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How Variations in Health Status Influence Retirement Decisions?

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HOW VARIATIONS IN HEALTH STATUS INFLUENCE RETIREMENT DECISIONS?

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ABSTRACT

Retirement date decisions are crucial for seniors. It is influenced by financial situation, health status, family conditions, planning for the rest of the life, etc. While some literature emphasizes economic well-being as a critical determinant, recent research suggests that health status is a more significant factor in retirement decisions. This thesis explores how variations in health status influence retirement decisions using panel data from the Health and Retirement Study (HRS). Building on the extensive use of HRS data in previous studies, this research expands their approaches and methodologies.

Both subjective and objective health variables are utilized to address the potential justification bias. Lagged health variables are employed to examine the impact of pre-retirement health on current retirement choices. Fixed effects models are also used to control for potential omitted variable bias. The findings indicate that poor pre-retirement health significantly increases the likelihood of retirement compared to excellent health across all specifications. Moreover, subjective health measures remain significant even when objective health measures are included.

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TABLE OF CONTENTS

I. Introduction:

Retirement timing is a crucial decision in everyone's life, influenced by various personal, financial, and health factors. In the United States, the Social Security Administration (SSA) outlines specific regulations and benefits tied to retirement timing. For many years, the full retirement age was set at 65. However, recognizing that people are living longer and generally healthier lives, Congress passed a law in 1983 to gradually raise the full retirement age. This change in the retirement age will increase incrementally until it reaches 67 for those born in 1960 and later.[1]

Despite these regulations, individuals still have the option to retire earlier or later than the designated full retirement age. Early and reduced retirement benefits are available starting at age 62. Conversely, delaying retirement benefits beyond the full retirement age up to 70 increases benefits.

The decision to retire, whether early, on time, or late, is influenced by various factors, such as the value placed on leisure time versus work, the financial capacity to maintain a comfortable living standard with retirement benefits, savings, expected longevity and, notably, the individual's health status. Health plays a pivotal role in this decision-making process, affecting the ability to continue working and the quality of life in retirement.

This article investigates the effect of health status on retirement decisions in the USA, examining whether self-reported health status or the diagnosis of health and mental problems influences retirement timing. Using data from the University of Michigan Health and Retirement Study (HRS), a longitudinal panel study surveying a representative sample of Americans, I analyze the relationship between health and retirement.

To study the impact of health on retirement, I regress retirement status and probability of working at 62 on self-reported health, the number of mental and health problems being diagnosed, and additional control variables.

I conduct ordinary least squares (OLS) and fixed effects (FE) regressions, using lagged health variables to address potential reverse causality. This approach allows for examining the impact of health status in the last year on the probability of working at age 62 and retirement status this year.

My findings indicate that reported poor health rather than excellent significantly increases the probability of retiring or decreasing the likelihood of working at 62. Furthermore, I employ fixed effects regressions to control for unobserved, time-invariant individual characteristics and reduce bias from omitted variables. In the fixed effects regression models, the coefficient of mental health problems (CESD score) is no longer statistically significant. However, the coefficients of other health variables remain significant with the

[1] This information is available at www.ssa.gov.

same sign as in the OLS regressions. Interestingly, their magnitudes are smaller by approximately 70 to 80% compared to the OLS regressions. This suggests that while the impact of self-reported health and diagnosed health problems on retirement outcomes persists in the fixed effects model, their effect sizes are attenuated after controlling for unobserved, time-invariant individual characteristics.

These results underscore the importance of considering individual health status when examining retirement decisions. These findings are consistent with prior research, highlighting the critical role of health status in shaping retirement behavior. Moreover, including fixed effects in the regression analysis helps mitigate biases arising from unobservable individual characteristics, enhancing the robustness of the results.

II. Literature review:

This section will review relevant literature to compare their variables, data, methodology, and findings with my research.

First, Blundell et al. (2023) examine the influence of health on labor supply near retirement age, utilizing data from the Health and Retirement Survey (HRS) in the United States and the English Longitudinal Study of Ageing (ELSA) in England. Their study incorporates subjective and objective health metrics and a cognition index. They obtain these results from education-specific employment regressions on the subjective and objective health and cognition index, controlling for a quadratic polynomial in age and year dummies. The findings reveal that health deterioration contributes to approximately 15% of the decline in employment between ages 50 and 70. Notably, the impact of health on employment differs between the United States and England due to institutional disparities. Individuals with lower levels of education exhibit more pronounced effects in the United States. Blundell et al. (2023) underscore the role of generous U.S. disability benefits, which encourage individuals with poorer health to exit the workforce prematurely. Conversely, unemployment benefits are more generous in England, though not tied to health status, and disability benefits are less ample than those in the United States.

Second, Dwyer and Mitchell (1999) explore how health problems influence men's retirement plans, particularly questioning the endogeneity of subjective health measures. Using data from the HRS, they employ an instrumental variable (IV) approach to address potential biases in self-reported health measures. Instruments include parents' health and mortality, respondent's weight-height ratio, nights spent in a hospital, age, and number of children. Their dependent variable is the expected age of retirement, and their findings show that poor health significantly advances retirement age, with men in poor health expecting to retire one to two years earlier than their healthier counterparts. Health status remains crucial despite the influence of economic variables like wealth and pension benefits. Their methodological contribution lies in using IV methods to minimize measurement errors, thus providing a more accurate estimate of health's impact on retirement timing. This research highlights the importance of health policies in retirement planning, emphasizing the need to consider subjective and objective health measures.

Third, McGarry (2004) examines the role of health and changes in health status in retirement decisions by using the HRS data and focusing on the subjective probability of working full-time at age 62. This approach allows the study to focus on current workers, avoiding biases from retired individuals. She finds that subjective health reports strongly predict continued work, with poor health significantly reducing these probabilities. Financial variables are less influential than health in determining retirement expectations. Her approach captures the nuances of retirement planning, indicating that health shocks significantly contribute to unplanned retirements.

Expanding on the role of health measures, researchers can use subjective health variables (self-reported health conditions) or objective health variables (actual diseases or health problems) to detect the effect of health conditions on retirement decisions. Justification bias occurs when individuals report poor health to rationalize their exit from the labor force. This bias, linked to self-reported health variables, can lead to inaccurate conclusions about the impact of health on early retirement decisions. A question that has arisen among researchers is whether self-reported health variables provide an accurate measurement of health status. I will focus on previous studies addressing this bias since I use self-reported health variables.

Kreider and Pepper (2007) directly address justification bias in their research, examining whether self-reported health and disability status in surveys are biased. Using data from the Health and Retirement Study (HRS) and the Survey of Income and Program Participation (SIPP), their nonparametric analysis accounts for potential reporting errors in these measures. They use analytic bounds instead of point estimates for potential reporting errors, finding that nonworkers tend to overreport disabilities. This suggests that conventional models might be flawed due to assumptions about error distribution, emphasizing the need to consider reporting biases when using self-reported health data to study employment outcomes.

On the other hand, Blundell et al. (2023) employ a unified framework to compare the effects of various health measures. They find that objective and subjective health indicators yield similar estimates, particularly when a comprehensive set of objective measures is employed.

Benitez-Silva et al. (2000) find insufficient evidence to support the existence of justification bias. They conclude that individuals' disability evaluations align with those of the SSA. Using data from the HRS survey and a bivariate probit model, they examine if self-reported disability status affects the decision to apply for disability benefits or the SSA's decision to award them. Their results indicate that, on average, people do not exaggerate their disabilities and use similar criteria to the SSA when reporting their disability status. Similarly, Dwyer and Mitchell (1999) find no evidence to support the justification hypothesis.

Although most of these studies find no evidence of justification bias on average, I still use both subjective and objective health measures to better understand how health impacts labor market attachment.

I use subjective and objective health variables to estimate retirement timing and the probability of working at 62. I partially utilize McGarry's (2004) method by choosing the probability of working at 62 (P62) as one of my dependent variables. However, my sample is much larger than hers, as I use all 15 waves and all observations reporting P62. In comparison, her sample was restricted to employed individuals under 61, and she utilized only two waves. My number of observations for P62 is 53,329, compared to her final sample of 5,498 observations.

Since McGarry (2004) finds that financial variables are less influential than health in determining retirement expectations, and Dwyer and Mitchell (1999) mention that health problems influence retirement plans more strongly than economic variables, I decided to focus solely on health variables to investigate their relationship and effect on retirement timing. My results align with previous research about health socks significantly contributing to unplanned retirement sooner than full retirement age. I find reporting poor health last year, compared to excellent health, is significantly associated with a 4.1 percentage point decrease in the probability of working at 62 (P62) or a 4.8 percentage point increase in the likelihood of retiring, holding all other variables constant. Interestingly, all these articles use the HRS dataset as I do, but I utilize all available waves. I include different controls and have a much larger sample size.

III. Data:

The data for this study is sourced from the Health and Retirement Study (HRS), a longitudinal survey conducted by the Institute for Social Research at the University of Michigan. It is a nationally representative panel survey of individuals over 50 and their spouses. This extensive survey provides comprehensive data on various aspects of aging in the U.S. from 1992 to 2020. The RAND Center for the Study of Aging created the RAND HRS Longitudinal File to enhance data usability. This streamlined dataset consolidates information from core and exit interviews with the HRS. The file includes data from fifteen waves of Core Interviews. It covers all seven entry cohorts. The RAND File comprises 42,405 unique respondents. It contains consistently named variables on demographics, health, insurance, Social Security, pensions, family structure, retirement plans, employment history, and imputed values for income, assets, and medical expenditures. My analyses utilize person-wave level data with respondent-level weights in the RAND dataset.

Regarding my health variables, I use self-reported health (subjective), which ranges from 1 (excellent health) to 5 (poor health), and the number of health conditions ranging from 0 to 8 (objective). This indicator variable denotes whether a respondent reports a doctor has ever told them they had the specified condition. The conditions are high blood pressure or hypertension, diabetes or high blood sugar, cancer or a malignant tumor of any kind except skin cancer, chronic lung diseases except asthma, such as chronic bronchitis or emphysema, heart attack, coronary heart disease, angina, congestive heart failure, or other heart problems, stroke or transient ischemic attack (TIA), emotional, nervous, or psychiatric problems, and Arthritis or rheumatism.

Additionally, I have another health variable: the number of mental health issues measured by the CESD score (subjective). This mental health index is derived using the Center for Epidemiologic Studies Depression (CESD) scale. The CESD score ranges from 0 to 8 and measures the frequency of depressive symptoms. It is calculated based on eight indicators: Six negative indicators: depression, everything being an effort, restless sleep, feeling lonely, feeling sad, and inability to get going. Each negative indicator adds 1 point to the CESD score if experienced all or most of the time. Two positive indicators are feeling happy and enjoying life. These are reverse-coded, meaning that not feeling happy or not enjoying life adds 1 point each to the score. A higher CESD score indicates more frequent depressive symptoms. For example, a score of 8 means the respondent experiences all six negative symptoms and does not feel happy or enjoy life, reflecting a high level of depressive symptoms.[2]

Regarding dependent variables, I choose two dependent variables. The first is self-reported retirement status. To focus on individuals with substantial work experience, I include only those who reported at least 20 years of work in the "Total Years Worked" variable. As a result, I exclude professions where the concept of retirement might have a different significance. For work status, individuals are classified as working full-time, part-time, retired full-time, part-time, disabled, unemployed, or not in the labor force. I exclude the unemployed, disabled, and those not in the labor force groups.[3]. Additionally, I combine partially retired individuals with fully retired ones to consider them retired people compared to those not retired. As a result, I create a dummy variable for retirement status.

The question to determine the retired dependent variable is: “At this time, do you consider yourself completely retired, partly retired, or not retired at all?”

The second dependent variable is the Probability of working at 62 (P62). Note that at age 62, people are entitled to early but reduced Social Security benefits. This is a numeric

[2] Note that in Wave 1, the allowable responses to these questions differ from those in other waves, so this measure is not derived for Wave 1.
[3] I was inspired by Aspen Gorry, Devon Gorry, and Sita Slavov (2015) to classify retirement variables.

variable ranging from 1 to 100. Following McGarry's approach, I rescale P62 to range between 0 and 1 by dividing all values by 100.

The question to determine the probability of working at age 62 (P62) dependent variable is: “Thinking about work generally and not just your present job, what do you think are the chances that you will be working full-time after age 62?”

In addition, I include demographic variables to classify respondents, including gender, race, Hispanic origin, education, and marital status. Race is categorized into three groups: White, Black, and Others. Respondents' education is grouped into five categories based on my expectations about their salary corresponding to their education level: "High School Level or Less," "Some College," "Bachelor’s Degree," "Graduate Degree," and "Professional Degree." Marital status is classified into three groups based on whether the respondent lives with a partner: "Married/Partnered," "Separated/Divorced," and "Widowed/Never Married."

Table 1 presents the summary statistics of the main variables in my study. After cleaning the data and dropping the missing values, I have 160,835 observations, including 25,878 individuals. Among them, 48% are men, and 52% are women, with about 63% of the sample reporting to be partially or fully retired. About 77% report excellent, very good, or good health, while 23% report fair or poor health. On average, the sample estimates a 49% chance of working at age 62. On average, individuals report having been diagnosed with approximately two health conditions and about one CESD score being diagnosed, which aligns with the majority reporting good health rather than poor health.

Regarding demographic variables, 79% of the observations are white, 69% report having a high school education or less, and 2% report having a professional degree. 68% report being married or living with a partner, and only 8% are Hispanic.

Additionally, Table 2 presents summary statistics that divide the sample by health status, where 'good health' includes excellent, very good, and good health, and 'poor health' includes fair and poor health. In other words, Table 2 compares variables across these two health groups. The number of observations for “good health” is 124,376, and for “poor health” is 36,459. In my sample, 58% of the individuals who report having good health are retired, while 78% of those who report having poor health are retired. Consequently, on average, those in poor health report an approximately 34 percent higher likelihood of retirement than those in good health.

Furthermore, individuals in good health report, on average, a 51% probability of working at age 62, compared to 37% for those in poor health. Regarding the number of health and CESD scores, individuals with poor health report more issues, which is consistent with their overall health status.

Regarding demographic variables: Within the poor health group, 12% are Hispanic, compared to 6% in the good health group. In the poor health group, the gender distribution is 50% men and 50% women, while in the good health group, it is 48% men and 52% women. Thus, the percentage of women in good health is higher. The average age in the good health group is 66, while in the poor health group is 69.

Among individuals in good health, 81% are White, 14% are Black, and 4% are of other races. In contrast, within the poor health group, 73% are White, 21% are Black, and 6% are of different races. Therefore, in the poor health group, there is a higher percentage of Black individuals, and in the good health group, there is a higher percentage of White individuals.

Regarding education, 65% of individuals in good health have a high school level education or less, 6% have some college, 17% have a bachelor's degree, 9% have a graduate degree, and 3% have a professional degree. Conversely, in the poor health group, 82% have a high school level education or less, 4% have some college, 8% have a bachelor's degree, 4% have a graduate degree, and 1% have a professional degree. Thus, the good health group has more individuals with college degrees and above, while the poor group has more with a high school education or less.

Regarding marital status, 71% of individuals in good health are married or live with a partner, 12% are separated or divorced, and 18% are widowed or never married. In the poor health group, 60% are married or live with a partner, 15% are separated or divorced, and 25% are widowed or never married. Therefore, a higher percentage of individuals in good health are married or live with a partner, while a higher percentage of individuals in poor health live alone.

IV. Methodology:

First, I use the OLS regression model to estimate the effect of health variables from last year on retirement timing this year. In other words, I aim to estimate the coefficient β in the following model:

$$R_{it} = \beta_0 + \beta H_{it-1} + \gamma X_{it} + \epsilon_{it}.$$

Where (R_{it}) represents whether the respondent is retired at time t or if they expect to be retired at age 67, (H_{it-1}) represents the lagged health variables, and (X_{it}) represents the control variables for age, age squared, gender, marital status, race, Hispanic, and highest degree.

I have two dependent variables: self-reported retirement status and probability of working at age 62. I regress each dependent variable on the lagged self-reported health variable, the lagged number of health conditions, mental health issues, and control variables, including education, race, Hispanic ethnicity, gender, marital status, age, and age squared.

I add control variables to account for socio-demographic factors that could influence health and the dependent variables, ensuring that the effects of health variables are accurately isolated. For instance, a higher level of education can affect health awareness, retirement savings and retirement patterns. Race and Hispanic ethnicity can capture potential cultural differences impacting health outcomes and retirement patterns. Gender can capture gender-specific differences, such as life expectancy and health issues influencing retirement behavior. Marital status can affect financial stability, impacting health and retirement decisions. Finally, age and age squared capture the varying impacts of aging on health and retirement decisions, with influence increasing near full retirement age and decreasing afterward.

Regarding health variables, I include lagged health variables separately based on self-reported health and the number of conditions. In another regression, I regress each dependent variable on all lagged health variables. I use lagged health variables to address potential reverse causality, ensuring that the observed relationships reflect the influence of health on the dependent variables rather than the other way around. By lagging the health variables, I ensure that health status is measured before retirement decisions. I include subjective and objective health variables to comprehensively understand health's impact on retirement timing and the probability of working at 62 (P62).

Second, I employ an individual fixed effects model using the same variables and approach to refine my analysis further. The fixed effects model can be specified as follows:

$$R_{it} = \beta_0 + \beta H_{it-1} + \gamma X_{it} + \alpha_i + \epsilon_{it}$$

Where α_i represents the individual-specific fixed effects, controlling for time-invariant characteristics of each respondent.

The fixed effects model allows me to control for unobserved, time-invariant individual characteristics that could bias the results, such as innate ability, innate health, personality traits, or early life experiences. This approach helps address any omitted variable bias stemming from individual-specific characteristics that do not change over time.

By utilizing the fixed effects model, I aim to isolate the effect of health variables on retirement status more accurately. This methodology allows me to control for unobserved characteristics, ensuring that the estimated coefficients reflect the impact of health changes within individuals over time rather than being confounded by differences between individuals.

In essence, the fixed effects model enhances the robustness of the analysis by accounting for unobserved, stable characteristics of respondents. This approach provides more credible and likely less biased results and clarifies how health dynamics influence retirement timing.

V. Results:

My analysis shows a clear association between health and retirement decisions. Specifically, individuals in poorer health are more likely to retire and less likely to continue working at age 62 compared to those in excellent health. This pattern holds across different regression analyses, reinforcing the robustness of our findings.

In my regression tables, the first three columns exhibit opposite trends to those in the other columns. This is logical because individuals more likely to work at 62 are less likely to retire with the same health status. Essentially, the probability of working at 62 implies the opposite of the likelihood of retiring.

Tables 3 and 4 show the OLS and fixed effects results with no controls, respectively. When comparing results from regressions with and without control variables, we observe that including controls provides more accurate and less biased coefficients. Without controls, the impact of health on retirement decisions is overestimated because other influencing factors are not accounted for, leading to inflated estimates. This occurs because controls affect reported health and retirement timing in different directions. For example, as shown in Table 3, reporting poor health last year significantly decreases the likelihood of working at age 62 by 21.4 percentage points and increases the probability of retiring by 31.9 percentage points. Similarly, in Table 4, reporting poor health compared to excellent health decreases the probability of working at age 62 by 5 percentage points and increases the likelihood of retiring by 16 percentage points.

Without controls, the CESD score does not have the expected sign when retirement is the dependent variable. It shows an association between a higher CESD score and a decreased probability of retiring, which is unexpected and confounded by the absence of controls. Including controls in the regression models results in higher R-squared values, indicating that the models better fit the data.

Further details from the OLS regression results in Table 5 show that poor health is significantly associated with a higher probability of retirement by 20.9 percentage points and a lower likelihood of working at age 62 by 20.5 percentage points. The number of health conditions diagnosed last year is also associated with a 3.1 percentage point increase in retirement probability and a 2.5 percentage point decrease in the likelihood of working at 62. Additionally, the number of mental conditions diagnosed last year is associated with a 0.9 percentage point increase in retirement probability and a 0.9 percentage point decrease in the likelihood of working at 62, ceteris paribus.

In the fixed effects regression results presented in Table 6, poor health increases the probability of retirement by 4.8 percentage points and decreases the likelihood of working at age 62 by 4.1 percentage points. The number of health conditions increases the possibility of retirement by 0.9 percentage points and decreases the probability of working at 62 by 0.6 percentage points. However, the number of mental health conditions is no longer significant (it reflects changes in status over time). As shown in the interpretations above, the coefficients, which include individual fixed effects, are approximately 70 to 80% lower than those in OLS. This difference may be driven by omitted factors in the fixed effect results. Additionally, it suggests that variations across individuals have a more significant impact on retirement than changes within individuals.

In columns 3 and 6, I include all health variables in the regressions. Although the coefficients are still significant and have the same sign, their magnitudes are smaller. Due to multicollinearity issues, these coefficients are more complex to interpret.

My analysis also highlights the impact of demographic variables on retirement decisions. Table 5(OLS) shows that being male is associated with a one-percentage-point decrease in the probability of retirement. Living alone without a partner reduces the likelihood of retirement compared to being married or living with a partner at some point, particularly being widowed or never married and separated or divorced, decreasing the probability of retiring by a 2.3 and 4.8 percentage point, respectively, ceteris paribus.

Additionally, individuals with professional degrees are less likely to retire than those with a high school diploma or less, decreasing the probability of retiring by 10.4 percentage points, ceteris paribus.

The coefficients on age are positive, and the coefficients on age-squared are negative, indicating that the probability of retirement increases with age at a decreasing rate.

Besides, in the fixed effects regressions, marital status and age effects remain significant with the same sign. With fixed effects included, the coefficients for marital status reflect changes in status over time. For example, individuals who become widowed or remain never married throughout the study period are less likely to retire by 1.7 and 3.1 percentage points, respectively, compared to those who are married or living with a partner at a relatively older age. This adjustment accounts for individual-specific factors that influence retirement decisions over time.

Finally, the F-statistics of all regressions are highly significant, indicating that the independent variables jointly have a meaningful effect on the dependent variables. However, the R-squared values for models where the probability of working at 62 is the dependent variable are low, suggesting that only a small percentage of the variation of P62 is explained by the included variables.

Comparing my OLS results with McGarry's, I notice that she finds smaller coefficients for poor health, but when I restrict my sample to those employed and under 61 and group fair and poor health, our results become similar. Appendix A shows her replicated results for 2 and 15 waves, respectively. Although the coefficient of fair/poor health with 15 waves is smaller, the standard errors are much smaller than with two waves. This makes sense because having more observations with 15 waves leads to more precise estimates.

These findings align with previous studies[4]. We all agree that poor health significantly decreases the likelihood of working at older ages or increases the probability of retirement. It supports the view that health shocks can precipitate earlier retirement.

Despite using different controls and waves, our results consistently show that worsening health is associated with an increased probability of retirement. Moreover, I observe that variations in reported health status across different waves impact the magnitude of the coefficients.

VI. Extension:

To check the robustness of my results, I ran all the OLS and fixed effects models using the current health variable instead of the lagged health variable. Appendix B shows the table results. All coefficients have the same sign and significance, with slightly larger magnitudes. I find that reporting poor health today relative to excellent health is significantly associated with an increase of 23.2 percentage points in the probability of retiring in the OLS model and 6.9 percentage points in the fixed effects model. These numbers were 20.9 and 4.8 percentage points when using lagged health variables, respectively. This suggests that there may be reverse causality where I use the health variable rather than the lagged variable. In other words, the observed relationships might reflect the influence of retirement on the health variables rather than the other way around.

Reverse causality in this context means that retired individuals might report poorer health due to changes in lifestyle, reduced social interaction, or loss of purpose, which can negatively impact health. Consequently, if current health status is used as an independent variable, it may capture the effect of retirement on health rather than the effect of health on retirement decisions. This can lead to overestimating the relationship between poor health and retirement probability. I mitigate this issue by using lagged health variables, as it ensures that health status is measured before the retirement decision, providing a clearer view of how health influences retirement timing.

[4] Blundell et al. (2023), Dwyer and Mitchell (1999), McGarry (2004).

VII. Conclusion:

Throughout my analysis, I conducted a series of regressions using OLS and fixed effects models that incorporate subjective and objective health variables to examine their impact on retirement decisions. Including self-reported health measures alongside objective indicators is crucial as it captures nuanced information that is not observable in empirical work that relies solely on clinical assessments. My findings consistently demonstrate that poor health significantly predicts labor market attachment and retirement decisions, robustly confirmed across different model specifications and health measurement approaches.

By combining objective and subjective health variables, my analysis offers a comprehensive understanding of how health influences retirement outcomes, highlighting the enduring impact of poor health on labor force participation. Policymakers can leverage these findings to address better the challenges posed by retirement age policies. Flexible retirement age policies that account for individual health status could accommodate those in poor health, potentially offering earlier retirement or disability benefits. Investing in preventive health measures and workplace accommodations can support older adults in maintaining their health and prolonging their working lives.

However, it is crucial to recognize that poorer health significantly increases the likelihood of early retirement. Policies that rigidly delay retirement may not effectively address the needs of individuals in poor health, potentially exacerbating their health issues and leading to increased healthcare costs and diminished well-being.

Examining the extent to which the differences between my findings and previous findings are due to adding new waves would be very interesting. This investigation would make an outstanding contribution and enhance earlier literature.

In conclusion, the association between poor health and increased retirement probability highlights the complex interplay between health and workforce participation. Policymakers should prioritize policies that promote health equity and support older adults in making sustainable retirement decisions that align with their health needs and overall well-being.

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Table 1: Summary statistics

Summary Statistics				
Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Self-reported health excellent	0.12	0.33	0	1
Self-reported health very good	0.32	0.47	0	1
Self-reported health good	0.33	0.47	0	1
Self-reported health fair	0.17	0.38	0	1
Self-reported health poor	0.05	0.22	0	1
Number of health conditions	1.88	1.43	0	8
CESD score	1.25	1.79	0	8
Retired	0.63	0.48	0	1
Probability of Working at Age 62(P62)	0.49	0.39	0	1
Race white	0.79	0.40	0	1
Race black	0.16	0.36	0	1
Race others	0.05	0.21	0	1
Education High School Level or Less	0.69	0.46	0	1
Education Some College	0.06	0.23	0	1
Education bachelor’s degree	0.15	0.35	0	1
Education Graduate Degree	0.08	0.27	0	1
Education Professional Degree	0.02	0.15	0	1
Marital Married/ Partnered	0.68	0.47	0	1
Marital Separated/divorced	0.12	0.33	0	1
Marital Widowed/Never married	0.19	0.40	0	1
Hispanic	0.08	0.26	0	1
Male	0.48	0.50	0	1
Age	66.71	10.28	33	109

Note: Number of observations =160,835, Number of observations for P62 = 53,329

Table 2: Summary statistics grouped by good and poor health

Variable	Good Health mean	Poor Health mean
Retired	0.58	0.78
	(0.49)	(0.42)
Probability of Working at Age 62	0.51	0.37
	(0.38)	(0.38)
Number of health conditions	1.6	2.84
	(1.29)	(1.48)
CESD score	0.9	2.43
	(1.46)	(2.26)
Hispanic	0.06	0.12
	(0.24)	(0.33)
Male	0.48	0.5
	(0.5)	(0.5)
Age	66.02	69.06
	(10.14)	(10.4)
Race White	0.81	0.73
	(0.39)	(0.45)
Race Black	0.14	0.21
	(0.35)	(0.41)
Race Others	0.04	0.06
	(0.2)	(0.25)
Education High School Level or Less	0.65	0.82
	(0.48)	(0.38)
Education Some College	0.06	0.04
	(0.24)	(0.2)
Education bachelor's degree	0.17	0.08
	(0.37)	(0.28)
Education Graduate Degree	0.09	0.04
	(0.29)	(0.19)
Education Professional Degree	0.03	0.01
	(0.16)	(0.11)
Marital Married/ Partnered	0.71	0.6
	(0.46)	(0.49)
Marital Separated/divorced	0.12	0.15
	(0.32)	(0.36)
Marital Widowed/Never married	0.18	0.25
	(0.38)	(0.43)

Note: Number of observations for Good Health: 124,376 and Poor Health: 36,459. Standard deviations are clustered in parentheses.

Table 3: OLS regressions without controls

	Dependent variable:					
	P62	P62	P62	Retired	Retired	Retired
OLS	(1)	(2)	(3)	(4)	(5)	(6)
Lagged self-reported health very good	-0.030***		-0.019***	0.086***		0.039***
	(0.006)		(0.006)	(0.004)		(0.004)
Lagged self-reported health good	-0.064***		-0.040***	0.141***		0.049***
	(0.006)		(0.006)	(0.004)		(0.004)
Lagged self-reported health fair	-0.124***		-0.084***	0.225***		0.093***
	(0.007)		(0.008)	(0.005)		(0.005)
Lagged self-reported health poor	-0.214***		-0.151***	0.319***		0.141***
	(0.011)		(0.012)	(0.007)		(0.008)
Lagged Number of health conditions		-0.027***	-0.017***		0.085***	0.077***
		(0.001)	(0.002)		(0.001)	(0.001)
Lagged CESD score		-0.010***	-0.005***		-0.002***	-0.007***
		(0.001)	(0.001)		(0.001)	(0.001)
Constant	0.549***	0.544***	0.560***	0.510***	0.483***	0.453***
	(0.005)	(0.003)	(0.005)	(0.004)	(0.002)	(0.004)
Observations	42,401	42,401	42,401	136,048	136,048	136,048
R^2	0.015	0.013	0.018	0.026	0.063	0.066
Adjusted R^2	0.015	0.013	0.018	0.026	0.063	0.066

Note: Standard errors clustered by household in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table 4: Fixed effects regressions without controls

	Dependent variable:					
	P62	P62	P62	Retired	Retired	Retired
Fixed effects	(1)	(2)	(3)	(4)	(5)	(6)
Lagged self-reported health very good	-0.010*		-0.006	0.089***		0.056***
	(0.005)		(0.005)	(0.004)		(0.004)
Lagged self-reported health good	-0.021***		-0.014**	0.129***		0.065***
	(0.006)		(0.006)	(0.005)		(0.005)
Lagged self-reported health fair	-0.030***		-0.019**	0.156***		0.063***
	(0.008)		(0.008)	(0.005)		(0.006)
Lagged self-reported health poor	-0.050***		-0.035***	0.160***		0.037***
	(0.012)		(0.013)	(0.008)		(0.008)
Lagged Number of health conditions		-0.010***	-0.008***		0.084***	0.081***
		(0.002)	(0.002)		(0.001)	(0.001)
Lagged CESD score		0.001	0.002		-0.008***	-0.008***
		(0.001)	(0.001)		(0.001)	(0.001)
Observations	42,401	42,401	42,401	136,048	136,048	136,048
R^2	0.001	0.001	0.002	0.008	0.039	0.041
Adjusted R^2	-0.517	-0.516	-0.516	-0.197	-0.159	-0.157

Note: Standard errors clustered by household in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table 5: OLS regressions with lagged health variables

OLS	P62 (1)	P62 (2)	P62 (3)	Retired (4)	Retired (5)	Retired (6)
Lagged self-reported health very good	-0.022***		-0.012**	0.033***		0.019***
	(0.006)		(0.006)	(0.003)		(0.003)
Lagged self-reported health good	-0.047***		-0.025***	0.058***		0.028***
	(0.006)		(0.006)	(0.003)		(0.003)
Lagged self-reported health fair	-0.107***		-0.069***	0.118***		0.070***
	(0.007)		(0.008)	(0.004)		(0.004)
Lagged self-reported health poor	-0.205***		-0.146***	0.209***		0.139***
	(0.011)		(0.012)	(0.005)		(0.006)
Lagged Number of health conditions		-0.025***	-0.016***		0.031***	0.024***
		(0.001)	(0.002)		(0.001)	(0.001)
Lagged CESD score		-0.009***	-0.004***		0.009***	0.004***
		(0.001)	(0.001)		(0.001)	(0.001)
Age	-0.044***	-0.044***	-0.044***	0.131***	0.130***	0.130***
	(0.007)	(0.007)	(0.007)	(0.001)	(0.001)	(0.001)
Age squared	0.0004***	0.0004***	0.0004***	-0.001***	-0.001***	-0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.00001)	(0.00001)	(0.00001)
Male	0.073***	0.068***	0.071***	-0.010***	-0.005**	-0.008***
	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)
Marital Separated/divorced	0.088***	0.088***	0.090***	-0.048***	-0.048***	-0.050***
	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)
Marital Widowed/Never married	0.040***	0.041***	0.042***	-0.023***	-0.024***	-0.024***
	(0.007)	(0.007)	(0.007)	(0.003)	(0.003)	(0.003)
Race black	-0.093***	-0.096***	-0.093***	0.002	0.007**	0.002
	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)
Race others	-0.016*	-0.020**	-0.016*	-0.037***	-0.032***	-0.036***
	(0.008)	(0.008)	(0.008)	(0.005)	(0.005)	(0.005)
Hispanic	-0.007	-0.019***	-0.012	-0.047***	-0.033***	-0.040***
	(0.007)	(0.007)	(0.007)	(0.004)	(0.004)	(0.004)
Degree Some College	0.024***	0.027***	0.023***	-0.015***	-0.020***	-0.016***
	(0.007)	(0.007)	(0.007)	(0.004)	(0.004)	(0.004)
Degree bachelor’s degree	0.043***	0.047***	0.042***	-0.033***	-0.037***	-0.032***
	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)
Degree Graduate Degree	0.014**	0.020***	0.013**	-0.001	-0.007*	0.0004
	(0.007)	(0.006)	(0.007)	(0.004)	(0.004)	(0.004)
Degree Professional Degree	0.140***	0.147***	0.139***	-0.104***	-0.111***	-0.103***
	(0.012)	(0.012)	(0.012)	(0.006)	(0.006)	(0.006)
Constant	1.573***	1.570***	1.572***	-4.734***	-4.700***	-4.719***
	(0.196)	(0.196)	(0.196)	(0.036)	(0.036)	(0.036)
Observations	42,284	42,284	42,284	135,790	135,790	135,790
R^2	0.044	0.043	0.047	0.427	0.428	0.431
Adjusted R^2	0.044	0.042	0.047	0.427	0.427	0.430

Note: Standard errors clustered by household in parentheses.

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 6: Fixed effects regressions with lagged health variables

	Fixed effects					
	Dependent variable:					
	P62	P62	P62	Retired	Retired	Retired
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged self-reported health very good	-0.010*		-0.009	0.010***		0.008**
	(0.005)		(0.005)	(0.003)		(0.003)
Lagged self-reported health good	-0.019***		-0.015**	0.018***		0.014***
	(0.006)		(0.006)	(0.004)		(0.004)
Lagged self-reported health fair	-0.025***		-0.020**	0.032***		0.025***
	(0.008)		(0.008)	(0.004)		(0.005)
Lagged self-reported health poor	-0.041***		-0.035***	0.048***		0.038***
	(0.012)		(0.013)	(0.006)		(0.007)
Lagged Number of health conditions		-0.006***	-0.004**		0.009***	0.007***
		(0.002)	(0.002)		(0.001)	(0.001)
Lagged CESD score		0.001	0.002*		0.001	0.0001
		(0.001)	(0.001)		(0.001)	(0.001)
Age	-0.027***	-0.027***	-0.027***	0.140***	0.141***	0.141***
	(0.007)	(0.007)	(0.007)	(0.001)	(0.001)	(0.001)
Age squared	0.0003***	0.0003***	0.0003***	-0.001***	-0.001***	-0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.00001)	(0.00001)	(0.00001)
Marital Separated/divorced	0.037***	0.037***	0.037***	-0.031***	-0.031***	-0.031***
	(0.010)	(0.010)	(0.010)	(0.006)	(0.006)	(0.006)
Marital Widowed/Never married	0.015	0.014	0.014	-0.017***	-0.017***	-0.017***
	(0.012)	(0.012)	(0.012)	(0.004)	(0.004)	(0.004)
Observations	42,284	42,284	42,284	135,790	135,790	135,790
R^2	0.007	0.007	0.007	0.373	0.373	0.374
Adjusted R^2	-0.508	-0.508	-0.508	0.244	0.244	0.244

Note: Standard errors clustered by household in parentheses. *p<0.1; **p<0.05; ***p<0.01

APPENDICES

Appendix A

Table A.1: McGarry's result with two waves

OLS

	Dependent variable:		
	P62	P62	P62
	(1)	(2)	(3)
Lagged self-reported health very good	-0.032**	-0.026*	-0.026*
	(0.016)	(0.015)	(0.015)
Lagged self-reported health good	-0.053***	-0.048***	-0.048***
	(0.016)	(0.016)	(0.016)
Lagged self-reported health fair/poor	-0.098***	-0.092***	-0.091***
	(0.023)	(0.023)	(0.023)
Age		-0.059***	-0.059***
		(0.017)	(0.017)
Age Squared		0.001***	0.001***
		(0.0002)	(0.0002)
Male		0.059***	0.062***
		(0.013)	(0.014)
Marital Separated/divorced		0.121***	0.121***
		(0.018)	(0.019)
Marital Widowed/Never married		0.052**	0.051**
		(0.023)	(0.024)
Race Black		-0.094***	-0.094***
		(0.018)	(0.018)
Race Others		0.020	0.018
		(0.034)	(0.034)
Hispanic		0.0004	-0.002
		(0.025)	(0.025)
Education Some College		0.026	0.026
		(0.028)	(0.028)
Education bachelor's degree		0.021	0.026
		(0.019)	(0.019)
Education Graduate Degree		0.001	0.005
		(0.023)	(0.024)
Education Professional Degree		0.128***	0.136***
		(0.037)	(0.038)
Earnings			-0.018
			(0.019)
Wealth			-0.003
			(0.019)
Constant	0.524***	1.717***	1.714***
	(0.011)	(0.451)	(0.451)
Observations	3,918	3,918	3,902
R^2	0.006	0.054	0.054
Adjusted R^2	0.005	0.051	0.050

Note: Standard errors clustered by household in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table A.2: McGarry's result with 15 waves

OLS

	Dependent variable:		
	P62	P62	P62
	(1)	(2)	(3)
Lagged self-reported health very good	-0.004	0.0002	-0.006
	(0.005)	(0.005)	(0.005)
Lagged self-reported health good	-0.034***	-0.014***	-0.020***
	(0.006)	(0.005)	(0.005)
Lagged self-reported health fair/poor	-0.068***	-0.041***	-0.045***
	(0.007)	(0.007)	(0.007)
Age		-0.064***	-0.061***
		(0.005)	(0.005)
Age Squared		0.001***	0.001***
		(0.00005)	(0.00005)
Male		0.039***	0.034***
		(0.004)	(0.004)
Marital Separated/divorced		0.084***	0.082***
		(0.005)	(0.005)
Marital Widowed/Never married		0.044***	0.046***
		(0.007)	(0.007)
Race Black		-0.113***	-0.112***
		(0.005)	(0.005)
Race Others		-0.021***	-0.023***
		(0.008)	(0.008)
Hispanic		-0.040***	-0.033***
		(0.007)	(0.007)
Education Some College		0.051***	0.037***
		(0.007)	(0.007)
Education bachelor's degree		0.065***	0.050***
		(0.005)	(0.005)
Education Graduate Degree		0.029***	0.017**
		(0.007)	(0.007)
Education Professional Degree		0.113***	0.108***
		(0.013)	(0.013)
Earnings			-0.013***
			(0.003)
Wealth			0.050***
			(0.003)
Constant	0.597***	1.906***	1.854***
	(0.004)	(0.136)	(0.135)
Observations	35,778	35,626	35,452
R^2	0.004	0.058	0.066
Adjusted R^2	0.004	0.057	0.065

Note: Standard errors clustered by household in parentheses. *p<0.1; **p<0.05; ***p<0.01

Appendix B
Table B.1: OLS regressions with health variables

OLS

	P62	P62	P62	Retired	Retired	Retired
	(1)	(2)	(3)	(4)	(5)	(6)
self-reported health very good	-0.004		0.004	0.027^{***}		0.011^{***}
	(0.005)		(0.005)	(0.003)		(0.003)
self-reported health good	-0.033^{***}		-0.013^{**}	0.055^{***}		0.020^{***}
	(0.005)		(0.005)	(0.003)		(0.003)
self-reported health fair	-0.117^{***}		-0.080^{***}	0.117^{***}		0.062^{***}
	(0.006)		(0.007)	(0.004)		(0.004)
self-reported health poor	-0.292^{***}		-0.232^{***}	0.232^{***}		0.151^{***}
	(0.010)		(0.011)	(0.005)		(0.005)
Number of health conditions		-0.030^{***}	-0.017^{***}		0.038^{***}	0.030^{***}
		(0.001)	(0.002)		(0.001)	(0.001)
CESD score		-0.013^{***}	-0.006^{***}		0.010^{***}	0.004^{***}
		(0.001)	(0.001)		(0.001)	(0.001)
Age	-0.041^{***}	-0.043^{***}	-0.041^{***}	0.127^{***}	0.123^{***}	0.123^{***}
	(0.007)	(0.007)	(0.007)	(0.001)	(0.001)	(0.001)
Age Squared	0.0004^{***}	0.0004^{***}	0.0004^{***}	-0.001^{***}	-0.001^{***}	-0.001^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.00001)	(0.00001)	(0.00001)
Male	0.071^{***}	0.064^{***}	0.068^{***}	-0.011^{***}	-0.004^{**}	-0.008^{***}
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Marital Separated/divorced	0.083^{***}	0.084^{***}	0.087^{***}	-0.045^{***}	-0.047^{***}	-0.048^{***}
	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)
Marital Widowed/Never married	0.034^{***}	0.036^{***}	0.038^{***}	-0.020^{***}	-0.022^{***}	-0.022^{***}
	(0.006)	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)
Race Black	-0.091^{***}	-0.093^{***}	-0.090^{***}	-0.001	0.002	-0.002
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Race Others	-0.010	-0.012^{*}	-0.008	-0.036^{***}	-0.033^{***}	-0.036^{***}
	(0.007)	(0.007)	(0.007)	(0.005)	(0.005)	(0.005)
Hispanic	-0.003	-0.016^{***}	-0.007	-0.053^{***}	-0.038^{***}	-0.045^{***}
	(0.006)	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)
Education Some College	0.026^{***}	0.032^{***}	0.027^{***}	-0.013^{***}	-0.020^{***}	-0.016^{***}
	(0.006)	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)
Education bachelor’s degree	0.049^{***}	0.055^{***}	0.047^{***}	-0.034^{***}	-0.038^{***}	-0.032^{***}
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Education Graduate Degree	0.020^{***}	0.027^{***}	0.019^{***}	-0.001	-0.007^{**}	-0.0002
	(0.006)	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)
Education Professional Degree	0.145^{***}	0.150^{***}	0.142^{***}	-0.104^{***}	-0.109^{***}	-0.102^{***}
	(0.012)	(0.012)	(0.012)	(0.006)	(0.006)	(0.006)
Constant	1.488^{***}	1.530^{***}	1.496^{***}	-4.584^{***}	-4.423^{***}	-4.443^{***}
	(0.178)	(0.178)	(0.177)	(0.033)	(0.033)	(0.033)
Observations	53,329	53,329	53,329	160,835	160,835	160,835
R^2	0.053	0.046	0.056	0.435	0.437	0.441
Adjusted R^2	0.053	0.045	0.056	0.435	0.437	0.441

Note: Standard errors clustered by household in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table B.2: Fixed effects regressions with health variables

Fixed effects

	Dependent variable:					
	P62	P62	P62	Retired	Retired	Retired
	(1)	(2)	(3)	(4)	(5)	(6)
self-reported health Very good	0.004		0.006	-0.002		-0.003
	(0.005)		(0.005)	(0.003)		(0.003)
self-reported health Good	-0.012^{**}		-0.007	0.007^{**}		0.003
	(0.006)		(0.006)	(0.004)		(0.004)
self-reported health Fair	-0.053^{***}		-0.042^{***}	0.024^{***}		0.015^{***}
	(0.007)		(0.008)	(0.004)		(0.004)
self-reported health Poor	-0.119^{***}		-0.099^{***}	0.069^{***}		0.054^{***}
	(0.012)		(0.013)	(0.006)		(0.006)
Number of health conditions		-0.030^{***}	-0.026^{***}		0.025^{***}	0.022^{***}
		(0.003)	(0.003)		(0.001)	(0.001)
CESD score		-0.005^{***}	-0.004^{***}		0.002^{***}	0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Age	-0.023^{***}	-0.023^{***}	-0.022^{***}	0.138^{***}	0.136^{***}	0.137^{***}
	(0.006)	(0.006)	(0.006)	(0.001)	(0.001)	(0.001)
Age Squared	0.0003^{***}	0.0003^{***}	0.0003^{***}	-0.001^{***}	-0.001^{***}	-0.001^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.00001)	(0.00001)	(0.00001)
Marital Separated/divorced	0.037^{***}	0.039^{***}	0.039^{***}	-0.028^{***}	-0.030^{***}	-0.029^{***}
	(0.009)	(0.009)	(0.009)	(0.005)	(0.005)	(0.005)
Marital Widowed/Never married	0.012	0.018^{*}	0.016	-0.016^{***}	-0.018^{***}	-0.017^{***}
	(0.010)	(0.010)	(0.010)	(0.004)	(0.004)	(0.004)
Observations	53,329	53,329	53,329	160,835	160,835	160,835
R^2	0.008	0.008	0.011	0.357	0.358	0.359
Adjusted R^2	-0.459	-0.460	-0.456	0.234	0.235	0.236
Note: standard errors clustered in parentheses.						*p<0.1; **p<0.05; ***p<0.01