems become increasingly more frequent and serious, and out-of-work benefits change rapidly[1]. We focus on individuals in the years leading to retirement, aged 50-70, and estimate the overall impact of health on their employment. 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 separate estimates by gender and race to investigate the extent to which systematic differences in employment across these groups are related to differences in health status, in the incidence of health shocks, or in other incentives to work.

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.[2] *First*, 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. *Second*, as for current shocks, we allow for the effects of past shocks to differ by the nature of the shock, whether persistent or transitory. And *third*, we control for person-specific

[1]See for example (Disney et al., 2006; Casanova, 2013; Capatina et al., 2018; Hosseini et al., 2021)

[2]For example,. Disney et al. (2006), Bound et al. (1999), Bound et al. (2010), De Nardi et al. (2017).

heterogeneity in health, wages, and preferences, allowing for the possibility that health and labor supply are correlated not only because of the impact of health on labor supply, but because some people in good heath have high wages and preferences for work, regardless of their health at a particular point in time. Put differently, we relax the assumption that the correlation between health and labor supply is exclusively driven by the effect of health on labor supply.

While estimates from the structural model are still in progress, our initial descriptive evidence has revealed some important facts. First, the employment rates among the non-white population are significantly lower than among the white population in the US, with racial gaps over 10 and 5 percentage points for, respectively, men and women in their 50s. In England racial differences in employment are modest.

Second, in both the US and England, non-white people are on average in worse health. These racial differences are larger in the US than in England, and are larger for women than men in both countries. These differences in health are evident in objective measures (reporting the incidence of medically diagnosed health conditions such as diabetes or heart attacks) as well as in more subjective measures of overall well-being.

Third, these racial differences in health largely explain differences in employment across races. In fact, once we condition on health and education, non-white people have higher employment rates than white people, with health explaining more than education.

Fourth, the impact of health shocks on employment are larger for non-white than for white people, and are larger in the US than England. For example, declining health can explain 13% (19%) of the employment decline for white (non-white) women in the US. Part, although not all, of these differences, are explained by the physical demands of the jobs held by non-white people.

2 Data

2.1 Datasets

Our estimates are based on two longitudinal datasets: the US Health and Retirement Study (HRS) and the English Longitudinal Survey of Aging (ELSA). The two datasets follow a similar design and collect similar information.

ELSA is a representative sample of non-institutionalized individuals living in England and aged 50 or older. Interviews were held biennially from 2002/03 onwards, with the eight currently available waves covering the period up to 2016/17. The sample was drawn from Health Survey for England (HSE) respondents 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 are interviewed in each wave, resulting in some respondents being younger than 50 at the time of the interview.

The HRS began in 1992 with a representative sample of individuals living in the United States aged 50 to 61 and their spouses. These individuals were initially interviewed biennially and refreshment samples were added every 6 years. Respondents were initially selected from the non-institutionalized population, but efforts were made to follow them in later waves even if they were admitted into nursing homes. We augment the HRS dataset with the RAND HRS Data File which contains 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 70. We observe their gender, race, education, employment status and health information (we will describe these outcomes later in this section) among other variables. We use waves 2 to 8 of ELSA and waves 3 to 13 of HRS data, covering the years up to 2016. We exclude the first wave of ELSA and the first two waves of HRS, consistent with Blundell et al. (2023), because there were non-negligible changes in the questionnaire in the initial waves.

Table 1 describes the samples. In total, the ELSA sample has 11,914 individuals, of whom 54% are women. 11.5% of our ELSA sample respondents are observed for all 8 waves, and more than 61% are observed for at least 3 waves. Our HRS surveys 18,867 individuals, with a slightly higher fraction of women than in ELSA, at 55%. 10.1% of the respondents are observed over the 8 waves that cover our age-window, and 77% are observed for at least 3 waves.

Table 1: ELSA and HRS samples by gender, race and education

	Men		Women	
	White	Non-white	White	Non-white
		ELSA		
High School Dropout	0.33	0.32	0.38	0.43
High School	0.44	0.31	0.46	0.38
College	0.23	0.39	0.16	0.19
N (Obs)	18,324	713	22,705	879
N (Respondents)	5,219	222	6,199	274
		HRS		
High School Dropout	0.14	0.34	0.16	0.32
High School	0.56	0.50	0.64	0.53
College	0.30	0.16	0.20	0.15
N (Obs)	29,825	68,56	38,015	10,859
N (Respondents)	6,746	1,675	8,009	2,437

Notes: ELSA and HRS samples are for individuals aged 50-70, observed in any of the waves up to 2016, and for whom we can observe gender, race, education, employment and health.

We split our sample in two racial groups, one for the white majority and the other encapsulating all non-white minority groups. The choice of these broad categories is dictated by the need to ensure sufficient sample sizes for non-white people. For ELSA, even this grouping yields very small sample sizes for the minority group, who are less than 5% of the total sample. This partly reflects the fact that non-white people were a small share of this cohort: census data reveals that nonwhite people only comprise 7% of the population for those 50-69 in 2011.[3] In the HRS, 21% of the respondents are from minority race groups, reflecting greater racial diversity in the US as a

[3]Data are from:
https://www.ethnicity-facts-figures.service.gov.uk/uk-population-by-ethnicity/demographics/age-groups/latest.

whole. This is consistent with US census data, which shows that non-white people comprise 24% of the 50-69 population in 2010.[4] Based on these, we believe our samples in both countries are representative of aggregate racial compositions.[5]

Both surveys include detailed demographic, health, employment and income information that we use to investigate the links between health and employment around retirement age. Table 2 describes the key variables that will be used in our analysis, and compares inter-racial differences in these outcomes in England and the US.

Both surveys contain a set of dichotomous variables that ascertain whether the respondent is currently suffering, or has suffered since the last interview, from a range of medically diagnosed illnesses. These are usually known as 'objective' measures, and include conditions such as cancer, diabetes or cardio-vascular diseases. The top panel in Table 2 under each survey shows the prevalence of these conditions by survey, gender and race, and presents p-values for between race comparisons of means. The bottom row of 'objective measures' shows the number of objective health conditions that individuals in each group report – for simplicity we call this 'co-morbidity'.

There is a clear racial divide, with non-white people reporting on average more conditions than white people in all cases (see figures for co-morbidity). The differences are larger in the US than England. Some diseases, notably diabetes and cardio-vascular diseases, are significantly more prevalent among non-white respondents, while other conditions, such as psychiatric problems, affect white respondents more. In other cases, the differences are less statistically significant and the patterns are less clear. For instance, arthritis is more common among white than non-white men in England, while non-white women are more likely to suffer from it in the US than white women. By comparison, gender differences are less obvious but also larger in the US than in England. Typically, women are more likely to have arthritis and psychiatric problems, especially in the US, but are less likely to have suffered from a stroke, heart attack or diabetes.

[4] Data are from: https://www.census.gov/data/tables/2010/demo/age-and-sex/2010-age-sex-composition.html

[5] While the current version of the paper only discusses racial differences along the white/non-white divide, we will in future work be able to separate black respondents from other non-white respondents in parts of the analysis for the US, given the larger sample sizes of HRS.

Table 2: Summary statistics

	Men			Women		
	White	Non-white	p-val	White	Non-white	p-val
			ELSA			
Objective Health Measures						
Cancer	0.03	0.02	0.38	0.03	0.03	0.81
Diabetes	0.10	0.21	0.00	0.06	0.14	0.00
Sight	0.02	0.03	0.07	0.02	0.04	0.01
Hearing	0.05	0.03	0.01	0.02	0.01	0.36
Blood pressure	0.30	0.38	0.02	0.24	0.33	0.00
Arthritis	0.25	0.18	0.02	0.35	0.35	0.99
Psychiatric	0.05	0.04	0.56	0.08	0.04	0.00
Lung Disease	0.04	0.02	0.00	0.04	0.00	0.00
Stroke	0.01	0.02	0.19	0.01	0.01	0.53
Heart Attack	0.02	0.03	0.20	0.01	0.01	0.62
Co-Morbidity	0.86	0.95	0.20	0.84	0.96	0.06
Subjective Health						
Health Good/Excellent	0.50	0.37	0.00	0.51	0.34	0.00
Health limits activities	0.40	0.40	0.98	0.53	0.56	0.29
Health limits work	0.25	0.27	0.43	0.25	0.30	0.10
Labour Market and Income						
Age	61.2	59.8	0.00	60.7	58.6	0.00
Employment rate	0.58	0.64	0.04	0.49	0.52	0.36
Initial job: physically demanding	0.35	0.23	0.01	0.20	0.19	0.67
Earnings (£pw)	318.2	325.3	0.79	231.5	235.4	0.87
Disability benefits (£pw)	10.7	12.5	0.52	7.7	8.3	0.70
Initial net wealth (millions of £)	0.38	0.34	0.23	0.35	0.29	0.06
			HRS			
Objective Health						
Cancer	0.09	0.08	0.08	0.12	0.08	0.00
Diabetes	0.17	0.25	0.00	0.13	0.28	0.00
Sight	0.03	0.07	0.00	0.03	0.07	0.00
Hearing	0.06	0.03	0.00	0.03	0.02	0.00
Blood pressure	0.48	0.59	0.00	0.44	0.65	0.00
Arthritis	0.45	0.43	0.06	0.57	0.61	0.00
Psychiatric	0.12	0.10	0.06	0.21	0.19	0.00
Lung Disease	0.08	0.06	0.00	0.10	0.09	0.17
Stroke	0.05	0.08	0.00	0.04	0.07	0.00
Heart Attack	0.02	0.02	0.81	0.01	0.01	0.03
Co-Morbidity	1.55	1.72	0.00	1.68	2.06	0.00
Subjective Health						
Health Good/Excellent	0.48	0.33	0.00	0.50	0.29	0.00
Health limits activities	0.54	0.53	0.44	0.65	0.72	0.00
Health limits work	0.23	0.30	0.00	0.25	0.33	0.00
Labour Market and Income						
Age	61.7	61.0	0.00	60.9	60.5	0.00
Employment rate	0.60	0.54	0.00	0.49	0.47	0.05
Initial job: physically demanding	0.48	0.64	0.00	0.55	0.66	0.00
Earnings ($pw)	1259.4	902.5	0.00	712.5	615.1	0.00
Disability benefits ($pw)	11.9	21.2	0.00	8.6	19.6	0.00
Initial net wealth (millions of $)	0.31	0.12	0.00	0.28	0.10	0.00

Notes: $p-val$ is for equality between white and non-white respondents. Heteroskedasticity consistent standard errors are clustered at the individual level. Co-morbidity is the total number of objective conditions. All health variables are indicators for whether the respondents have a current diagnosis of the disease (in the case of objective health measures) or report subjective health as described. 'Employment' is an indicator for whether the respondent is currently working. 'Initial job: physically demanding' is an indicator for whether the job respondents held when first observed requires strenuous physical activity; it is only observed among those working when first in the sample.

The within-country race and gender health gaps are dwarfed by differences across countries, with American individuals reporting almost double the number of health conditions that their English counterparts do (co-morbidity figures). The prevalence of objective health conditions is larger in the US than England regardless of race or gender, and is often three times larger in magnitude. For example, cancer prevalence is 3% in ELSA for both white men and women, but the figures in the HRS are, respectively, 9% and 12%. Other serious health conditions like lung disease or strokes, as well as chronic diseases like diabetes, are all also more prevalent in the US.

These reported health differences between the US and England have been well documented in previous research (Banks et al., 2016). They may reflect a combination of differences across the two countries in health status, diagnosing rates and respondents' information about their health conditions. Banks et al. (2006) use additional biomarker information to show that Americans are in worse health than the English. Diagnosing rates and information about one's health conditions may also differ systematically within country across racial and gender groups, if they depend on access to good quality medical care. Particularly in the US, minorities and women tend to have lower insurance coverage, which could impact diagnosing rates and result in under-reporting of health conditions. This would lead us to understate racial differences in health, especially in the US.

The surveys also collect self-reported information on overall health status, which summarises well-being and working capacity. These are usually known as 'subjective' health measures. The common variables across the two surveys are described in the next set of rows in the Table, under each survey. Consistent with the racial differences in objective health measures, we see that white people are more likely to report good health status than non-white people in both countries, by a significant margin, and that non-white people are more likely to report that their health limits work and other daily activities, particularly in the HRS. By contrast, gender differences in subjective health measures are small. What is more surprising is that, despite the higher incidence of health issues in the US, and especially of those serious health problems that can be impairing, Americans reporting of their health status and ability to work is not on average different from that of English people.

The last set of rows under each survey describes other variables we use. We see that, in England, the employment rate is higher among non-white than it is among white respondents, but white respondents tend to do jobs that are more physically demanding. Interestingly, the exact opposite happens in the US, where employment rates are lower for non-white respondents, but their jobs are on average more physically demanding. Whereas in England racial differences in earnings, disability benefit income, and wealth are modest, non-white respondents in the US have significantly lower earnings and wealth, and receive significantly more disability benefits than their white counterparts. Lastly, non-white respondents are younger than white in both countries. This fact is especially important for interpreting racial differences in employment. For example, while white women in ELSA have lower employment rates than non-white, they have higher employment rates when conditioning on ages, as we show below.

2.2 Measuring health status

A critical issue for our analysis is how to summarise the rich health information in ELSA and the HRS in a way that reflects the relevant measure of health for labour supply. The literature on the effects of health has raised concerns that estimates of these impacts may be biased due to measurement error in health.[6] One problem is that only limited health measures are generally available, and each of those available variables 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.[7] Most likely, this type of measurement error leads to an understatement of the effect of health on labour supply. Another problem is that estimates

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

[7] 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.

of the effect of health status and labour supply potentially suffer from "justification bias", as those who are not working might see their health problems as more limiting of their ability to work.[8] This would likely lead to an overstatement of the effect of health on labour supply. In most 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 follow the approach of Blundell et al. (2023) to deal with measurement error in health, by combining information on health conditions afflicting the individual at the time of the interview (objective health measures), and on self reported health status (subjective health measures) to construct a single, composite health index. The index is constructed in two steps. First, we extract the first factor from a principal component analysis of the set of subjective health measures; this should deal with random misreporting due to error. Second, we instrument this subjective health factor with objective measures of health; this should take care of justification bias as objective measures are less likely to be sensitive to it. The health indexes are demeaned and the variance of the health indexes are normalized to 1. We describe our principal components analysis in more detail in appendix A.

Our choice to synthesise all the health information shown in Table 2 in a single index is simple and parsimonious, but is only adequate for the purpose of measuring the impact of health on employment if it is capable of summarising the relevant health information for employment. In an earlier paper (Blundell et al., 2023) 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 (Hosseini et al. (2022) also provide a detailed analysis of the role of detailed health measures). Furthermore, using over-identification tests we find that we cannot reject the restriction of a single health index.

The differences in health across groups that we discussed earlier are more evident when in-

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

spected through the lenses of these indices. Table 3 shows that, in all cases, non-white respondents have on average worse health than white, and that the racial gaps are larger in the US than in England, and for women than men.

Table 3: Racial gaps in composite health measures

	Men			Women		
	White	Non-white	p-val	White	Non-white	p-val
			ELSA			
Subjective health index	0.06	-0.07	0.06	-0.04	-0.27	0.00
Instrumented health index	0.11	-0.12	0.00	-0.07	-0.48	0.00
			HRS			
Subjective health index	0.12	-0.08	0.00	0.01	-0.32	0.00
Instrumented health index	0.20	-0.14	0.00	0.02	-0.54	0.00

Note: The subjective health index is the first principal component from the combination of the three subjective health measures. The instrumented health index is the predicted health from a regression of the subjective health index on all objective measures of health described in Table 2. The indices are standardised to have mean zero and standard deviation one. Heteroskedasticity consistent standard errors are clustered at the individual level.

Figure 1 plots, by survey and gender, the age profile of the racial gap in the instrumented health index. A similar figure for the subjective health index can be found in Appendix A, and it shows similar patterns to those shown here.We see very large racial gaps in both England (left panel) and the US (right panel), with white people reporting better health than non-white people. The gaps are systematically larger among women, varying between 0.3 and 0.5 of a standard deviation in the two countries. For men, the gaps are lower, hoovering between 0.1 and 0.3 of a standard deviation. Figures for the HRS, which are less volatile than those for ELSA due to the larger sample size, show a clear decline in the gap with age among both women and men, consistent with health problems becoming increasingly widespread with age.

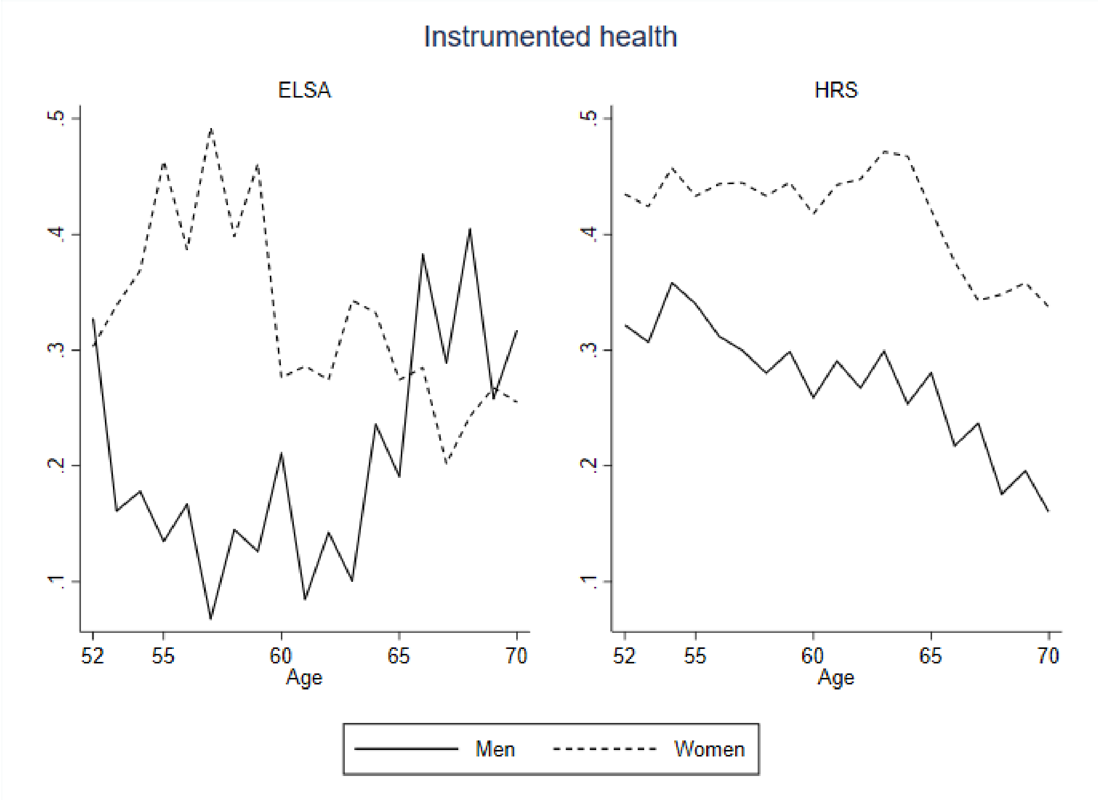

Figure 1: Racial gaps in the instrumented health index (in SDs), by survey, gender and age

Note: Graphs show moving averages of three age groups. Gaps are for white versus non-white population, measured in standard deviations. Figures are for England on the left panel, and the US on the right.

2.3 Employment and health heterogeneity by race and gender

Our measure of labour supply is employment. Figure 2 shows gaps in employment rates in England (on the left) and the US (on the right). Similarly to the gaps in health, employment is higher among white respondents. In England, the gaps are positive for women (meaning that white women are more likely to be in work than non-white women), but they are close to zero for men. In the US, the employment gaps are larger for men than they are for women, but they are positive for both groups. In both countries, gaps in employment close in approaching the typical retirement age of 65.

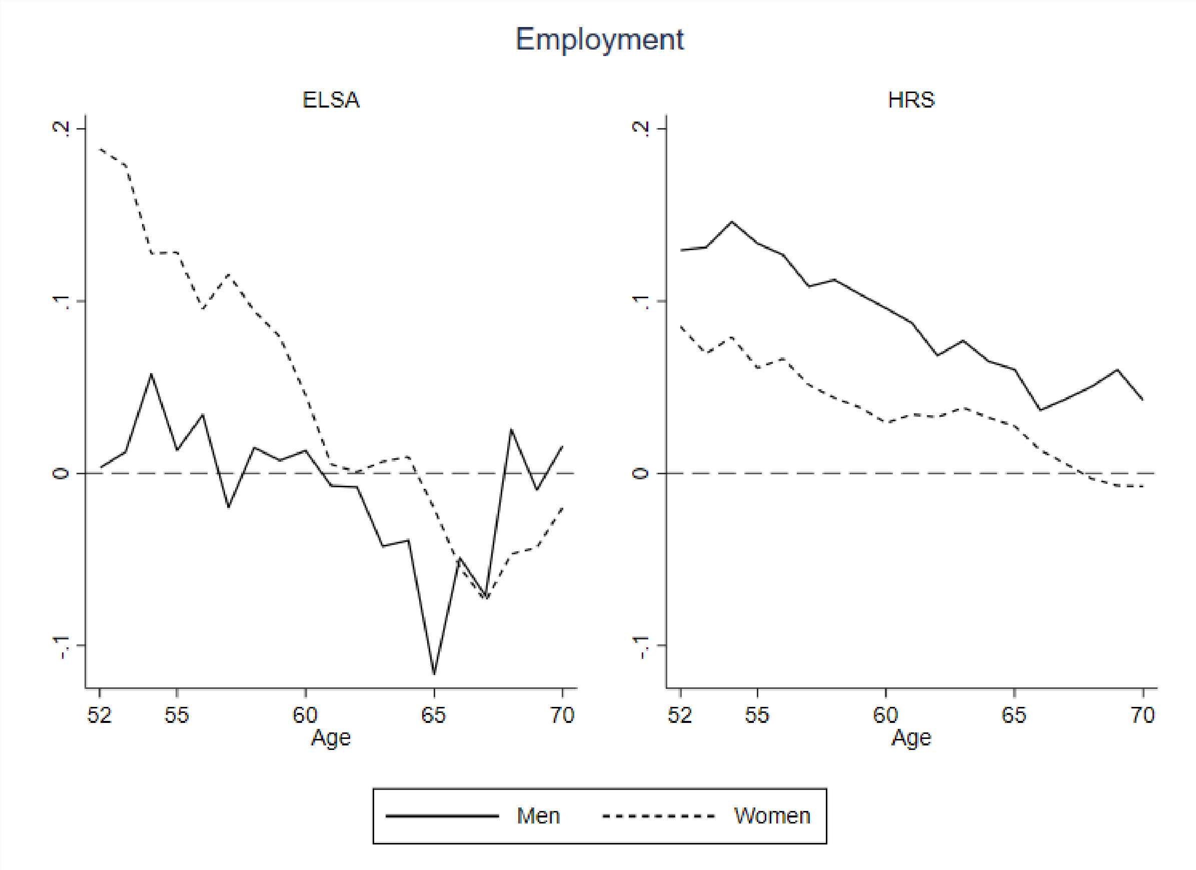

Figure 2: Racial gaps in employment rates (in percentage points), by survey, gender and age

Note: Graphs show moving averages of three age groups. Gaps are for white versus non-white populations. Figures are for England on the left panel, and the US on the right.

To investigate how much of the racial employment gaps can be attributed to across-race differences in health and education, we use the method proposed by Gelbach (2016). The method compares estimates of the race coefficient in two regression models of employment, baseline and full, and calculates how much of that difference can be attributed to the inclusion of additional regressors that are simultaneously related to employment and race - in our case, we add health and education. The decomposition allows us to assess the fraction of the change in the race coefficient accounted for by cross-race differences in health and education.

The baseline and full models are described in equations (1) and (2) below

$$Y_{it} = \alpha_0 + \alpha_1 White_i + \alpha_X X_{it} + e_{it} \quad (1)$$

$$Y_{it} = \beta_0 + \beta_1 White_i + \beta_{H0} H_{it_0} + \beta_H H_{it} + \beta_S S_i + \beta_X X_{it} + u_{it} \quad (2)$$

In the above, i and t index individuals and age, $White_i$ is an indicator for whether individual i is white, X_{it} is the vector of baseline control variables (a quadratic in age and wave fixed effects), H_{it} is the instrumented health index in the current period and H_{it_0} is the instrumented health index from the first time the individual is observed in the survey, S_i are indicators for highest qualification, and (e_{it}, u_{it}) are the unexplained parts of employment in each model.

Table 4 shows estimates of the race coefficient in each of the two models in the top panel, and decomposes the difference in these coefficients between health and education in the bottom panel. Estimates for the baseline model confirm the patterns reported in Figure 2, specifically that white people in this age group are more likely to be employed than non-white with the exception of men in ELSA, for who we find no significant race gap. For all groups, estimated race gaps are smaller in the full model than in the baseline model. In some cases (men in ELSA and women HRS) the estimated race gaps become negative; in the other cases, they drop towards zero and lose statistical significance. This means that, when comparing individuals of similar education and health levels, if anything it is the non-white group that is more likely to be in work.

Table 4: OLS Estimates of Racial Employment Gap and Gelbach (2016) Decomposition

	ELSA		HRS	
	Men	Women	Men	Women
Race gaps in employment				
Baseline regression model (α_1)	-0.004	0.072	0.083	0.036
	(0.028)	(0.027)	(0.010)	(0.010)
Full regression model (β_1)	-0.040	0.016	0.011	-0.053
	(0.025)	(0.023)	(0.009)	(0.009)
Difference ($\alpha_1 - \beta_1$)	0.036	0.057	0.072	0.089
	(0.014)	(0.013)	(0.006)	(0.005)
Fraction of difference in race gaps ($\alpha_1 - \beta_1$) explained by:				
Current Health	0.489	0.456	0.406	0.419
	(0.129)	(0.065)	(0.039)	(0.035)
Initial Health	0.535	0.465	0.249	0.304
	(0.112)	(0.068)	(0.044)	(0.036)
Education	-0.024	0.079	0.346	0.277
	(0.130)	(0.051)	(0.040)	(0.023)
Number of observations	19,036	23,581	36,681	48,874

Note: Standard errors (in parenthesis) are bootstrapped to include the construction of the health index, based on 100 iterations. $(\alpha_1 - \beta_1)$ is decomposed into parts explained by each covariate. For example, the fraction explained by current health H_{it} is $\frac{\gamma_H \beta_H}{\alpha_1 - \beta_1}$, where β_H is defined in equation (2) and γ_H is the regression coefficient on H_{it} from a regression of $White_{it}$ on $(H_{it}, H_{it_0}, S_i, X_{it})$.

The bottom panel in the table describes the roles of health and education in closing, and in some cases reversing, the racial gap in employment. For ELSA we see that race differences in education play no role in closing the gaps in employment. This is consistent with our earlier observation that education is similarly distributed across race in England. Instead, the drops in the estimated race gaps in employment can be fully attributed to health differences across race, and is evenly explained by differences in initial and current health.

By contrast, race gaps in education attainment exist in the HRS, and explain about one-third of the closing race gap in employment; the remaining two-thirds can be explained in roughly similar proportions by differences in current and initial health. Interestingly, the drop in the race gap in employment from the baseline to the full model is smaller in England than in the US, and the difference between the two is similar to the proportion of the closing gap explained by education in the US.

3 The impact of health on employment

3.1 Heterogeneity by race and gender

To quantify the effect of health on employment rates of older workers by gender and race, we estimate the following linear probability model of employment:[9]

$$Y_{it} \ = \ \theta_0 + \theta_H H_{it} + \theta_X X_{it} + v_{it}. \tag{3}$$

In the above, Y_{it} is an indicator for whether the respondent is employed, H_{it} is the instrumented health index, X_{it} is a set of independent variables that includes a quadratic in age, survey wave fixed effects, education fixed effects, as well as a set of initial conditions comprising of health status when the respondent was a child, and the health index, employment status, marital status and net wealth (inclusive of housing) for the respondent's first survey observation.

Table 5 shows the estimated θ_H from equation (3). The health indices are normalised, so estimates show the impact in employment of a 1 standard deviation change in health. Panel A shows estimates for ELSA, while estimates for the HRS are shown in panel B. For ELSA, we see that, among white men, a 1 standard deviation increase in health status is associated with almost 10 percentage points higher employment rates (first column, first row). For non-white respondents, the relationship between health and employment is even stronger, with a difference of 13.6 percentage points in employment for 1 standard deviation in health (first row, second column). The patterns are very similar for women, though the estimates are in all cases slightly smaller (first row, columns 3-4).

[9] We have also estimated a similar model of employment using a probit regression. Results are in all very similar to those obtained under linear probabilities and are shown in Appendix B.

Some of these differences will reflect persistent differences in employment by health rather then the impact of new health problems on employment. To measure the latter, we add initial conditions to the regression. Estimates for ELSA are shown in the second row in the Table (columns 1-4). With the exception of non-white men, estimates of the effects of health shocks are smaller when we add initial conditions, but they remain nevertheless large and statistically significant. We see that a 1 standard deviation drop in health reduces employment rates by between 6 (white women) and 16 (non-white men) percentage points.

Table 5: Effect of health on employment (θ_H), by survey, race and gender

	Estimated θ_H				p-val: test equality of θ_H across groups			
	Men		Women		By Race		By Gender	
	White	Non-white	White	Non-white	Men	Women	White	Non-white
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A: ELSA				
Without ICs	0.099	0.136	0.086	0.123	0.100	0.090	0.042	0.370
	(0.006)	(0.028)	(0.004)	(0.027)				
With ICs	0.070	0.163	0.057	0.112	0.030	0.110	0.143	0.216
	(0.009)	(0.049)	(0.007)	(0.043)				
Sample Size	18,324	713	22,705	879				
				Panel B: HRS				
No ICs	0.107	0.163	0.092	0.167	0.000	0.000	0.005	0.365
	(0.004)	(0.007)	(0.004)	(0.007)				
With ICs	0.106	0.156	0.096	0.171	0.000	0.000	0.147	0.190
	(0.007)	(0.012)	(0.007)	(0.010)				
Sample Size	29,825	6,856	38,015	10,859				

Note: IC stands for 'initial conditions', which include health as a child and values for the health index, employment status, marital status and wealth when the respondent was first observed in the sample. All regressions also include a full set of education dummies, a quadratic polynomial in age, Columns 1 to 4 show estimates of the impacts of health (measured by the instrumented health index) on employment from the regression model 3 (θ_H) assuming linear probabilities. Standard errors shown in parenthesis under each estimate are bootstrapped to include the construction of the health index, based on 100 iterations. Columns 5-6 and 7-8 show p-val for the testing equality of estimated θ_H across, respectively, race and gender groups.

The bottom panel shows similar estimates for the US. The patterns are similar to those observed for England, but the effects are larger by about 50%. Conditional on initial conditions, we find that a 1 standard deviation reduction in health is associated with a 10 percentage points drop in employment rates among white respondents, and 15 to 17 percentage points drop among non-white men and women (second row in panel B, columns 1-4).

Columns 5 to 8 show p-val for the t-tests comparing estimates of the health effect on employment across groups. For ELSA, we see that, though estimated effects are systematically larger for men and for non-white respondents, differences are in most cases not statistically significantly different from zero. However, the differences in estimated health effects across race (but not gender) that we observe in the US are statistically significant.

Estimates of the effects of health on employment can be used to calculate the fraction of the employment decline that happens between the ages of 50 and 70 that is explained by declining health. Following Blundell et al. (2023), this is

$$\delta_H = \frac{\theta_H(\bar{H}_{70} - \bar{H}_{50})}{\bar{Y}_{70} - \bar{Y}_{50}} \tag{4}$$

where θ_H measures the effect of a one standard deviation change in the health index on employment rates, $\bar{H}_{70} - \bar{H}_{50}$ is the change in average health between the ages off 50 and 70, predicted from an individual fixed effects regression of instrumented health on an quadratic polynomial in age to account for the unbalanced nature of our samples, and $\bar{Y}_{70} - \bar{Y}_{50}$ is the change in employment rate over the same period. Table 6 shows estimates of these parameters by gender, race, and country, from regressions excluding and including initial conditions.

For England, health decline can explain a modest 5-10% of the decline in employment among most groups; one exception is non-white men, for whom health is a stronger driver of the decline in employment, explaining about 15% of that decline once initial conditions are controlled for. Consistently with our earlier discussion, health is a stronger driver of employment decline in the US, explaining about 15% of those changes among the white population. The impacts are stronger for non-white respondents, for whom about a fifth of the decline in employment can be explained by health shocks.

Table 6: Share of employment decline explained by health decline, by survey, race and gender

	Men		Women	
	White	Non-white	White	Non-white
	Panel A: ELSA			
Without initial conditions	0.106	0.169	0.076	0.080
	(0.012)	(0.082)	(0.007)	(0.059)
With initial conditions	0.059	0.153	0.040	0.059
	(0.009)	(0.081)	(0.006)	(0.046)
Sample Size	18,324	713	22,705	879
	Panel B: HRS			
Without initial conditions	0.165	0.227	0.149	0.218
	(0.010)	(0.021)	(0.009)	(0.022)
With initial conditions	0.134	0.181	0.130	0.194
	(0.011)	(0.019)	(0.011)	(0.022)
Sample Size	29,825	6,856	38,015	10,859

Note: Table shows estimates of δ_H as specified in equation 4, using the estimated impacts of health on employment detailed in Table 5. Standard errors shown in parenthesis under each estimate are bootstrapped using 100 iterations.

3.2 The role of job occupations

Good health may be especially important for some occupations, while it is also possible that some occupations are linked to quicker health deterioration than others. Therefore, the impact of declining health on employment may depend on the type of job one does. Here we investigate the extent to which the large racial differences in the role of health in driving employment can be rooted in differences in the types of occupations that white and non-white people have. To do so, we focus on the sub-sample of individuals who were actively in work when first observed in our samples.[10] For them, we have information on how physically demanding their occupation was. This information comes in different formats in each of the surveys. ELSA respondents in active work are asked if their jobs involve 'physical work', 'heavy manual work' or are a 'sedentary occupation', or 'standing occupation'; we construct an indicator variable for physically demanding jobs (or heavy jobs) that equals 1 in the former two cases. HRS workers are asked if their jobs

[10] Among individuals initially in work, 8% reported missing initial occupation type in the ELSA and 3.9% in the HRS.

require much physical work 'all/almost all the time' 'most of the time', 'sometimes', 'rarely'; our indicator variable for physically heavy jobs equals one in the former two cases.

We estimate the regression model in equation (3) by race and nature of initial job among those employed in their first period in the sample.[11] Results can be found in Table 7 for the model with initial conditions.

Table 7: Effects of health on employment (θ_H), by survey, race and initial occupation

	Estimated θ_H				p-val: test equality of θ_H across groups			
	White		Non-white		By occupation		By Race	
	Heavy	Light	Heavy	Light	White	Non-white	Heavy	Light
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ELSA estimates	0.074	0.047	0.120	0.108	0.028	0.460	0.321	0.089
	(0.011)	(0.008)	(0.098)	(0.045)				
Sample Size	7,645	20,383	213	797				
HRS estimates	0.097	0.091	0.158	0.150	0.297	0.316	0.000	0.000
	(0.007)	(0.007)	(0.010)	(0.013)				
Sample Size	34,486	31,692	11,127	6,030				

Note: Columns 1-4 show estimates of the impact of health on employment (θ_H in equation 3) among those in active work in the first observation in the sample, by race (white/non-white), nature of initial job (heavy/light for how physically demanding the job is) and survey. Regressions also control for a quadratic polynomial in age, a full set of education dummies, gender, and initial conditions, including the health index, marital status and wealth when the respondent was first observed in the sample. Standard errors shown in parenthesis under each estimate are bootstrapped to include the construction of the health index, based on 100 iterations. Columns 5-6 and 7-8 show p-val for the testing equality of estimated θ_H across, respectively, occupations (for white and non-white respondents) and gender (for those employed in physically heavy and light jobs).

Overall, our estimates of the impact of health shocks on the employment of individuals who were employed when first drawn into the survey are very similar in magnitude to the estimates we obtained for the entire sample of employed and non-employed individuals. For ELSA, workers initially doing physically demanding jobs are more likely to respond to shocks in health by moving out of employment than those in comparatively lighter jobs (compare estimates is columns 1 and 2 for white respondents, and 3 and 4 for non-white respondents, top panel). However, the differences

[11] The small sample sizes for the non-white minority do not support further splitting by gender. Instead, we run a set of regressions by gender and nature of initial job. Like for our earlier gender analysis, gender differences are not statistically significant in most cases. Estimates for the gender split can be found in appendix B.

are small, and only statistically significant for white respondents. For the US, the differences in health effects across types of jobs are even more muted, and never statistically significant (bottom panel). For both countries, the patterns across races are similar to those described earlier, with stronger impacts of health being registered for the non-white minority.

These patterns suggest that the types of jobs white and non-white people do are unlikely to be important determinants of the differences in the role of health in driving employment at older ages. However, it is possible that health declines at different rates among those working in different types of jobs and of different races, compounding and magnifying the differences in the estimates of θ that we reported above. To investigate this, we calculate the share of employment decline explained by the decline in health by survey, race and type of initial job. Estimates are shown in Table 8.

Table 8: Share of employment decline explained by health decline, by survey, race and initial occupation

	White		Non-white	
	Heavy	Light	Heavy	Light
ELSA estimates	0.103	0.040	0.174	0.070
	(0.017)	(0.008)	(0.187)	(0.046)
Sample Size	7,645	20,383	213	797
HRS estimates	0.146	0.129	0.201	0.186
	(0.013)	(0.011)	(0.024)	(0.021)
Sample Size	34,486	31,692	11,127	6,030

Note: Table shows estimates of δ_H for individuals who were working when first observed in the surveys. Standard errors shown in parenthesis under each estimate are bootstrapped using 100 iterations.

For ELSA, but not for the HRS, the fraction of employment decline explained by health decline is substantially larger in heavy occupations than in light ones, and that occupational differences are particularly large among non-white respondents (though the large standard errors due to the small size of the non-white sample do not lend statistical significance to that difference). For the US, the differences across occupations are again much more muted. Overall, we conclude that differences in the health content of occupations as described by our (arguably rough) measure cannot explain race differences in the impact of health on employment.

4 Measuring the return to work

In the analysis below, we will measure the impact of health on employment, controlling for the financial incentives to work that individuals face. We calculate those incentives in a multi-step procedure. We first use information on disability benefits and sick benefits entitlements among those not in work, and we regress these entitlements against our measure of health. Using these estimates we then predict, for all who are working, their potential entitlement to benefits had they not been working. We use gross weekly earnings among employees and deduct tax liabilities and social security contributions from those. We then regress these net earnings on a polynomial in age, our health index and education, and we use these estimates to predict net earnings to all. Our final measure of financial incentives to work is imputed earnings net of predicted disability benefits.

5 Model

The previous section documented the gaps in health and employment by race and gender, and how these health differences impact employment. Here we consider how to formalise the relationship between health and employment in a dynamic model of labour supply that can be used to unpick the mechanisms underlying the gaps we identified. We formalise the employment choices of workers in a model that represents many of the ways in which health affects employment, and does so in a framework that allows for heterogeneity in observed as well as unobserved dimensions. In what follows, we briefly formalise the model.

In our model, individuals decide in each period whether to work, how much to consume and how much to save for the future. They do so in a risky environment, where they face uncertainty in future health, earnings from work and the utility cost of working. Health-related benefits, or disability benefits, partially insure against income losses associated with bad health but, as with other social insurance instruments, they also change the financial incentives to work. One would expect low-wage individuals to be more responsive to these incentives since progressive benefit formulas replace a higher share of their earnings. Savings provide further insurance against the economic consequences of health and other shocks.

All parts of the model are education-, gender- and race-specific. We consider the education and race split defined before, in section 2. In what follows, the gender, education and race dependencies are omitted to simplify the notation.

Individuals are indexed by i. For simplicity of notation, we also omit this index. They seek to maximize the expected discounted value of their present and future utility by choosing employment at each age $t \in \{t_0, ..., T\}$, where t_0 is the youngest age group in our sample, 50-51. We consider a single cohort, so age and time are used interchangeably.

Per-period utility This is:

$$U\left(C_t,\, P_t,\, x_t, H_t, \pi_t^U, \epsilon_t^U\right) = P_t \times \left(\theta_0 + x_t\theta_x + \theta_H H_t + \pi_t^U + \ \epsilon_t^U\right) + \frac{C_t^{1-\gamma}}{1-\gamma} \tag{5}$$

where U is the per-period utility function, C is consumption, P is employment status, H is health, x are demographics including age, gender, education, and race, and $\left(\pi^U,\, \epsilon^U\right)$ represent unobserved idiosyncratic persistent and transitory preferences for work, respectively. We assume that the persistent component follows a random walk process

$$\pi_t^U \quad = \quad \pi_{t-1}^U + \omega_t^U, \tag{6}$$

where $\left(\pi_{t_0}^U,\, \omega_t^U,\, \epsilon_t^U\right)$ are independent and normally distributed random variables of mean zero and variances $\left(\sigma^2_{\pi^U_{t_0}},\, \sigma^2_{\omega^U},\, \sigma^2_{\epsilon^U}\right)$.

Budget Sets The asset accumulation equation is:

$$A_{t+1} = (1+r)\left[A_t + P_t W_t \left(1 - \tau_t\left(W_t,\, H_t\right)\right) + B_t\left(H_t\right) - C_t\right]. \tag{7}$$

where $W_t\,(1-\tau_t\,(W_t,\,H_t))$ is the net return to work of worker i at time t, with W representing potential earnings and τ_t being the participation tax rate; $B_t(H_t)$ is benefit entitlement, including to disability benefits and pensions. Disability benefits are only available for those not working or on low incomes, so the tax rate τ accounts for the taxing away of these benefits.

Net return to work This is the disposable income in work net of out-of-work benefits, which in our case are disability benefits. In logs:

$$\ln W_t + \ln(1-\tau_t\,(W_t,\,H_t)) \;=\; \delta_0 + x_t\delta_x + \delta_H H_t + \pi_t^W + \epsilon_t^W, \tag{8}$$

where $\left(\pi_t^W,\,\epsilon_t^W\right)$ are the persistent and transitory wage shocks, respectively, π_t^W is a random walk

$$\pi_t^W \;=\; \pi_{t-1}^W + \omega_t^W,$$

and $\left(\pi_{t_0}^W,\,\omega_t^W,\,\epsilon_t^W\right)$ are independent and normally distributed random variables, with mean zero and variances $\left(\sigma^2_{\pi^W_{t_0}},\,\sigma^2_{\omega^W},\,\sigma^2_{\epsilon^W}\right)$.

Health and mortality The health process is

$$H_t \;=\; \beta_0 + x_t\beta_x + \pi_t^H + \epsilon_t^H \tag{9}$$

where again $\left(\pi_t^H,\epsilon_t^H\right)$ are the persistent and transitory components of the shocks to health, π_t^H follows an AR(1) process with innovation ω_t^H

$$\pi_t^H \;=\; \rho\pi_{t-1}^H + \omega_t^H,$$

and $\left(\pi_{t_0}^H,\,\omega_t^H,\,\epsilon_t^H\right)$ are independently and normally distributed random variables with mean zero and variances $\left(\sigma^2_{\pi^H_{t_0}},\,\sigma^2_{\omega^H},\,\sigma^2_{\epsilon^H}\right)$. In equation (9), x includes an age polynomial and the health outcomes of the individual as a child.

We also formalise the impact of health on survival: a worker alive at age t with health status H survives to age $t+1$ with probability $s(t,H_t)$.

Structure of the unobserved components We allow for arbitrary correlation between the initial values of the persistent heterogeneity terms, $\left(\pi_{t_0}^U, \pi_{t_0}^W, \pi_{t_0}^H\right)$. Unexpected shocks to health, wages and preferences, $\left(\epsilon_t^U, \epsilon_t^W, \epsilon_t^H\right)$, are assumed serially uncorrelated, mutually independent and independent from all other unobserved heterogeneity components.

The individual's problem The state vector at age t is

$$\Omega_t = \left(t, A_t, H_t, W_t, x_t, \pi_t^U, \pi_t^W, \pi_t^H, \epsilon_t^U\right)$$

In recursive form, the worker's problem is

$$V_t\left(\Omega_t\right) = \max_{P_t, C_t} \left\{ U\left(C_t,\, P_t,\, H_t, \pi_t^U, \epsilon_t^U\right) \;+\; \beta\, s(t, H_t)\, \mathrm{E}_t V_{t+1}\left(\Omega_{t+1}\right)\right.$$

subject to the asset accumulation equation (7), and given the law of motion for preference shocks (6), net return to work (8 and 9), and health (9 and 10). In the above equation, β is the subjective discount factor.

6 Estimation Procedure

The model described above is complex and difficult to solve and estimate. We set out a three-step estimation procedure that identifies the key model parameters for understanding the inter-linked dynamic processes of health and employment near retirement and how these differ by gender, ethnicity and education. Step one estimates the parameters characterising the dynamics of health; step two estimates the wage process; step three estimates the preference parameters.

Step 1 The parameters in the health process are $(\beta_0, \beta_x, \rho, \sigma_\omega, \sigma_{\pi_{t_0}}, \sigma_\epsilon)$ (see equation 9 and surrounding text). They can be estimated using an error components model. We estimate equation (9) by OLS, to obtain estimates of the parameter vector (β_0, β_x) where X is a second order polynomial in age. The residual from this regression is $\hat{\pi}_t^H + \hat{\epsilon}_t^W$. The remaining parameters are then estimated by minimum distance to match the empirical auto-covariance matrix of health residuals, where the health residuals are obtained from the OLS regeression. The auto-covariances of individual-level health residuals separate the structure of the persistent and transitory health shocks.[12] The parameters of the health model can be estimated without any reference to the employment decision.

Step 2 Let $\tilde{W}$ denote net return to work. We start by taking first differences of equation 8, which describes the process of $\tilde{W}$. This removes permanent heterogeneity:

$$\begin{aligned}\Delta \ln \tilde{W}_{it} &= \delta_x \Delta X_{it} + \delta_H \Delta H_{it} + \Delta \pi_{it}^W + \Delta \epsilon_{it}^W \\ &= \delta_x \Delta X_{it} + \delta_H \Delta H_{it} + \omega_{it} + \Delta \epsilon_{it}^W\end{aligned}$$

The parameters (δ_x, δ_H) are estimated using an augmented Heckman selection model, that conditions on employment at time t and $t-1$. For England, we use reforms to the state pension age that gradually increased the age at which workers are entitled to their state pensions over the cohorts in our sample, as the exclusion restriction in the first stage employment regression. Likewise, for the US we also exploit reforms to the Social Security system over our sample period; in particular, the repeal of the Earnings Test for those above the Normal Retirement Age and the increase in the Normal Retirement Age. We then estimate a similar Heckman selection model for the return to work in levels after netting out the predictions $\hat{\delta}_x X_{it} + \hat{\delta}_H H_{it}$ (which can be constructed from estimates of the model in first differences). This estimates δ_0. Finally, the parameters governing the unobserved component of the net return to work $\left(\sigma_\omega, \sigma_{\pi_{t_0}}, \sigma_\epsilon\right)$ are estimated by minimum distance to fit the auto-covariance matrix of the predicted residuals from the regressions of net returns to work in levels and first differences.

Step 3 The final step estimates the other model parameters using the Method of Simulated Moments conditional on the structure of the health and net return to work processes, which are estimated in the first two steps.[13] The estimation procedure at this stage is conditional on the parameters driving the health and wage shocks.

[12] 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.

[13] Original references are McFadden (1989) and Pakes and Pollard (1989).

The employment equation can be derived from the model, as shown in the appendix. It is

$$\begin{aligned} P_{it} &= \mathbf{1}\left\{(\theta_0 + \theta_H H_{it} + x_{it}\theta_x) + (C_{it}^0)^{-\gamma} W_{it}(1-\tau_t) + \pi_{it}^U + \epsilon_{it}^U > 0\right. \\ &= \mathbf{1}\left\{P_t^* > 0\right\} \end{aligned} \tag{10}$$

where $\mathbf{1}\{A\}$ is an indicator function that assumes the value one if condition A is true, or zero otherwise.

Here we aim to estimate the preference parameters $(\theta_0, \theta_H, \theta_x)$ and the variances of the residuals in preferences $\left(\sigma^2_{\pi^U_{t_0}}, \sigma^2_{\omega^U}, \sigma^2_{\epsilon^U}\right)$. Since we assume that the residuals (π^U, ϵ^U) are normally distributed and independent, the employment equation (10) is a probit. We estimate this model by the simulated method of moments, using estimates of the health and earnings processes obtained from steps 1 and 2. We simulate the health and earnings paths of all individuals in our sample, using random draws of the residuals from the estimated distributions. Given a set of estimating parameters $\Theta = \left(\theta_0, \theta_H, \theta_x, \sigma^2_{\pi^U_{t_0}}, \sigma^2_{\omega^U}, \sigma^2_{\epsilon^U}\right)$, we also simulate the employment profiles of each worker using random draws of $\left(\pi^U, \epsilon^U\right)$ from the corresponding distributions. We then build the set of moments used for estimation, which include the auto-covariance matrix of employment, the matrix of cross-correlations between employment and health, and the vector of employment rates by age and education. All moments are independently calculated by gender, ethnicity and survey. We contrast these moments with those obtained using observed data (ELSA or HRS), and iterate to select the parameters that minimise the GMM criterion:

$$\left(\hat{M}^d - M^m(\Theta)\right)' \hat{Q}^{-1} \left(\hat{M}^d - M^m(\Theta)\right) \tag{11}$$

where $(\hat{M}^d, M^m)$ are the data and model simulated moments, respectively, and $\hat{Q}$ is the estimated variance-covariance matrix of the data moments estimates.

7 Conclusion

Using representative data for both the US and England, we estimate the impact of health on employment by country, gender and race for the population aged 50-70. We also present a framework for structurally estimating the deeper mechanisms for these differences. While estimates from the structural model are still in progress, our initial descriptive evidence has revealed the following important facts.

First, employment rates of non-whites are significantly lower in the US. In England racial differences in employment are modest. However, in the US employment rates of white men (women) are over 10 (5) percentage points higher than for non-whites in their 50s.

Second, in both the U.S. and England, nonwhites are on average in worse health. These racial differences in health are larger in the U.S. than in England. Furthermore, these racial differences in health are larger for women than men in both countries. These differences in health are observed in objective measures (such as diabetes, heart attacks) as well as in more subjective measures of overall well-being.

Third, these racial differences in health largely explain differences in employment across races. In fact, once we condition on health and education, non-whites have higher employment rates than whites, with health explaining more than education.

Fourth, the impact of health shocks on employment are larger for non-whites than for whites and are larger in the US than England. For example, declining health can explain 13% (19%) of the employment decline for white (non-white) women in the US. Part, although not all, of these differences, are explained by the physical demands of the jobs held by non-whites.

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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, following Blundell et al. (2023).

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

$$\tilde{H}_{i,t} = \hat{\psi}_1 H^S_{i,t,1} + \hat{\psi}_2 H^S_{i,t,2} + \hat{\psi}_3 H^S_{i,t,3} \tag{12}$$

We then take this index and estimate

$$\tilde{H}_{i,t} = \alpha + X'_{i,t}\delta + \sum_{k=1}^{7} \rho_k H^O_{i,t,k} + \epsilon_{i,t} \tag{13}$$

where $X'_{i,t}$ is vector including an age polynomial, survey wave fixed effects, 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 14

$$H_{i,t} = \hat{\alpha} + X'_{i,t}\hat{\delta} + \sum_{k=1}^{7} \hat{\rho}_k H^O_{i,t,k} \tag{14}$$

Appendix B: Derivation of the employment decision rule

Here we derive the employment equation in the text. Define $\tilde{\Omega}_t = \left(H_t, W_t, x_t, t, \pi_t^U, \pi_t^W, \pi_t^H, \epsilon_t^U\right)$ as the collection of all state variables other than assets, so $\Omega_t = (\tilde{\Omega}_t, A_t)$. In the structural model, the work decision is

$$P_t = \mathbf{1}\left\{ \begin{array}{l} \max_{C_t^1, A_{t+1}^1} \left[U\left(C_t^1,\, 1,\, x_t, H_t, \pi_t^U, \epsilon_t^U\right) \,+\, \beta\, s(t, H_t)\, \mathrm{E}_t V_{t+1}\left(\tilde{\Omega}_{t+1}, A_{t+1}^1\right)\right] - \\ \max_{C_t^0, A_{t+1}^0} \left[U\left(C_t^0,\, 0,\, x_t, H_t, \pi_t^U, \epsilon_t^U\right) \,+\, \beta\, s(t, H_t)\, \mathrm{E}_t V_{t+1}\left(\tilde{\Omega}_{t+1}, A_{t+1}^0\right)\right] > 0 \end{array} \right\} \quad (15)$$

where $\left(C_t^1, C_t^0\right)$ and $\left(A_{t+1}^1, A_{t+1}^0\right)$ are the optimal consumption and savings choices if working and not working, respectively.

We can then rewrite equation (15) as

$$\begin{aligned}
P_t &= \mathbf{1}\left\{ \begin{array}{l} \left(\theta_0 + \theta_H H_t + x_t\theta_x + \pi_t^U + \epsilon_t^U\right) + \left(\frac{\left(C_t^1\right)^{1-\gamma}}{(1-\gamma)} - \frac{\left(C_t^0\right)^{1-\gamma}}{(1-\gamma)}\right) + \\ \beta s(t, H_t)\left[\mathrm{E}_t V_{t+1}\left(\tilde{\Omega}_{t+1}, A_{t+1}^1\right) \text{-} \mathrm{E}_t V_{t+1}\left(\tilde{\Omega}_{t+1}, A_{t+1}^0\right)\right] > 0 \end{array} \right\} \\
&\simeq \mathbf{1}\left\{ \begin{array}{l} \left(\theta_0 + \theta_H H_t + x_t\theta_x + \pi_t^U + \epsilon_t^U\right) + \left(C_t^0\right)^{-\gamma}\left(C_t^1 - C_t^0\right) + \\ \beta s(t, H_t)(1+r)\frac{\partial \mathrm{E}_t V_{t+1}\left(\tilde{\Omega}_{t+1}, A_{t+1}^0\right)}{\partial A_{t+1}^0}\left[W_t(1-\tau_t) - \left(C_t^1 - C_t^0\right)\right] > 0 \end{array} \right\} \\
&= \mathbf{1}\left\{(\theta_0 + \theta_H H_t + x_t\theta_x) + (C_t^0)^{-\gamma} W_t(1-\tau_t) + \pi_t^U + \epsilon_t^U > 0\right. \\
&= \mathbf{1}\left\{P_t^* > 0\right\}
\end{aligned}$$

which is equation (10) in the main text. Here $C_{it}^{-\gamma}$ is the marginal utility of consumption, $W_{it}(1-\tau_{it})$ is the change in income induced by a move into work, τ_{it} is an abbreviation for $\tau_t\left(W_{it}Y_{it},\, H_{it}\right)$ and Y_{it}^* is the latent employment index. In the derivation we exploit the first order Taylor series approximations[14], and that, by the envelope theorem the marginal utility of consumption is equal

[14]The least straightforward step is:

$$\begin{aligned}
\left(\frac{\left(C_{it}^1\right)^{1-\gamma}}{(1-\gamma)} - \frac{\left(C_{it}^0\right)^{1-\gamma}}{(1-\gamma)}\right) &= \left(\left(C_{it}^1/C_{it}^0\right)^{1-\gamma} - 1\right)\frac{\left(C_{it}^0\right)^{1-\gamma}}{(1-\gamma)} \\
&= \left((1+e)^{1-\gamma} - 1\right)\frac{\left(C_{it}^0\right)^{1-\gamma}}{(1-\gamma)} \\
&\approx \left((1 + (1-\gamma)(1)^{-\gamma} e) - 1\right)\frac{\left(C_{it}^0\right)^{1-\gamma}}{(1-\gamma)} \\
&= \left((1-\gamma)e\right)\frac{\left(C_{it}^0\right)^{1-\gamma}}{(1-\gamma)} \\
&= \left(C_{it}^1/C_{it}^0 - 1\right)\left(C_{it}^0\right)^{1-\gamma} \\
&= \left(C_{it}^1 - C_{it}^0\right)\left(C_{it}^0\right)^{-\gamma}
\end{aligned}$$

to next periods' discounted marginal valuation of assets:
$(C_{it}^{0})^{-\gamma} = \beta s(t, H_{it}) \frac{\partial \mathrm{E}_t V_{t+1}(\tilde{\Omega}_{it+1}, A_{it}^{0})}{\partial A_{it+1}^{0}} (1+r)$. This is the discrete choice version of the marginal rate of substitution condition, a condition that holds exactly as the time periods become arbitrarily short.

Appendix C: Additional tables and figures

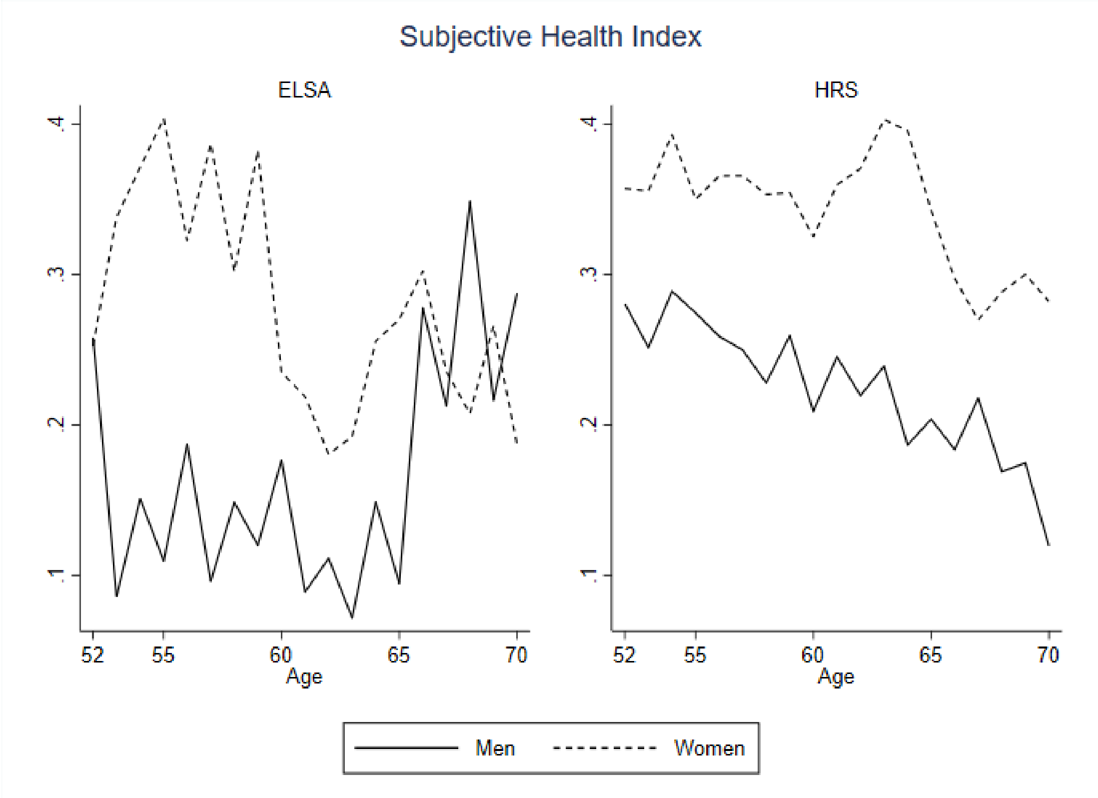

Figure 3: Racial gaps gaps in the subjective health index, by survey, gender and age

Note: Graphs show moving averages of three age groups. Gaps are for whites versus non-whites, measured in standard deviations. Figures are for England on the left panel, and the US on the right.

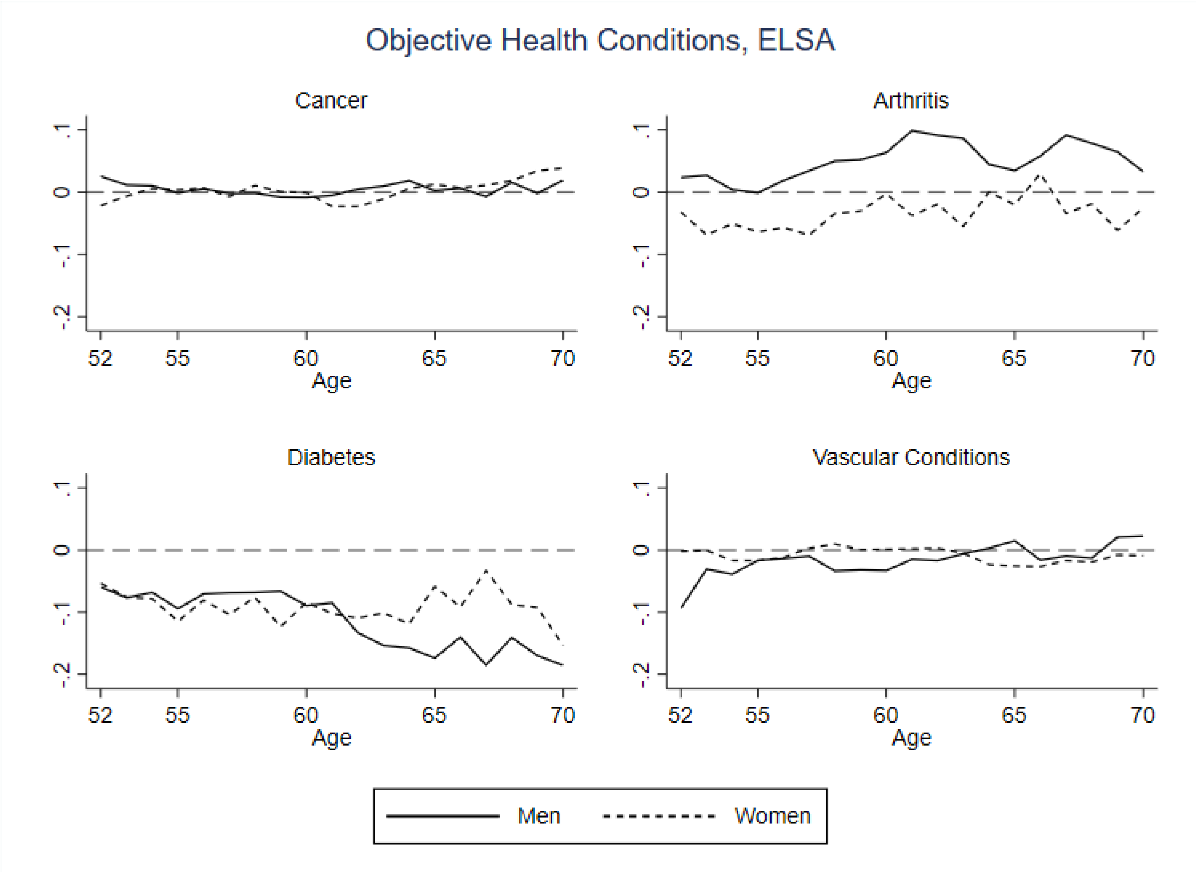

Figure 4: Racial gaps in objective health measures in England, by gender and age

Note: Graphs show moving averages of three age groups. Gaps are for whites versus non-whites. Figures are for gaps in prevalence rates of cancer (top left), arthritis (top right), diabetes (bottom left) and cardio-vascular conditions (bottom right).

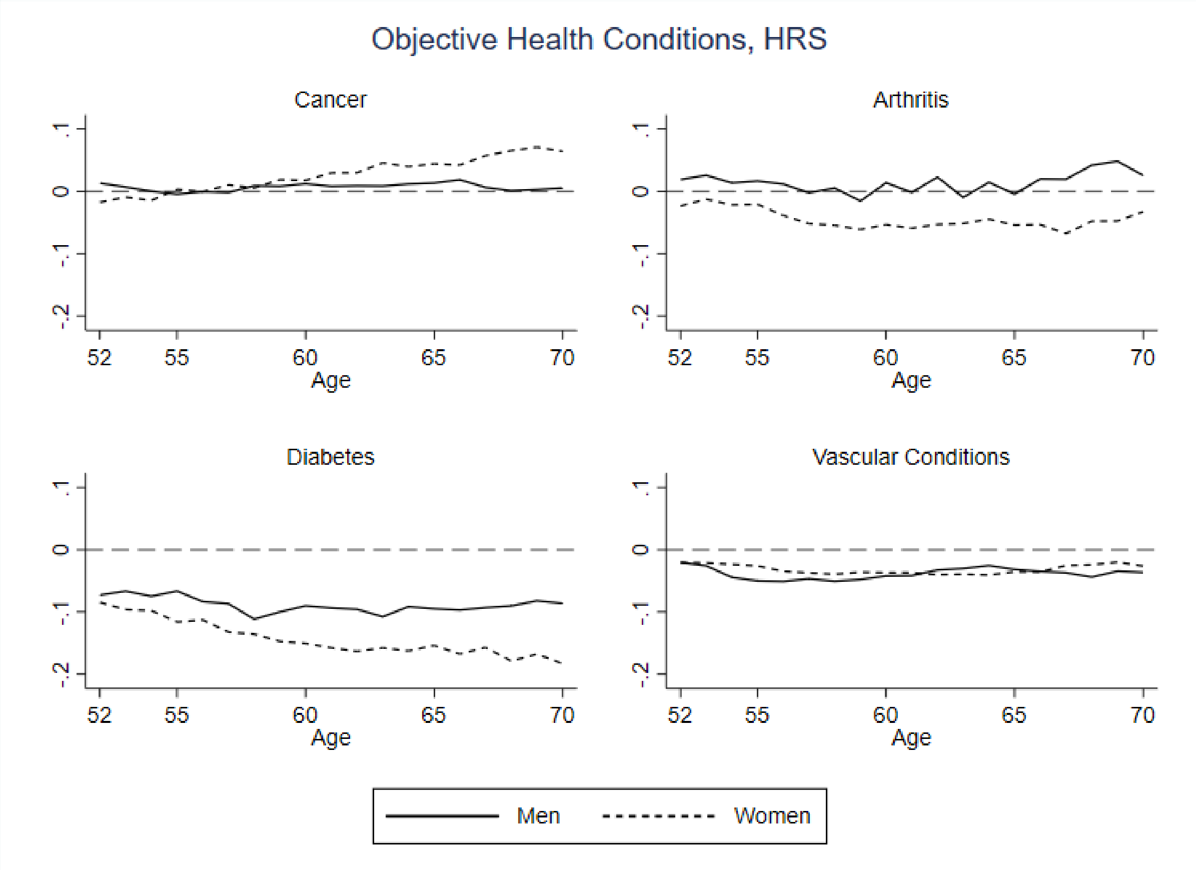

Figure 5: Racial gaps in objective health measures in the US, by gender and age

Note: Graphs show moving averages of three age groups. Gaps are for whites versus non-whites. Figures are for gaps in prevalence rates of cancer (top left), arthritis (top right), diabetes (bottom left) and cardio-vascular conditions (bottom right).

Table 9: Probit Estimates, Effect of Health on Employment by survey (θ_H), race and gender

	Effects of health on employment (θ_H)				p-val for comparison of θ_H			
	Men		Women		By Race		By Gender	
	White	Non-white	White	Non-white	Men	Women	White	Non-White
				Panel A: ELSA				
Without ICs	0.093	0.117	0.083	0.116	0.100	0.090	0.042	0.370
	(0.005)	(0.024)	(0.004)	(0.025)				
With ICs	0.067	0.140	0.056	0.117	0.064	0.089	0.307	0.353
	(0.014)	(0.046)	(0.018)	(0.043)				
Sample Size	18,324	713	22,705	879				
				Panel B: HRS				
No ICs	0.100	0.151	0.090	0.159	0.000	0.000	0.005	0.365
	(0.004)	(0.007)	(0.004)	(0.007)				
With ICs	0.098	0.147	0.093	0.168	0.000	0.000	0.313	0.119
	(0.007)	(0.013)	(0.007)	(0.010)				
Sample Size	29,825	6,856	38,015	10,859				

Note: Table shows probit estimates of θ_H. IC stands for 'initial conditions', which include health as a child and values for the health index, employment status, marital status and wealth when the respondent was first observed in the sample. All regressions also include a full set of education dummies, a quadratic polynomial in age, Columns 1 to 4 show estimates of the impacts of health (measured by the instrumented health index) on employment from the regression model 3 (θ_H). Standard errors shown in parenthesis under each estimate are bootstrapped to include the construction of the health index, based on 100 iterations. Columns 5-6 and 7-8 show p-val for the testing equality of estimated θ_H across, respectively, race and gender groups.

Table 10: Probit Estimates, Share of Employment Decline Explained by Health (δ_H), by race and gender

	Fraction Explained (δ_H)				p-val for comparison of δ_H			
	Men		Women		By Race		By Gender	
	White	Non-white	White	Non-white	Men	Women	White	Non-White
				Panel A: ELSA				
Without ICs	0.098	0.145	0.074	0.076	0.223	0.473	0.021	0.210
	(0.011)	(0.070)	(0.007)	(0.056)				
With ICs	0.057	0.132	0.039	0.062	0.155	0.324	0.178	0.215
	(0.013)	(0.072)	(0.013)	(0.047)				
Sample Size	18,324	713	22,705	879				
				Panel B: HRS				
No ICs	0.154	0.209	0.146	0.208	0.003	0.002	0.138	0.391
	(0.009)	(0.019)	(0.009)	(0.021)				
With ICs	0.125	0.170	0.127	0.191	0.011	0.007	0.435	0.242
	(0.010)	(0.019)	(0.012)	(0.022)				
Sample Size	29,825	6,856	38,015	10,859				

Note: Table shows probit estimates of δ_H as specified in equation 4, using the estimated impacts of health on employment detailed in Table 5. Standard errors shown in parenthesis under each estimate are bootstrapped to include the construction of the health index, based on 100 iterations.