The Joint Effect of Health Shocks and Eligibility for Social Security on Labor Supply

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Abstract

This paper investigates whether or not suffering a health shock, and becoming eligible for Social Security, have a joint effect on labor supply. Despite millions of people experiencing both of these events each year, no paper has focused exclusively on the joint effect that these events may have on work outcomes. This is surprising given that experiencing a health shock may impact on how a worker responds to becoming eligible for Social Security. With data from the Health and Retirement Study, I model weekly hours of work as a function of health shocks, Social Security eligibility, and their interaction. I find that this interaction leads to a 3 to 4 hour reduction in weekly hours of work for men but has no effect for women. The results are robust to using different work outcomes, age groups, health shock definitions, subgroups, as well as falsification and placebo tests. The results appear to be driven by men who would have had to return to work with impaired health. Policies that promote a more flexible work situation for older men may alleviate these problems in the future.

JEL classification: J22; J26; I10; H55.

Keywords: Labor Supply; Health Shocks; Social Security.

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1 Introduction

Both health shocks and access to Social Security payments have been shown to have negative effects on labor supply. While the separate effects that each of these events have on labor supply are well known there has been a dearth of research focusing on the joint effect that they may have. However, there are a number of reasons why research on this joint effect is warranted. The first reason is the sheer number of people who experience these events each year. For example, each year in the U.S., 735,000 people have a heart attack [1], 795,000 have a stroke [2], and 1.7 million people are diagnosed with cancer [3]. Similarly, in 2017, the Social Security Administration reported that 5.5 million new people gained access to Social Security benefits [4]. While the number of people who would be considered relevant for public policy is smaller than this (for example, 18% of those diagnosed with cancer will die in the first year [5] and, of those that survive, only 64% will return to work [6]), it is important for policy makers to be aware of any joint effect that these events may have since it has the potential to affect such large numbers of the population.

The second reason is the timing of the events. This is because workers experience both of these events at roughly the same age. Workers become eligible for early Social Security payments from the age of 62 and eligible for full benefits from the age of 65 (which is rising to 67). Meanwhile, according to the Centers for Disease Control and Prevention's (CDC) health statistics report, 25% of the people who report being diagnosed with cancer are between the age of 65-74 [7]. Similar number are available for stroke (24%), heart disease (22%), emphysema (27%), and chronic bronchitis (13%)[7]. Given that there will be a large number of workers who experience both these events simultaneously, examining the effect of health shocks without considering the joint effect of Social Security eligibility could lead to us ignoring important information on the workers' labor supply decisions.

The third reason is that, given the nature of the two events, it is very likely that they have some sort of interaction with one another. Workers who have had a health shock may want to reduce their labor supply but can't because they still need to work, while Social Security allows people to reduce their labor supply while maintaining a flow of income. It is easy to imagine how workers who have had a health shock might react differently to becoming eligible for Social Security compared to workers who have not had a health shock.

Using data from the Health and Retirement Study, I model work outcomes as a function of a health shock, becoming eligible for Social Security, and their interaction. I find that the interaction between health shocks and Social Security eligibility leads to an approximately 3 - 4 hour reduction in the number of weekly hours worked for men, while the interaction has no effect on the number of hours worked for women. This reduction in labor supply occurs at the extensive margin for men as it leads to an approximate 6 - 10 percentage point fall in the probability of working. The interaction has no effect at the intensive margin for women but has a small effect for men. The results are also robust to using different age groups, different health shock definitions, different subgroups, falsification tests, and placebo tests. The effects appear to be driven by how much the respondents' health is limiting their work. Male respondents who have had a health shock and remain working are more likely to report that their health is limiting their work compared to male workers who have not had a health shock. This effect is absent for women. This suggests that the mechanism behind the result is men returning to work before they have fully recovered from the health shock. This is supported by the fact that this effect is only present for men who work at least 40 hours per week, but not present for men who work fewer than 40 hours per week. Policies that promote a flexible working environment such as reduced daily hours, a reduced work week, or the option to work from home on certain days, could be used to prevent such sudden withdrawals from the labor market in the future.

This paper fills a gap in the literature by examining the joint effect of health shocks with Social Security eligibility. While there have been papers which have considered the joint effects of health shocks in the presence of disability insurance [8], or labor shocks in the presence of Social Security eligibility [9], no paper has thoroughly examined the joint effect of health shocks with Social Security eligibility. Knowing the joint effect that health shocks and Social Security eligibility has on labor supply can help contribute towards the development of public policy in numerous ways. From the worker's perspective, if they are returning to work too soon it may delay their recovery time. From the firm's perspective, if workers are returning to work before they have returned to full health then this may affect the firm's productivity. In this case, both the worker and the firm may benefit from an extended recovery period for the worker. Also, from the government's perspective, the associated strain placed on public finances by Social Security and Medicare due to an aging population can be alleviated by knowing how and why it is that the workers are reducing their labor supply. For example, policies designed to retain workers in the labor force and prevent exits are likely to differ from policies aimed at allowing people who are already in the labor force to modify their hours of work.

The rest of the paper proceeds in the following way: Section 2 discusses the related literature. The econometric model and data are outlined in section 3. The results are presented in section 4 and their robustness is examined in section 5. Section 6 discusses the results and possible mechanisms behind them. Finally, section 7 concludes.

2 Related literature

Regarding previous studies, the negative effect that health shocks have on employment outcomes have been well documented throughout the world. Evidence from the U.S. [10]; [11]; [12]; [13]; [14]; [15], Australia [16], Canada [17], Denmark [12], Germany [18], the Netherlands [19], Spain [20], the UK [21]; [22]; [23]; [24], and Europe as a whole [25]; [26], shows that health shocks have negative consequences for the probability of working, hours of work, and personal finances. While the definition of a health shock varies greatly by study, a common measure is to define it as suffering from an acute health event such as cancer, heart problems, lung disease, or stroke[1]. Other research using exogenous variation in health shocks such as road injuries [43] and commuting accidents [44] have also found negative effects of health shocks on work outcomes.

[1] More recently, a new strand of literature has emerged which focuses specifically on the effect of cancer on labor supply. Evidence from the U.S. [27]; [28]; [29]; [30]; [31]; [32]; [33]; [34]; [35], Europe [36]; [37]; [38]; [39]; [40], and elsewhere [41]; [42], shows that cancer, like other health shocks, has generally been found to have a negative effect on labor supply.

In the U.S., Social Security is the name for the federal program which provides old-age benefits for workers once they reach a certain age. Historically, the age at which people become eligible for full payments was 65, however this is being raised to 67. It is also possible to become eligible for early (but reduced) payments from the age of 62. The reduction is between 20-25% depending on whether the worker's full retirement age is 65 or 66. With regards to Social Security, the effect that it has on labor supply is resoundingly negative. Using structural models, Gustman and Steinmeier [45] show that the peaks observed in retirement behavior at 62 and 65 are due to Social Security and pension payments. Gustman and Steinmeier [46] also show that if the early entitlement age for Social Security benefits were to be delayed until 64 it could induce 5% of the population to delay retiring. Ferreira and dos Santos [47] use a life-cycle general equilibrium approach to show that the increase in generosity of Social Security benefits (and the introduction of Medicare) accounts for most of the increase in the number of retirements over the period from 1950 to 2000. Blau [48] uses a hazard model to show that Social Security benefits have large effects on labor force transitions, while other elements of workers budget constraints appear relatively unimportant. In the reduced form literature, Krueger and Pischke [49] use the 1977 amendments to the Social Security Act to show Social Security benefits have a negative, though extremely modest, effect on labor supply. Also, Mastrobuoni [50] finds that the incremental increase of the normal retirement age by two months per year for cohorts born in 1938 (and after) increases the age at which the effected cohorts retire by half as a much as the increase in the normal retirement age. See Coile [51] for an excellent review of the surrounding literature.

One effect that has not been well documented is the joint effect of suffering a health shock and being eligible for Social Security. The only other paper to examine the joint effect is Coile [11]. In her examination of the effects of health shocks on couples' labor supply decisions, Coile finds that health shocks have negative effects on the labor supply of men and women. She also interacts whether the respondent is diagnosed with a health shock and whether they are eligible for Social Security. The effect of a health shock on those who are not eligible for Social Security is still negative and significant but the coefficient on the interaction term is very small and not statistically different from zero. While this is the same model that I will be estimating in this paper, it is important to notice that there are several substantive differences between the two papers. While we both use data from the Health and Retirement Study, Coile [11] only uses data from waves 1 to 6. I use almost twice as many waves, using all available waves from 1 to 11. Similarly, Coile [11] uses an age range of 50 to 69 while the age range used in this analysis is 60 to 63, with smaller age bands either side of the eligibility threshold used in some of the analyses. Finally, this paper presents a robust examination of this model with different specifications and subgroups while the estimation of this model in Coile [11] was itself a robustness check.

3 Methods and Data

3.1 Empirical model and estimation

In order to estimate the joint effect of a health shock and being eligible for Social Security on labor supply, I model work outcomes (Y) as a function of becoming eligible for Social Security (ESS), a health shock (HS), and their interaction ($ESS \times HS$). This can be summarized by the following econometric equation,

$$Y_{it} = \beta_0 + \beta_1 ESS_{it} + \beta_2 HS_{it} + \beta_3 (ESS_{it} \times HS_{it}) + u_{it}, \tag{1}$$

where i indexes an individual and t indexes a time period. The main outcome measure which will be used in the analysis is hours of work per week. Hours of work is a continuous variable (for positive values). If a worker is not working then their hours are set to zero (from missing). ESS status is measured with a binary variable which refers to whether the respondent is eligible for Social Security. I follow Coile [11] and Coile and Levine [9] and define the respondent as eligible if they are 62 or older in period t and ineligible if they are younger[2]. HS status will be represented as another binary variable indicating

[2]Coile and Levine [9] interact Social Security eligibility ages (62, 63, and 64) with unemployment insurance, rather than health shocks, but the idea is the same.

whether they have suffered a HS. Respondents in the HRS are asked "Since we last talked to you, that is since [last interview date], has a doctor told you that you have . . . " and a number of conditions are listed. While previous studies have defined HS in many different ways, I follow Smith [14] and define a HS as a current diagnosis of cancer, heart problems, stroke, or lung disease[3].

For the estimators of the parameters in the model to be unbiased, the conditional mean assumption,

$$E(u_{it}|ESS_{it}, HS_{it}) = E(u_{it}), \tag{2}$$

needs to be met. Since ESS status is exogenously determined by an age threshold, ESS status can be thought of as being as good as randomly assigned for the respondents just above the threshold and just below the threshold. If ESS is randomly assigned then the following condition is satisfied,

$$E(u_{it}|ESS_{it}) = E(u_{it}), \tag{3}$$

which means that ESS status is not correlated with the error term. In this case, the estimators of parameters β_1 and β_3 will be unbiased, even if HS status is correlated with the error term, and equation (1) can be estimated including only the ESS, HS, and interaction variables. To see this, look at the effect of a HS on work outcomes for those who are ESS,

$$\begin{aligned} &E(Y_{it}|ESS_{it} = 1, HS_{it} = 1) - E(Y_{it}|ESS_{it} = 1, HS_{it} = 0) \\ &= \beta_2 + \beta_3 + E(u_{it}|ESS_{it} = 1, HS_{it} = 1) - E(u_{it}|ESS_{it} = 1, HS_{it} = 0), \end{aligned} \tag{4}$$

and those who are not ESS,

$$\begin{aligned} &E(Y_{it}|ESS_{it} = 0, HS_{it} = 1) - E(Y_{it}|ESS_{it} = 0, HS_{it} = 0) \\ &= \beta_2 + E(u_{it}|ESS_{it} = 0, HS_{it} = 1) - E(u_{it}|ESS_{it} = 0, HS_{it} = 0). \end{aligned} \tag{5}$$

[3]In the HRS, the cancer variable is defined as cancer or a malignant tumor of any kind except skin cancer. The heart problems variable is defined as heart attack, coronary heart disease, angina, congestive heart failure, or other heart problems. Stroke is defined as stroke or transient ischemic attack. Lung disease is defined as chronic lung disease except asthma such as chronic bronchitis or emphysema.

In this case, β_2 represents both the direct effect of HS on outcomes for the ESS group and the total effect of HS on outcomes for the non-ESS group. The causal effect of interest, the joint effect of HS and ESS on labor supply, can then be identified by subtracting equation (5) from equation (4),

$$
\begin{aligned}
& E(Y_{it}|ESS_{it} = 1, HS_{it} = 1) - E(Y_{it}|ESS_{it} = 1, HS_{it} = 0) \\
& - (E(Y_{it}|ESS_{it} = 0, HS_{it} = 1) - E(Y_{it}|ESS_{it} = 0, HS_{it} = 0)) \\
& = \beta_3.
\end{aligned} \tag{6}
$$

It is important to notice that equation (6) does not contain the error terms that were listed in equations (4) and (5) as they have been differenced out. However, this result does not rely on the error terms within equations (4) and (5) being equal. In fact, I expect respondents who suffer HS to have different unobservables compared to respondents who do not suffer HS. In this case, the identification of the interaction parameter comes from the fact that I expect those who are ESS to have the same unobservables as those who are not ESS, conditional on whether or not they receive a HS. If ESS status is randomly assigned, then the following conditions hold,

$$E(u_{it}|ESS_{it} = 1, HS_{it} = 1) = E(u_{it}|ESS_{it} = 0, HS_{it} = 1), \tag{7}$$

$$E(u_{it}|ESS_{it} = 1, HS_{it} = 0) = E(u_{it}|ESS_{it} = 0, HS_{it} = 0), \tag{8}$$

and the parameter β_3 can be identified as these errors are differenced out across equations (4) and (5).

While it is easy to imagine the random assignment criteria being met for respondents who are slightly above and slightly below the threshold age of 62, it is harder to justify for the entire sample which will contain respondents as young as 60 and as old as 63. It is possible that the respondents who are 62 - 63 could have different unobservables to the respondents who are 60 - 61. In this case, it may be more appropriate to adjust the model to take this into account. This can be done with the following equation,

$$Y_{it} = \beta_0 + \beta_1 ESS_{it} + \beta_2 HS_{it} + \beta_3 (ESS_{it} \times HS_{it}) + \alpha_i + \theta_t + e_{it}, \tag{9}$$

where α_i represents an individual-specific fixed effect, θ_t represents time period fixed effects, and e_{it} is the traditional idiosyncratic error. If ESS status cannot be treated as randomly assigned then α_i needs to be included in the model in order for the conditional mean assumption in equation (2) to be satisfied. To be specific, an example of α_i would be something like smoking behavior which both determines your labor supply (smokers are less likely to work than non-smokers) and is related to HS status (smoking increases the risk of all the diseases included as HS) and ESS status (ESS respondents who are older may be more likely to smoke than non-ESS respondents who are younger). Omitting this variable from the regression would cause bias in the estimators since it both determines the outcomes and is correlated with ESS and HS. While confounding variables such as smoking behavior can be observed and included in the model there are often other variables which fulfill these characteristics that are unobserved. Fortunately, this problem can be overcome by removing α_i from this equation with differencing. Taking the first-difference of equation (9) gives

$$\Delta Y_{it} = \theta_t + \beta_1 \Delta ESS_{it} + \beta_2 \Delta HS_{it} + \beta_3 \Delta (ESS_{it} \times HS_{it}) + \Delta e_{it}. \tag{10}$$

In this case, the estimators of parameters β_1 and β_3 will be unbiased if the following conditional mean assumption is met,

$$E(\Delta e_{it} | \Delta ESS_{it}) = E(\Delta e_{it}). \tag{11}$$

What this assumption means is that any change in ESS status is unrelated to changes in the error term. For ESS status, given that this change is based on an age threshold, it should not be related to changes in the error term and this condition should be satisfied. In fact, it is also plausible that the condition $E(\Delta e_{it} | \Delta HS_{it}) = E(\Delta e_{it})$ is satisfied given that the shocks included in the model are the onset of sudden, severe conditions such as cancer diagnosis or stroke. The assumption that the effect of health shocks on employment can be identified by differencing away any time-constant unobserved heterogeneity is standard within the health shock literature since experimental or quasi-experimental methods cannot be used with the data at hand (see Garcia-Gomez et al.[19], Trevisan and Zantomio [26], and Candon [32] for examples). Empirical evidence to support the assumptions that underpin the two models is presented in the final two subsections of this section.

In all models, the parameters are estimated using OLS. Because an individual can appear in more than one observation, the standard errors in the regression analysis are clustered at the individual level to correct for any serial correlation and heteroscedasticity.

3.2 Data

The data used in this analysis comes from the Health and Retirement Study (HRS). The HRS is a longitudinal study of aging set in the U.S. and it contains information on the employment status, health status, and Social Security status, of the respondents[4]. It is a biennial survey and the first 11 survey waves, spanning the years 1992 to 2012, are included here. The version used here is the RAND version which combines and cleans all 11 waves.

The following restrictions are imposed on the data. The respondents must be working in period $t-1$ in order to observe the effect of health shocks and Social Security on labor supply. This means there must be at least two periods of data for each individual. They also cannot be ESS (62 or older) in period $t-1$ so as to observe their pre-ESS labor market behavior. This restriction extends to any other Social Security program, such as Social Security Disability Insurance and Supplemental Security Income, for the same reason. This means that any not ESS to ESS transition is unique, though respondents may appear multiple times with regards to their not ESS work behavior. In period t,

[4] The HRS [52] is sponsored by the National Institute on Aging (grant number NIA U01AG009740) and is conducted by the University of Michigan.

I remove workers who are over the age of 65 to remove any confounding effect from eligibility to Medicare. This also means there is only one type of eligibility for Social Security payments, early eligibility. In order to make sure those who are ESS and not ESS are as similar as possible, I also remove respondents who are below the age of 60 and above the age of 63 in period t. Therefore, the respondents are ESS in period t if they are between the ages of 62 - 63 and not ESS if they are between the ages of 60 - 61. These and the other minors restrictions which are imposed are presented in more detail in Table A1 of the Appendix. Imposing these restrictions leaves a final sample of 11,967 observations. Because this is a panel data set, individuals may appear more than once. Of the 11,967 observations, 7,872 are unique individuals. This mean that there are 7,872 individuals that I observe at least two periods of information for, with some individuals providing three periods of information. The age distribution of the respondents left in the sample is presented in Table 1. The observations are separated by sex because the econometric models will be estimated separately for men and women.

Some additional variables, measured in period $t-1$, will be added as controls in some analysis. These include indicator variables for whether the respondent is not white, whether they have a college education (some or full), and whether they are married (or partnered). Some health related variables that are included are whether they have had a health shock, whether they are in poor or fair health (as opposed to good, very good, or excellent health), whether they have ever smoked, whether they smoke now, whether they drink alcohol, and whether they are obese (BMI $\geq$ 30). I also include some variables related to the respondents' working life such as whether or not they have a spouse who works, whether they are self-employed, whether they have employer-provided health insurance, whether they have a physical job, and their weekly hours of work. Information on the respondents' earnings and their household income are also included. These variables are adjusted to 2011 dollars using the Bureau of Labor Statistics inflation calculator and included with an inverse hyperbolic sine (IHS) transformation[5]. This transformation can be thought of as similar to the logarithmic transformation. However,

[5]This transformation of wealth, W, is $w = \ln(W + \sqrt{W^2 + 1})$.

IHS is preferred since it behaves like the logarithmic function for positive values but does not exclude cases where the variable is negative or zero.

3.3 Descriptive statistics

The assumption underpinning the first model presented was that I expect the respondents who are ESS to have the same unobservables as those who are not ESS, conditional on whether or not they receive a HS. While this assumption is fundamentally untestable since it involves unobservables it is possible to check how plausible it is by seeing if it is satisfied for observable characteristics. This can be done by examining the descriptive statistics for both groups. These are presented in Table 2. I break down the descriptive statistics of the sample by their HS status and ESS status in period t. The first panel contains information on potential control variables, measured at their period $t-1$ level, before anyone is ESS. While I expect to find differences between respondents who suffer HS and those who don't, I expect to find that the ESS and non-ESS groups are similar when being compared within HS status. Indeed, this is exactly what I find. When comparing columns (1) to (2), (3) to (4) etc. it is possible to see that there is little difference between the ESS and non-ESS groups. If these groups appear equivalent based on their observable characteristics then it lends support to the idea that they are also balanced with respect to their unobservable characteristics. Further descriptive statistics containing information on standard deviations, and statistically significant differences between the groups, are contained in the Appendix in Tables A2 and A3.

The second panel includes information on employment outcomes for the groups in period t. Men who are ESS are less likely to be employed and work fewer hours compared to men who are not ESS. Similarly, men who have suffered a HS are less likely to be employed and work fewer hours compared to men who have not had a HS. The men who are have suffered a HS, and are ESS, have the worst work outcomes. The situation is slightly different for women. While the women who are ESS work less than the women who are not ESS, this effect varies little by HS status. In short, the effect of being ESS on work outcomes differs based on HS status for men but does not appear to differ based on HS status for women. This will be a common feature of the econometric analysis presented in the Results section.

3.4 Trends over time

The main assumption underpinning the second model is that changes in ESS status are unrelated to changes in unobservables. In order to justify this assumption, I demonstrate that the ESS group and the non-ESS group have similar outcome trajectories over time. To do this, I plot the proportion of the respondents who report themselves as being in poor health for each of the four groups. I have chosen the poor health variable since it should obviously be different for the HS and non-HS groups but no difference should be observed within the groups based on ESS status. The plots are also done separately for men and women and they are presented in Figures 1 and 2. Again, the pattern is similar to the one which was observed for the descriptive statistics. The groups which have HS have worse health outcomes than the groups which do not have HS. However, within the HS group, there is no difference in health outcomes based on ESS status. Also, within the non-HS group, there is no difference in health outcomes based on ESS status. In fact, none of the differences between the ESS and non-ESS groups are statistically significant at the 10% level for either men or women at any time period in the graphs. Taken together, the information presented in Table 2 and Figures 1 and 2 show that the groups should not differ by ESS status and that I should be able to identify the joint effect of HS and ESS on labor supply.

4 Results

4.1 The effect of health shocks and eligibility for Social Security on hours of work

Panel A in Table 3 shows the results of estimating equation (1) by OLS for both men and women. The first column shows that men who are eligible for Social Security, and who have not suffered a health shock, work 6.9 fewer hours per week compared to men who have not suffered a health shock and are not eligible for Social Security. Men who have suffered a health shock, but are not eligible for Social Security, work 1.7 fewer hours per week compared to that same group. The men who have suffered a health shock, and who are eligible for Social Security, work 3 hours fewer compared to the men who are either only eligible for Social Security, or who have only suffered a health shock. This interaction coefficient tells us that men who are eligible for Social Security, and suffer a health shock, reduce their labor supply at a greater rate than men who are only eligible for Social Security, even after taking the direct effect of a health shock into account. In other words, how the male workers react to becoming eligible for Social Security differs based on whether or not they have had a health shock, even if the reduction in labor supply due to that shock has already been controlled for. In the second column, I add in the period $t-1$ control variables listed in Table 2, and some wave and region dummy variables, and the interaction coefficient increases slightly in magnitude to 3.1. The coefficient on the interaction term is statistically significant at the 1% level in both models. For women, the interpretation of the coefficients remains the same but the results are quite different. The third and fourth columns show that while the coefficients on eligibility for Social Security and health shock both have the expected negative sign, the interaction effect is not significantly different from zero in either specification.

Panel B shows the results from the first-difference model. Because one of the restrictions imposed on the sample was that respondents had to be working in period $t-1$, no observations are lost in the first-difference model. Again, this shows that even after the reduction in hours due to the health shock is taken into account, the men who are both eligible for Social Security and have suffered a health shock work 4.5 hours fewer than the men who are just eligible for Social Security. The addition of wave dummies to this model has very little effect. For women, the interaction coefficient is very small and not significantly different from zero in either specification. These two results are repeated throughout the rest of this paper: the effect of this interaction on male labor supply is negative and statistically significant while the effect of this interaction on female labor supply is close to zero and statistically insignificant.

4.2 Using different employment outcomes

In the original models, there were three important variables: the outcome variable; the eligibility for Social Security variable; and the health shock variable. I now re-estimate the models using different classifications for each of these variables to see how sensitive the results are to these changes. I begin by using different employment outcomes. This will help us understand whether the reduction in labor supply takes place at the extensive margin or the intensive margin. I now estimate the hours of work models with the restriction that the respondents must be working in period t. As can be seen from Panel A in Table 4, men and women who are eligible for Social Security, but have not had a health shock, do reduce the number of hours that they work even if they are still working in period t. Workers who suffer a health shock, but are not eligible for Social Security, do not reduce their labor supply if they return to work. What is interesting in this analysis is that the interaction coefficient is not statistically significant in the pooled model for men, but it is statistically significant a the 5% level in the first-difference model. Despite the fact that both results are qualitatively similar at between 1.2 -1.5 hours, they are smaller than the coefficients in Table 3, which were between 3 - 4.5 hours. For women the effect is still close to zero. So while being eligible for Social Security may help men who suffer a health shock to reduce the number of hours they work, it appears that it plays only a small role in allowing them to reduce the number of hours they work within a job.

If the reductions are not coming at the intensive margin it should be the case that I find reductions at the extensive margin. To check this, I now replace the dependent variable with a binary variable indicating whether or not the respondent is working. Respondents are recorded as working if they report working full-time, part-time, or part-retired and recorded as not working if they report being unemployed, retired, disabled, or not in the labor force. The results are presented in Panel B of Table 4. The first two columns show that men who are eligible for Social Security and suffer a health shock are between 6 and 10 percentage points less likely to be working than respondents who are just eligible for Social Security. This means that they are more likely to stop working compared to the respondents who are only eligible for Social Security, even after taking the negative effect of the health shock into account. For women, the interaction coefficient is positive in one model, and negative in another, but it is never statistically different from zero. In summary, the results are the same as in Table 3: the interaction has a significant negative effect on male labor supply, while it has no effect on female labor supply.

4.3 Using different age groups

A potential problem when using this type of estimation strategy is that, while the unobservables between respondents either side of the exogenous threshold may be identical, they differ the further you move away from that threshold. In this analysis, this translates into a concern that respondents who are 61 and 62 may be comparable, but not those who are 60 and 63. In order to test how sensitive the results are to the age of the respondents, I re-estimate the model using different age groups. The results are presented in Panel A of Table 5 and there is little difference between these results and those presented in Table 3. This shows that including respondents who are two years away from the age threshold gives similar results to including those who are only one year either side of the age threshold. In fact, if the age band is widened to include those who are 59 to 64 then the results still have the same overall pattern. Panel B of Table 5 shows that the interaction coefficient is slightly smaller in magnitude in both models for men, though the results are still statistically significant at the 1% level. Once again, the coefficients are small and statistically insignificant in the models for women. The analysis shows that the main results are not sensitive to any one particular definition of Social Security eligibility.

4.4 Using different health shocks

In order to mitigate any issues surrounding the choice of variables included as a health shock, I re-estimate the model using different definitions of the health shock variable. Currently, the definition is based on Smith [14] where a health shock is defined as a current diagnosis of cancer, heart problems, stroke, or lung disease. The aggregation of these health conditions could pose a problem for two reasons. For men, it could be the case that only one of these variables has a negative effect on labor supply but, because the different shocks are all pooled together, it appears as if they all have a significant negative effect. For women, it could be the exact opposite case: one of the health conditions could have a negative effect on labor supply but it is being drowned out since it is combined with other health conditions which do not have an effect.

I estimate the model again using four different definitions of the health shock. In each new model I use only one of the four original health shock variables. The results from this new set of analyses are presented in Table 6. While there are two cases where the pooled OLS interaction coefficient is not statistically significant for men (cancer and stroke) all of the FD interaction coefficients are significant at the 5% level. For women, it is the case that almost all of the interaction coefficients are still not statistically different form zero. However, the interaction coefficient in the FD model for strokes is statistically significant at the 10% level, and it is relatively large in magnitude when compared with the results from previous tables. So while the overall picture for women appears to be that becoming eligible for Social Security has no effect on the women who suffer health shocks, it may be the case that women who have suffered a stroke are more likely to reduce their labor supply once they become eligible for Social Security, in the same way that men do.

5 Robustness Checks

5.1 Placebo tests

One concern with the results is that it is not the receipt of Social Security which is exogenously determined but eligibility for Social Security. Not every respondent who is eligible for Social Security will avail of Social Security. This means that it is possible that the estimates observed in the previous regressions could simply be due to the interaction between health shock status and advancing age, and that being eligible for Social Security plays no role in the reduction of labor supply. In other words, the respondents who are 62 or 63 just react differently to health shocks than those who are 60 and 61. In order to demonstrate why this should not be the case, I perform a placebo test. This test involves using just the subgroup of respondents who are not ESS in period t. Currently, the respondents in this group are 60 and 61 years of age. I now define fake Social Security (FSS) to be used in the model instead of the original eligibility variable. The FSS variable is zero for respondents who are 60 and one for respondents who are 61. This test is similar to one performed by Finkelstein [53][6]. The results from using this FSS variable are presented in Panels A and B of Table 7 using the hours of work outcome and the working outcome. Since no other avenue to leave employment is available for the respondents who are FSS, there should not be a significant difference with how they react to a health shock. For the most part, the results from this analysis are statistically insignificant. There is one case which shows up as statistically significant: the first-difference model for hours of work with women. While the size of the coefficient is smaller than the coefficients that we have seen for the men in the previous analyses, and the result is only statistically significant at the 10% level, it may suggest that the 61 year old women are reacting differently to the health shocks when compared to the 60 year old women. However, this result does not show up when using the working variable.

5.2 Falsification tests

Another issue with this type of analysis is that the treatment status, while undoubtedly exogenous, is predictable. Respondents are aware of when they will turn 62 and may adjust their behavior in anticipation of their treatment status changing. In order to demonstrate that this is not the case, I also use a falsification test that involves testing the treatment and interaction on a outcome which should not have been affected by the

[6]Finkelstein [53] uses this method with regards to a tax change, rather the Social Security eligibility, but the principle is the same.

treatment. In this case, I use the hours of work variable from period $t-1$ as the outcome variable in equation (1). Since no respondents were eligible for Social Security in period $t-1$, the Social Security variable and interaction should have no effect on this outcome. I also do this for the subset of respondent who have information on hours of work going back to period $t-2$ by using the difference in lagged hours of work in the first-difference model. The results are presented in Panel C of Table 7. Again, the interaction variable is not a significant predictor of this outcome for either men or women. Despite the fact that one of the placebo tests showed up a statistically significant result for women, the overall body of evidence presented in this table seems to suggest that it is the interaction between health shock status and Social Security status which is causing the extra reductions in labor supply for men but this interaction has a negligible effect for women.

5.3 Adjusting for the timing of health shocks

Currently, the health shock variable is constructed with regards to the most recent diagnosis of the health condition. This is potentially a problem for two reasons. First of all, it does not distinguish between respondents who have a health shock in period t and respondents who have a health shock in period t and period $t-1$. In other words, it does not distinguish between respondents who have suffered health shocks in multiple periods and those who have just suffered them in one period. Second of all, it may not capture the immediate effect of a health shock on labor supply if it does not account for people who may have had a health shock 10 - 15 years ago, have now returned to work, and have suffered a new health shock before becoming eligible for Social Security.

A way of dealing with this is to use another variable in the HRS which asks the respondents "Have you ever been diagnosed with one of the following conditions ... ?". Any previous health shock that a respondent may have suffered will be recorded under this variable, whether it happened in the last wave or some period even further back. Using this definition of a health shock in the analysis to capture new diagnoses will ensure that a) we observing only one transition from not having a health shock to having a health shock and b) we are observing the most recent health shock that it is possible to observe with the data at hand. This addresses both of the concerns related to the original definition of the health shock that was listed above. I now redo the analysis from Tables 3 and 4 using this new definition of health shocks. The results are presented in Table 8. The magnitude of the interaction coefficients increases for men and remains statistically significant. The interaction coefficients for women remain close to zero and statistically insignificant. It appears that these results are robust to different definitions of a health shock where timing may be a factor.

5.4 Subgroup analysis

As a final way to examine the robustness of the previous results, I now estimate the model using only subgroups of the original sample. I do this by removing those respondents who display "unhealthy" characteristics in period $t-1$. This includes those in poor health, those who have ever smoked, those who currently smoke, those who drink alcohol, and those who are obese. The first reason is that these are the variables which are considered risk factors for the health shocks that are included in the analysis. Removing respondents who display these characteristics may remove a portion of the sample who are driving the results. If the subgroup who are driving the results can be found then any policies that are developed to help these workers can be targeted at the appropriate group. The second reason for excluding these groups is the exogenity assumption discussed in Section 3. While I argued that this assumption is satisfied for the entire sample, it is harder to justify that this assumption is still met when focusing on smaller subgroups of the main sample. However, if we are focusing on the groups which are relatively healthier then the health shock is more likely to be considered exogenous in it's own right, without relying on the assumptions from Section 3. Table 9 presents the results of the 5 separate subgroup analyses conducted for both men and women with the OLS and FD models. The interaction between whether the respondent suffered a health shock and whether they are eligible for Social Security is statistically significant at the 5% level in 9 out of the 10 tests for men. It is not significant at the 10% level in 9 out of the 10 tests for women. Overall, this final set of robustness tests reaffirms the effects that the interaction between health shock status and Social Security status has on male and female labor supply.

6 Discussion

6.1 How should these results be interpreted?

Throughout the analysis it has been consistently shown that the interaction between health shocks and being eligible for Social Security has a significant negative effect on labor supply for men but it has little to no effect for women. Why is this the case? A potential explanation for what this negative effect is measuring is men who would have normally returned to work after a health shock but now have an extra pathway to reduce their labor supply. To see this, look at the results presented in Table 4. In Panel A, the coefficient on health shocks shows the effect that a health shock has on hours of work for those who are still working and ineligible for Social Security. For both men and women the coefficients are close to 1 in absolute terms and none are statistically significant. However, Panel B clearly shows that if you are a man who has a health shock, and you are eligible for Social Security, then the probability that you stop working increases by between 6 and 10 percentage points over and above being eligible for Social Security, even after taking the direct effect of the health shock into account. To see how these results are linked, consider that for some respondents, the effect of the health shock on their health is so bad they have to withdraw from the labor market, regardless of whether or not they are eligible for Social Security. There will also be some respondents whose health is negatively effected by the health shock but could still return to work if they had to. If these respondents are not eligible for Social Security then they return to work and they report working similar hours to those who have not had a health shock. This is what the results in Panel A show. However, if these respondents are eligible for Social Security, then they will be able to withdraw from the labor market. This is what the results in Panel B show. In both cases, the men would like to leave the labor market because their health has been badly affected but only those who are eligible for Social Security have to the ability to do so.

6.2 Is there evidence to support this explanation?

If it is the case that the group of men who are just below the Social Security eligibility threshold are waiting to become eligible in order for them to leave the labor market, then I would expect them to report that their health has been affected. There is a binary variable in the HRS which asks whether or not your health is limiting the amount or kind of work you can do. I now regress this variable on health shock status for those who are still working in period t. The results are presented in Table 10. For the men who are still working in period t, and are ineligible for Social Security, those who have a had a health shock are almost 11 percentage points more likely to report that their health is limiting their work. These results are statistically significant at the 1% level. Women who have had a health shock are 2 - 4 percentage points more likely to report that their health is limiting their work, though the results are not significant. It is also possible to break these results down based on whether or not the respondents report themselves as doing a physical job. As expected, men who have suffered a health shock in physical jobs are 17 - 18 percentage points more likely to report that their health is limiting their work. Again, these results are significant at the 1% level. It should also be noted that men who have a health shock and do not work in physical jobs are more likely to report that their health is limiting their work, though the effect is smaller at around 7 percentage points. For women, regardless of whether they are working in a physical job or not, the effect of a health shock on whether their health is limiting their work is close to zero or statistically insignificant. These results help to explain the mechanism behind the results from the main body of the paper: being eligible for Social Security has an effect on men who have had a health shock since their ability to work has been effected by the health shock; however, it does not have an effect on women since the women who return to work seem to show no ill effects of the shock.

6.3 Why are these results important?

It has now been shown that men who return to work after a health shock report working the same number of hours as those who have not had a health shock. However, they are much more likely to report that their health is limiting their work than those who have not had a health shock. Also, the group who are statistically equivalent to them leave the labor market once they become eligible for Social Security. Taken altogether, these results suggest that while these men are working, they may still be recovering from their health shock. The commonly used term in the literature for continuing to work while sick, or recovering from illness, is presenteeism. Presenteeism is a topic which has received an increasing amount of attention in the last 10 years for a number of reasons. Firstly, studies have shown that the productivity losses from presenteeism can actually be greater than those of absenteeism. A recent literature review found that it was presenteeism, not absenteeism, or pharmacy costs, or medical costs, that accounted for the majority of the costs of health conditions to firms for a number of well known illnesses [54]. Secondly, presenteeism has been shown to be risk factor for future work absences due to sickness, as well as for decreases in self-reported health [55]. In situations like these, both the firm and worker may benefit from an extended recovery period for the worker. Finally, new research has also focused on policies that can reduce presenteeism. For example, Pichler and Ziebarth [56] recently found evidence to this effect by showing that the implementation of sick pay mandates which allowed workers to take sick days reduced contagious presenteeism in cities in the U.S. Unfortunately, there is no direct measure of presenteeism in the HRS, something which is not uncommon in this literature (see Jones et al. [57] for a recent example). However, the fact that male workers report that their health limits their work, and that they are even more reactive to becoming eligible for Social Security than healthy workers, is consistent with the idea that the men are not working at full capacity.

6.4 How do these results compare to other studies?

Concerning the other studies in the literature, there is no discernible pattern for how workers' hours of work change when they return to work after a health shock. For example, Cai et al. [16] finds that health shocks reduce hours of work for men and women by approximately 1 - 2 hours per week for those whose health was made worse by the health shock. However, respondents whose health was made much worse by the health shock reduce their hours of work by 7 - 9 hours. Trevisan and Zantomio [26] find that there is no adjustment in hours of work for women who return after a health shock. They also find that male full-time workers work more hours after suffering a health shock but male part-time workers work fewer hours. Meanwhile, Jones at al. [23] find that there is no reduction in hours of work in the year directly after the health shock for either full-time or part-time workers. They do, however, find a reduction of approximately 2.5 hours in the subsequent year. Focusing on cancer specifically, Candon [32] finds no difference in hours of work between those who return after the health shock and the healthy workers. Since the evidence from these papers is mixed, it is reassuring that the results found here are clear and robust. It also suggests that other studies who find no effect on hours of work for workers who return may be overlooking the fact that the workers may not be working to the same capacity as the healthy workers.

6.5 What are the policy implications arising from these results?

To see how these results can help inform future policy decisions the focus must turn to the mechanism behind the results. To this end, the contrast between the results for men and women can be particularly illuminating. Remember that throughout the analysis the interaction coefficient was negative and significant for men but close to zero and insignificant for women. Also, men were reporting that their health was limiting their work after the health shock but this was not case for women. Regardless of whether they were in a physical job or not, the women who returned to work after the health shock were no more likely than the non-health shock workers to report that their health was limiting their work. This can explain why, once the negative effect from the health shock has been differenced away, the health shock women react to becoming eligible for Social Security in the same way that the non-health shock women do. Why do women not report that their health is limiting their work after a health shock? A potential explanation for this is that, because of women's historically weaker attachment to the labor market, they may only return to work once they are fully recuperated from their health shock. Men, because of their historically stronger attachment to the labor market, are likely to return even if they are not fully recovered. Because of this, they react in a different way to becoming eligible for Social Security when compared to the other respondents. This suggests that if men were to return to work at the point where their health was no longer limiting their work then the interaction between the Social Security and health shock variables would not show up as having such a negative effect.

Future policies designed to mitigate this behavior could be targeted towards making sure more flexible working conditions are available. These policies could include reduced daily hours, a reduced work week, or the option to work from home on certain days. In situations like this, firms may benefit from employees working fewer hours at full capacity rather than full hours at a reduced capacity, which then further delays recovery. In turn, this could prevent immediate withdrawal from the labor market once the worker becomes eligible for Social Security. This is particularly relevant considering that it is workers who were working full-time in period $t-1$, as opposed to part-time or are part-retired, who reduce their labor supply once they become eligible for Social Security. The results presented in Table 11 show that this reduction occurs for workers who are classified as full-time by their own declaration (Panel A) and those working 40 hours a week (Panel D) or greater than 40 hours a week (Panel E). If these men are trying to return at the same level as they were at before the health shock then it may explain why we see such a huge reduction in their labor supply once they become eligible for Social Security. Interestingly though, the effect also doesn't seem to depend on the insurance status of the respondents as the effect is present for men with and without EPHI (for the FD model at least) and is not present for women. So it does not appear to be driven by people who returned to work simply to maintain their EPHI coverage.

While the policies mentioned above directly effect the amount of time a worker would spend in work, another important factor could be assisting workers in getting them access to rehabilitative services. This factor was found to increase employment in working women who had been diagnosed with breast cancer in a recent study by Neumark et al. [34]. Given that cancer is one of the health shocks included in this analysis, this accommodation could be used to help those who suffer from health shocks in general.

7 Conclusion

Despite the millions of people who suffer health shocks each year, and the millions of people who become eligible for Social Security every year, very little is known about the joint effect that being eligible for Social Security and suffering a health shock has on labor supply. Using data from the HRS, I model work outcomes as a function of a health shock, becoming eligible for Social Security, and their interaction. I find that male workers who are diagnosed with a health shock, and are eligible for Social Security, reduce their hours of work more than male workers who are just eligible for Social Security, even after the effect of the health shock has been differenced out. For women, I find that the interaction has little to no effect on the number of hours worked. With respect to labor market exits, the same pattern arises: men who are who are diagnosed with a health shock, and are eligible for Social Security, are more likely to leave the labor market than male workers who are only eligible for Social Security, even after the health shock has been accounted for. Again, the joint effect is zero for women. The effects are robust to numerous specifications. The results appear to be driven by men who would have had to return to work with impaired health. Policies that promote a more flexible work situation for older men may alleviate these problems in the future. Further research should focus on the reasons behind why men report that their health limits their work when they return to work but women do not. Such research could help shed valuable light on the exact mechanism behind the results found in this study.

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Tables

Table 1: Age distribution

Age in period t	ESS	Men	Women
60	No	1,592	1,608
61	No	1,606	1,673
62	Yes	1,533	1,439
63	Yes	1,229	1,287
Total		5,960	6,007

Table 2: Descriptive statistics

	Men				Women			
	No HS		HS		No HS		HS	
	Not ESS	ESS	Not ESS	ESS	Not ESS	ESS	Not ESS	ESS
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Period $t-1$								
Non-white	0.19	0.17	0.15	0.13	0.23	0.22	0.20	0.16
College	0.51	0.49	0.53	0.50	0.48	0.45	0.48	0.45
Married	0.86	0.85	0.86	0.88	0.64	0.64	0.62	0.62
HS	0.02	0.02	0.71	0.71	0.01	0.01	0.79	0.79
Poor health	0.10	0.09	0.26	0.25	0.10	0.10	0.25	0.26
Smoker (ever)	0.66	0.67	0.73	0.75	0.49	0.49	0.58	0.57
Smoker (now)	0.19	0.18	0.24	0.20	0.17	0.16	0.23	0.22
Drink alcohol	0.68	0.67	0.64	0.64	0.54	0.53	0.53	0.49
Obese	0.27	0.24	0.30	0.31	0.29	0.28	0.32	0.31
Working spouse	0.57	0.54	0.58	0.54	0.44	0.41	0.42	0.37
Self-employed	0.20	0.23	0.17	0.21	0.12	0.13	0.12	0.12
EPHI	0.71	0.69	0.72	0.71	0.61	0.59	0.63	0.64
Physical job	0.39	0.40	0.36	0.37	0.35	0.34	0.35	0.36
Hours of work	43.12	41.82	43.52	42.23	35.93	34.99	36.32	35.33
IHS (earnings)	9.89	9.57	10.15	10.00	9.71	9.47	9.79	9.72
IHS (HH income)	11.86	11.84	11.93	11.90	11.59	11.57	11.55	11.54
Period t								
Working	0.87	0.76	0.82	0.65	0.83	0.74	0.80	0.72
Hours of work	36.84	29.95	35.11	25.21	29.48	24.50	28.65	24.36
Age	60.49	62.44	60.53	62.46	60.51	62.46	60.52	62.50
Observations	2,455	2,028	743	734	2,553	2,083	728	643

Note: ESS - Eligible for Social Security; HS - Health shock; EPHI - Employer provided health insurance; IHS - inverse hyperbolic sine; HHI - household income. All variables measured as proportions except for age (years), hours of work (per week), earnings and HHI (transformed with IHS).

Table 3: The Effect of ESS and HS on Hours of Work

	Men		Women	
	Panel A: Hours of work (Pooled model)			
ESS	-6.893***	-6.174***	-4.986***	-4.446***
	(0.538)	(0.541)	(0.488)	(0.492)
HS	-1.729**	-2.021*	-0.833	-3.157***
	(0.806)	(1.031)	(0.762)	(1.077)
ESS*HS	-3.015***	-3.139***	0.692	0.853
	(1.157)	(1.124)	(1.044)	(1.025)
Wave dummies	No	Yes	No	Yes
Region dummies	No	Yes	No	Yes
Period $t-1$ controls	No	Yes	No	Yes
Observations	5,960	5,960	6,007	6,007
	Panel B: Hours of work (FD model)			
ESS	-5.242***	-5.271***	-3.936***	-3.940***
	(0.544)	(0.545)	(0.505)	(0.506)
HS	-1.917**	-1.813*	-3.304***	-3.212***
	(0.952)	(0.964)	(1.056)	(1.057)
ESS*HS	-4.554***	-4.663***	0.226	0.101
	(0.931)	(0.934)	(0.847)	(0.847)
Wave dummies	No	Yes	No	Yes
Region dummies	No	No	No	No
Period $t-1$ controls	No	No	No	No
Observations	5,960	5,960	6,007	6,007

Note: All models estimated by OLS. Clustered standard errors in parentheses. * Result significant at the 10% level. ** Result significant at the 5% level. *** Result significant at the 1% level. ESS - Eligible for Social Security; HS - Health shock; FD - First-differences.

Table 4: Using Different Work Outcomes

	Men		Women	
	Pooled	FD	Pooled	FD
	Panel A: Hours of work (if working)			
ESS	-2.375***	-2.006***	-1.466***	-1.127***
	(0.367)	(0.384)	(0.325)	(0.348)
HS	0.760	0.634	-0.714	-1.164
	(0.607)	(0.629)	(0.683)	(0.738)
ESS*HS	-1.165	-1.463**	0.343	0.510
	(0.740)	(0.676)	(0.647)	(0.551)
Observations	4,781	4,781	4,692	4,692
	Panel B: Working			
ESS	-0.105***	-0.099***	-0.092***	-0.091***
	(0.011)	(0.011)	(0.012)	(0.012)
HS	-0.062***	-0.056***	-0.085***	-0.074***
	(0.022)	(0.021)	(0.028)	(0.026)
ESS*HS	-0.065***	-0.096***	0.018	-0.006
	(0.025)	(0.021)	(0.026)	(0.021)
Observations	5,960	5,960	6,007	6,007

Note: All models estimated by OLS. Clustered standard errors in parentheses. The Pooled regressions contain wave and region dummies and the period $t-1$ control variables. The FD regressions contain wave dummies. * Result significant at the 10% level. ** Result significant at the 5% level. *** Result significant at the 1% level. ESS - Eligible for Social Security; HS - Health shock; FD - First-differences.

Table 5: Using Different Ages

	Men		Women	
	Pooled	FD	Pooled	FD
	Panel A: Hours of work (for ages 61 - 62)			
ESS	-4.320***	-3.822***	-3.317***	-2.833***
	(0.730)	(0.720)	(0.669)	(0.669)
HS	-2.077	-2.073	-6.126***	-6.086***
	(1.435)	(1.289)	(1.456)	(1.425)
ESS*HS	-3.354**	-4.601***	1.025	-0.232
	(1.542)	(1.269)	(1.423)	(1.135)
Observations	3,139	3,139	3,112	3,112
	Panel B: Hours of work (for ages 59 - 64)			
ESS	-6.616***	-5.642***	-4.646***	-4.112***
	(0.492)	(0.499)	(0.441)	(0.456)
HS	-2.523***	-2.177**	-2.805***	-2.993***
	(0.895)	(0.860)	(0.913)	(0.901)
ESS*HS	-2.761***	-4.330***	0.598	-0.089
	(1.023)	(0.902)	(0.932)	(0.821)
Observations	7,741	7,741	7,939	7,939

Note: All models estimated by OLS. Clustered standard errors in parentheses. The Pooled regressions contain wave dummies, region dummies, and the period $t-1$ control variables. The FD regressions contain wave dummies. * Result significant at the 10% level. ** Result significant at the 5% level. *** Result significant at the 1% level. ESS - Eligible for Social Security; HS - Health shock; FD - First-differences.

Table 6: Using Different Health Shock Definitions

	Men		Women	
	Pooled	FD	Pooled	FD
	Panel A: Hours of work (health shock is only lung disease)			
ESS	-6.198***	-5.467***	-4.438***	-3.883***
	(0.542)	(0.564)	(0.493)	(0.522)
HS	-1.697	-0.815	-4.374**	-2.644
	(2.103)	(1.698)	(1.878)	(1.718)
ESS*HS	-4.851*	-8.726***	2.487	-0.619
	(2.490)	(1.965)	(1.878)	(1.485)
Observations	4,779	4,779	4,997	4,997
	Panel B: Hours of work (health shock is only cancer)			
ESS	-6.126***	-5.541***	-4.405***	-4.031***
	(0.542)	(0.561)	(0.493)	(0.519)
HS	-0.203	0.229	-0.132	0.129
	(1.651)	(1.480)	(1.659)	(1.541)
ESS*HS	-2.303	-3.241**	0.154	-0.267
	(1.867)	(1.571)	(1.545)	(1.229)
Observations	4,879	4,879	5,148	5,148
	Panel C: Hours of work (health shock is only heart problems)			
ESS	-6.195***	-5.265***	-4.435***	-4.007***
	(0.541)	(0.554)	(0.493)	(0.518)
HS	-2.239*	-1.176	-1.890	-2.029
	(1.295)	(1.192)	(1.446)	(1.399)
ESS*HS	-2.303*	-4.722***	0.782	-0.550
	(1.392)	(1.143)	(1.436)	(1.189)
Observations	5,374	5,374	5,273	5,273
	Panel D: Hours of work (health shock is only stroke)			
ESS	-6.178***	-5.516***	-4.410***	-4.053***
	(0.543)	(0.567)	(0.494)	(0.527)
HS	-4.264	-1.266	-7.330***	-4.271*
	(2.805)	(1.927)	(2.807)	(2.227)
ESS*HS	-3.642	-8.946***	-0.508	-4.518*
	(3.719)	(2.764)	(3.247)	(2.553)
Observations	4,611	4,611	4,746	4,746

Note: All models estimated by OLS. Clustered standard errors in parentheses. The Pooled regressions contain wave dummies, region dummies, and the period $t-1$ control variables. The FD regressions contain wave dummies. * Result significant at the 10% level. ** Result significant at the 5% level. *** Result significant at the 1% level. ESS - Eligible for Social Security; HS - Health shock; FD - First-differences.

Table 7: Placebo and Falsification Tests

	Men		Women	
	Pooled	FD	Pooled	FD
	Panel A: Placebo test on hours of work			
FSS	-2.305***	-1.790***	-0.241	-0.154
	(0.662)	(0.649)	(0.611)	(0.605)
HS	-2.533*	-2.831**	-2.712*	-3.441***
	(1.376)	(1.228)	(1.404)	(1.334)
FSS*HS	-0.619	-1.506	-1.879	-1.971*
	(1.456)	(1.101)	(1.293)	(1.029)
Observations	3,198	3,198	3,281	3,281
	Panel B: Placebo test on working			
FSS	-0.039***	-0.032**	-0.006	-0.006
	(0.013)	(0.013)	(0.015)	(0.014)
HS	-0.071**	-0.066**	-0.077**	-0.078**
	(0.029)	(0.026)	(0.036)	(0.034)
FSS*HS	-0.009	-0.031	-0.034	-0.032
	(0.030)	(0.023)	(0.032)	(0.024)
Observations	3,198	3,198	3,281	3,281
	Panel C: Falsification tests using hours of work $(t-1)$			
ESS	-1.269***	-0.958***	-0.732***	-0.374
	(0.296)	(0.371)	(0.279)	(0.341)
HS	0.507	0.236	0.598	1.928**
	(0.590)	(0.606)	(0.695)	(0.794)
ESS*HS	-0.061	-0.036	-0.275	-0.137
	(0.616)	(0.522)	(0.589)	(0.510)
Observations	5,960	4,701	6,007	4,725

Note: All models estimated by OLS. Clustered standard errors in parentheses. The regressions contain wave dummies, region dummies, and the period $t-1$ control variables. * Result significant at the 10% level. ** Result significant at the 5% level. *** Result significant at the 1% level. ESS - Eligible for Social Security; HS - Health shock; FSS - Fake Social Security. FSS is zero for respondents who are 60 and one for respondents who are 61.

Table 8: Adjusting for the Timing of Health Shocks

	Men		Women	
	Pooled	FD	Pooled	FD
	Panel A: Hours of work			
ESS	-6.122***	-5.271***	-4.283***	-3.820***
	(0.539)	(0.544)	(0.487)	(0.502)
HS	-2.714**	-3.121**	-4.404***	-4.568***
	(1.275)	(1.249)	(1.270)	(1.311)
ESS*HS	-3.468***	-4.787***	0.211	-0.384
	(1.134)	(0.936)	(1.056)	(0.865)
Observations	5,959	5,959	6,003	6,003
	Panel B: Hours of work (if working)			
ESS	-2.308***	-1.933***	-1.465***	-1.112***
	(0.363)	(0.380)	(0.323)	(0.348)
HS	1.081	0.667	-1.306	-1.718*
	(0.709)	(0.734)	(0.831)	(0.924)
ESS*HS	-1.483*	-1.823***	0.350	0.447
	(0.761)	(0.704)	(0.664)	(0.561)
Observations	4,781	4,781	4,690	4,690
	Panel C: Working			
ESS	-0.104***	-0.100***	-0.087***	-0.089***
	(0.011)	(0.011)	(0.012)	(0.012)
HS	-0.085***	-0.088***	-0.114***	-0.111***
	(0.028)	(0.027)	(0.034)	(0.033)
ESS*HS	-0.073***	-0.098***	-0.002	-0.014
	(0.025)	(0.021)	(0.027)	(0.021)
Observations	5,959	5,959	6,003	6,003

Note: All models estimated by OLS. Clustered standard errors in parentheses. The Pooled regressions contain wave dummies, region dummies, and the period $t-1$ control variables. The FD regressions contain wave dummies. * Result significant at the 10% level. ** Result significant at the 5% level. *** Result significant at the 1% level. ESS - Eligible for Social Security; HS - Health shock; FD - First-differences.

Table 9: Health Related Subgroup Analysis

	Men		Women	
	Pooled	FD	Pooled	FD
	Panel A: Hours of work (excluding respondents in poor health in $t-1$)			
ESS*HS	-3.553***	-4.394***	0.785	0.500
	(1.250)	(1.040)	(1.145)	(0.958)
Observations	5,151	5,151	5,204	5,204
	Panel B: Hours of work (excluding respondents who have ever smoked in $t-1$)			
ESS*HS	-4.017**	-4.207**	1.947	2.002
	(2.043)	(1.736)	(1.479)	(1.234)
Observations	1,890	1,890	2,951	2,951
	Panel C: Hours of work (excluding respondents who smoke in $t-1$)			
ESS*HS	-3.239***	-4.319***	2.061*	1.405
	(1.235)	(1.021)	(1.132)	(0.930)
Observations	4,796	4,796	4,912	4,912
	Panel D: Hours of work (excluding respondents who drink alcohol in $t-1$)			
ESS*HS	-2.605	-5.165***	1.367	0.666
	(1.903)	(1.570)	(1.448)	(1.202)
Observations	1,984	1,984	2,809	2,809
	Panel E: Hours of work (excluding respondents who are obese in $t-1$)			
ESS*HS	-3.961***	-5.018***	-0.020	0.078
	(1.314)	(1.109)	(1.244)	(1.044)
Observations	4,356	4,356	4,261	4,261

Note: All models estimated by OLS. Clustered standard errors in parentheses. The Pooled regressions contain wave dummies, region dummies, and the period $t-1$ control variables. The FD regressions contain wave dummies. * Result significant at the 10% level. ** Result significant at the 5% level. *** Result significant at the 1% level. ESS - Eligible for Social Security; HS - Health shock; FD - First-differences.

Table 10: The effect of HS on your ability to work for workers who are not ESS

	Men		Women	
	Pooled	FD	Pooled	FD
	Panel A: Whether your health limits your work			
HS	0.106***	0.107***	0.038	0.023
	(0.024)	(0.027)	(0.030)	(0.037)
Observations	2,729	2,729	2,660	2,660
	Panel B: Whether your health limits your work (physical jobs)			
HS	0.166***	0.175***	0.011	0.015
	(0.045)	(0.049)	(0.052)	(0.067)
Observations	1,007	1,007	911	911
	Panel C: Whether your health limits your work (non-physical jobs)			
HS	0.073***	0.067**	0.051	0.024
	(0.028)	(0.032)	(0.037)	(0.044)
Observations	1,718	1,718	1,746	1,746

Note: All models estimated by OLS. Clustered standard errors in parentheses. The Pooled regressions contain a lagged value of the dependent variable, wave dummies, region dummies, and the period $t-1$ control variables. The FD regressions contain wave dummies. * Result significant at the 10% level. ** Result significant at the 5% level. *** Result significant at the 1% level. HS - Health shock; FD - First-differences.

Table 11: Policy Relevant Subgroup Analysis

	Men		Women	
	Pooled	FD	Pooled	FD
	Panel A: Hours of work (respondents who work full-time in $t-1$)			
ESS*HS	-4.042***	-5.876***	1.044	-0.172
	(1.252)	(1.042)	(1.339)	(1.110)
Observations	5,100	5,100	4,126	4,126
	Panel B: Hours of work (respondents who work part-time/part-retired in $t-1$)			
ESS*HS	1.703	1.314	-0.077	0.228
	(2.422)	(1.727)	(1.474)	(1.155)
Observations	860	860	1,881	1,881
	Panel C: Hours of work (respondents who work $<$ 40 hours in $t-1$)			
ESS*HS	-0.627	-1.616	0.669	-0.087
	(2.023)	(1.594)	(1.304)	(1.014)
Observations	1,048	1,048	2,556	2,556
	Panel D: Hours of work (respondents who work 40 hours in $t-1$)			
ESS*HS	-3.828**	-5.836***	2.315	0.245
	(1.745)	(1.412)	(1.699)	(1.360)
Observations	2,450	2,450	2,439	2,439
	Panel E: Hours of work (respondents who work $>$ 40 hours in $t-1$)			
ESS*HS	-3.434*	-4.797***	-3.375	-0.131
	(1.887)	(1.563)	(2.963)	(2.553)
Observations	2,462	2,462	1,012	1,012
	Panel F: Hours of work (excluding respondents with EPHI in $t-1$)			
ESS*HS	-3.191	-5.124***	1.886	0.341
	(2.084)	(1.688)	(1.560)	(1.300)
Observations	1,748	1,748	2,361	2,361
	Panel G: Hours of work (including respondents with EPHI in $t-1$)			
ESS*HS	-3.113**	-4.357***	0.382	0.061
	(1.333)	(1.119)	(1.340)	(1.105)
Observations	4,212	4,212	3,646	3,646

Note: All models estimated by OLS. Clustered standard errors in parentheses. The Pooled regressions contain wave dummies, region dummies, and the period $t-1$ control variables. The FD regressions contain wave dummies. * Result significant at the 10% level. ** Result significant at the 5% level. *** Result significant at the 1% level. ESS - Eligible for Social Security; HS - Health shock; FD - First-differences.

Figures

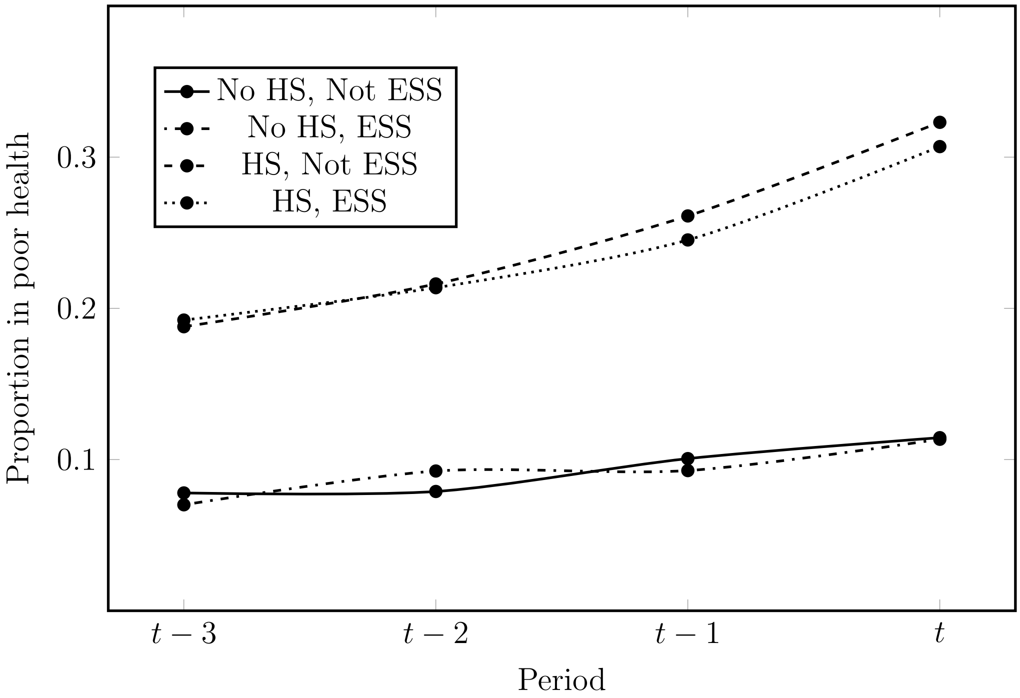

Figure 1: Health comparison (Men)

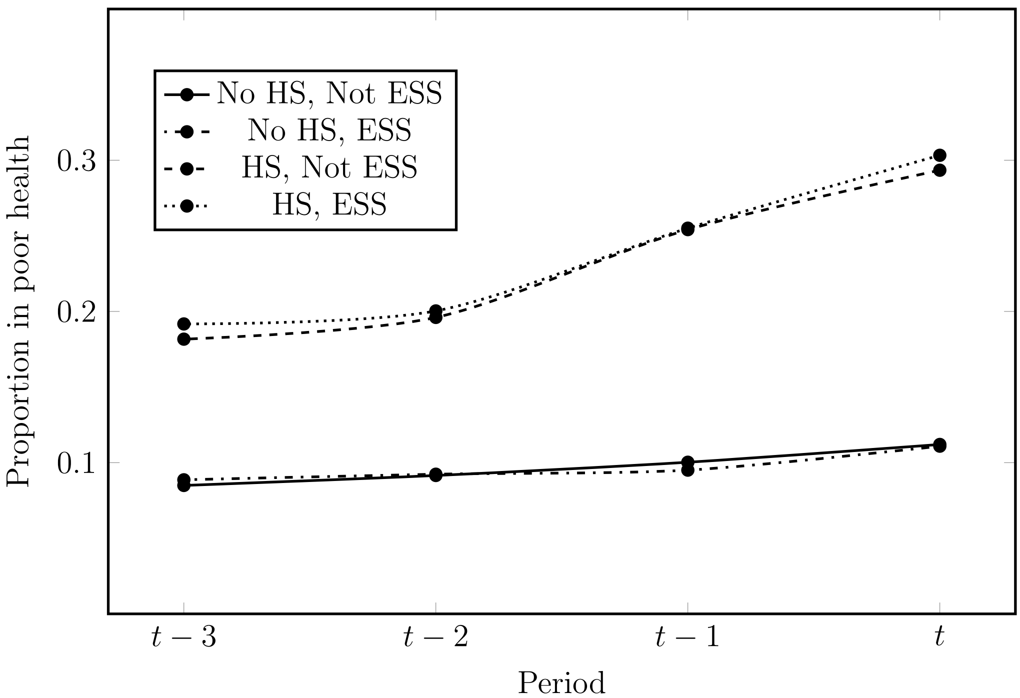

Figure 2: Health comparison (Women)

Appendix

Table A1: Sample information

Exclusion criteria	Observations
Unrestricted sample	207,816
Not working in period $t-1$	139,408
ESS in period $t-1$	21,459
Claiming SSDI or SSI in period $t-1$	412
Younger than 60 or older than 63 in period t	32,347
Reporting no hours when working (and vice versa) in either period	300
Working more than 80 hours a week in either period	139
Missing information for control variables in $t-1$	1,784
Restricted sample	11,967

Note: Observations refers to person-wave observations (i.e one individual in the survey for 10 waves appears as 10 observations). ESS - Eligible for Social Security; SSDI - Social Security Disability Insurance; SSI - Supplemental Security Income.

Table A2: Descriptive statistics (Men)

	No HS				HS			
	Not ESS		ESS		Not ESS		ESS	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Period $t-1$								
Non-white	0.19	0.39	0.17	0.38	0.15	0.36	0.13	0.34
College	0.51	0.50	0.49	0.50	0.53	0.50	0.50	0.50
Married	0.86	0.35	0.85	0.36	0.86	0.35	0.88	0.33
HS	0.02	0.14	0.02	0.14	0.71	0.45	0.71	0.45
Poor health	0.10	0.30	0.09	0.29	0.26	0.44	0.25	0.43
Smoker (ever)	0.66	0.47	0.67	0.47	0.73	0.44	0.75	0.44
Smoker (now)	0.19	0.39	0.18	0.38	0.24*	0.43	0.20	0.40
Drink alcohol	0.68	0.47	0.67	0.47	0.64	0.48	0.64	0.48
Obese	0.27**	0.44	0.24	0.43	0.30	0.46	0.31	0.46
Working spouse	0.57**	0.49	0.54	0.50	0.58	0.49	0.54	0.50
Self-employed	0.20**	0.40	0.23	0.42	0.17*	0.38	0.21	0.41
EPHI	0.71	0.45	0.69	0.46	0.72	0.45	0.71	0.45
Physical job	0.39	0.49	0.40	0.49	0.36	0.48	0.37	0.48
Hours of work	43.12***	11.41	41.82	12.45	43.52**	11.79	42.23	12.90
IHS(earnings)	9.89***	3.96	9.57	4.17	10.15	3.66	10.00	3.85
IHS(HH income)	11.86	1.24	11.84	1.22	11.93	1.13	11.90	1.21
Period t								
Working	0.87***	0.33	0.76	0.42	0.82***	0.38	0.65	0.48
Hours of work	36.84***	18.08	29.95	20.58	35.11***	19.60	25.21	21.96
Age	60.49***	0.50	62.44	0.50	60.53***	0.50	62.46	0.50
Observations	2,455		2,028		743		734	

Note: ESS - Eligible for Social Security; HS - Health shock; SD - Standard deviation; EPHI - Employer provided health insurance; IHS - inverse hyperbolic sine; HHI - household income. All variables measured as proportions except for age (years), hours of work (per week), earnings and HHI (transformed with IHS). * Difference between columns (1) and (3), or columns (5) and (7), statistically significant at the 10% level. ** Difference between columns (1) and (3), or columns (5) and (7), statistically significant at the 5% level. *** Difference between columns (1) and (3), or columns (5) and (7), statistically significant at the 1% level.

Table A3: Descriptive statistics (Women)

	No HS				HS			
	Not ESS		ESS		Not ESS		ESS	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Period $t-1$								
Non-white	0.23	0.42	0.22	0.42	0.20*	0.40	0.16	0.37
College	0.48	0.50	0.45	0.50	0.48	0.50	0.45	0.50
Married	0.64	0.48	0.64	0.48	0.62	0.48	0.62	0.49
HS	0.01	0.10	0.01	0.10	0.79	0.41	0.79	0.40
Poor health	0.10	0.30	0.10	0.29	0.25	0.44	0.26	0.44
Smoker (ever)	0.49	0.50	0.49	0.50	0.58	0.49	0.57	0.49
Smoker (now)	0.17	0.38	0.16	0.37	0.23	0.42	0.22	0.42
Drink alcohol	0.54	0.50	0.53	0.50	0.53	0.50	0.49	0.50
Obese	0.29	0.45	0.28	0.45	0.32	0.47	0.31	0.46
Working spouse	0.44**	0.50	0.41	0.49	0.42*	0.49	0.37	0.48
Self-employed	0.12	0.33	0.13	0.34	0.12	0.32	0.12	0.32
EPHI	0.61	0.49	0.59	0.49	0.63	0.48	0.64	0.48
Physical job	0.35	0.48	0.34	0.47	0.35	0.48	0.36	0.48
Hours of work	35.93***	11.97	34.99	12.60	36.32	12.17	35.33	12.06
IHS(earnings)	9.71**	3.43	9.47	3.64	9.79	3.39	9.72	3.37
IHS(HH income)	11.59	1.32	11.57	1.17	11.55	1.24	11.54	1.18
Period t								
Working	0.83***	0.38	0.74	0.44	0.80***	0.40	0.72	0.45
Hours of work	29.48***	17.39	24.50	18.43	28.65***	17.75	24.36	18.45
Age	60.51***	0.50	62.46	0.50	60.52***	0.50	62.50	0.50
Observations	2,553		2,083		728		643	

Note: ESS - Eligible for Social Security; HS - Health shock; SD - Standard deviation; EPHI - Employer provided health insurance; IHS - inverse hyperbolic sine; HHI - household income. All variables measured as proportions except for age (years), hours of work (per week), earnings and HHI (transformed with IHS). * Difference between columns (1) and (3), or columns (5) and (7), statistically significant at the 10% level. ** Difference between columns (1) and (3), or columns (5) and (7), statistically significant at the 5% level. *** Difference between columns (1) and (3), or columns (5) and (7), statistically significant at the 1% level.