PRELIMINARY, DO NOT CITE

Health Shocks and Disability Transitions Among Near-elderly Workers

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ABSTRACT

Between the ages of 50 and 64, seven percent of full-time workers will have a major adverse health event, such as a heart attack, a stroke, or a new onset of cancer. Evidence shows clearly that the labor force response to health shocks differs systematically across groups. Relative to the 12 percent of full-time workers overall who apply for or receive disability insurance (DI) within four years after a health shock, the share is 27 percent among those with less than a high school degree. For blacks, the application or receipt rate is 21 percent. We analyze these issues empirically using 1994-2008 data from the Health and Retirement Study (HRS). Our paper first presents a simple model of the response to an adverse health shock, emphasizing the importance of health capital and labor supply theories of disability application decisions. We then test the implications of these models regarding differences across demographic groups and the importance of health and labor supply variables as determinants of the DI application decisions. In a sample of older workers, after controlling for the onset of a new major health shock, demographic differences diminish only slightly, but they disappear after controlling further for labor market variables. Among the subset of workers who experience a health shock, we find further evidence that the nature of the health shock and prior health status matters a great deal for the DI application decision, as do labor market related variables. A rich model of health and labor supply factors explains 40 to 60 percent of the variation in DI application. However, health and labor supply variables in our models cannot explain large differences in DI application by education and race.

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1. Introduction

As people age, their health deteriorates. Between the ages of 50 and 64, seven percent of full-time workers will have a major adverse health event, such as a heart attack, a stroke, or a new onset of cancer. For some of these workers, disability insurance is the answer. Within four years of a major health shock, 12 percent have applied for or are receiving disability insurance. But other people continue working full-time. Over the same four-year window, 60 percent of workers with a major shock remain on full-time employment, 4 percent cut back their hours but stay in the labor force part-time, and 22 percent retire but do not apply for disability.

What determines these different trajectories after a health shock? To what extent do public policies, the nature of work, and earnings influence the response to health events? The answers to these questions have taken on additional importance in light of recent Trustee reports predicting that the DI trust fund will be exhausted by 2018 (Board of Trustees 2011), along with the long run deficit in the Social Security and Hospital Insurance trust funds.

The different trajectories are not just random. Relative to the 12 percent of full-time workers overall who apply for or receive disability insurance within four years after a health shock, the share is 27 percent among those with less than a high school degree. For blacks, the application or receipt rate is 21 percent. Among lower income individuals (those in the bottom 40% of earnings), the application or receipt rate is 19 percent. Understanding these different transitions is the goal of this paper.

We first present a simple model of the response to an adverse health shock, demonstrating two approaches to labor force determination: the health capital approach and labor supply approach. These two approaches differ in how they conceptualize the decision to apply for DI. In the health capital approach, health affects earnings directly because health affects productivity, and thus disability application rises when health decrements are serious enough that potential earnings while working fall below expected income under DI. Furthermore, the likelihood of this occurring depends on the nature of one's job, as a physical health problem will adversely affect individuals in jobs that require more physical effort. In the labor force approach, DI application behavior responds to economic conditions (which are reflected in the wage faced by individuals in a given labor market at a point in time) and the fact that low human capital workers have relatively high (and over time increasing) replacement rates (Bound and Burkhauser 1999; Autor and Duggan 2006).

After describing the model above, we present basic facts regarding the frequency and nature of health shocks and labor force transitions out of full-time work for older workers. We then analyze the response to a health shock, considering the health capital and labor supply models. We find limited evidence for our model of health capital and strong support for the importance of theories of labor supply. First, the nature of the health shock matters; new stroke victims are nearly 13 percentage points more likely to apply for DI within four years compared with workers who experience a heart attack. However, the presence of prior health conditions and the physical and mental effort in one's work do not predict DI application.

After describing the model above, we present basic facts regarding the frequency and nature of health shocks and labor force transitions out of full-time work for older workers. We then analyze the response to a health shock, considering our framework regarding health capital and labor supply factors. We find mixed evidence regarding the relative roles of health capital versus labor supply. First, the nature of the health shock matters; new stroke victims are nearly 13 percentage points more likely to apply for DI within four years compared with workers who experience a heart attack. Second, the presence of pre-existing conditions predicts DI application after a new health shock, but it explains only a fraction of demographic differences in DI application/receipt. In contrast, controlling for measures that capture the labor supply features in our framework, education gradients in DI application/receipt virtually disappear. However, it is difficult to pinpoint a particular aspect of labor supply (earnings, unearned income, job characteristics) as important in the labor supply decisions, since the effects of these are measured with relatively high uncertainty after controlling for health factors in detail. On balance, we conclude that major health shocks act as a catalyst in the decision to apply for DI, but conditional on having a health shock, labor market characteristics are at least as important as the severity of the health shock. The remainder of the paper is structured as follows. Section 2 describes a conceptual framework that draws on a rich literature on disability application decisions to motivate our empirical work. Section 3 presents the data and methods for this work. Section 4 presents results, and section 5 concludes.

2. Conceptual Background: Response to a Health Shock

To motivate our empirical work, we conceptualize the response to a health event in two ways. The first is based on a standard health capital model (Grossman, 1972). This model is focused on the stock of health, and people work as long as their health is above a threshold related to their productivity in the labor market. From this perspective the response to a health shock will depend on the severity of the shock, the stock of health before the shock, and the health requirement for work (i.e. physical and mental effort). All else equal, people who have more severe health shocks or who were in worse health before the health shock will be more likely to apply for disability insurance than will others. Similarly, people with more physically or mentally demanding jobs will be more likely to apply after a health shock.

The second framework is that of optimal labor supply (Bound and Burkhauser, 1999). The choice between disability insurance, retirement (or leaving the labor market), and labor force participation (full or part-time) is made in light of income effects, substitution effects, and tastes for leisure. In this model, the behavioral differences across people will be explained by the relative disability insurance replacement rate (disability applications should be greater among people with higher replacement rates), the amount of other earnings in the household (including non-cash benefits such as health insurance), and the extent to which the person dislikes work.

We use a simple, static model of labor supply to illustrate these ideas and bring them together in a unified framework. Individuals choose whether to work (W), retire (R), or apply for disability insurance (D). This is a one-time decision, and inputs such as wages, unearned income, retirement benefits, and health are all taken as exogenous.

Utility depends on consumption and health. The value of consumption is given by a function u with diminishing marginal returns while, for simplicity, health has a separate, linear impact. For workers, consumption is equal to earned plus unearned income. Earnings are wHK, where w is an efficiency wage, H is the health stock, and K is human capital. Unearned income is denoted y. Retirees have no earnings but may receive a retirement benefit r, which would be a private pension benefit for ages under 62. Health affects utility as $\alpha_W H$ for workers and $\alpha_L H$ for retirees (who are at "leisure"). Thus utility for workers and retirees are, respectively:

(1) $$U_W = u(wHK + y) + \alpha_W H\ ;$$

(2) $$U_R = u(r + y) + \alpha_L H\ .$$

Individuals who apply for DI will be accepted with a probability that depends on their health stock, $p(H)$, which is decreasing in H, and if accepted will receive a monetary benefit b.

They cannot work but also receive the retirement benefit r. There is also a utility cost of applying, c, and so the expected utility of applying for DI is

$$(3) \qquad U_D = [1 - p(H)]\, u(r + y) + p(H)\, u(b + r + y) + \alpha_L H - \mathrm{c}\ .$$

The labor supply decision is then $\max\{U_W, U_R, U_D\}$, with the constraint that health must be above a job-specific threshold in order to work. Denoting the threshold for job j as $\underline{H}_j$, the optimization problem can be formally stated as

$$\max\{U_W, U_R, U_D\} \text{ if } H \geq \underline{H}_j,$$

$$\max\{U_R, U_D\} \text{ if } H < \underline{H}_j.$$

Most implications of this model are straightforward. Following a health shock, and depending on the severity of that shock and the prior stock of health, H is more likely to fall below $\underline{H}_j$. The impact of higher job-specific health requirements is also readily apparent. For those in this situation with $H < \underline{H}_j$, the decision about whether to apply for benefits is determined by

$$(4) \qquad U_D - U_R = p(H)\, [\, u(b + r + y) - u(r + y)\,] - \mathrm{c}\ .$$

This suggests that individuals with higher retirement benefits (r) or unearned income (y) are less likely to apply because the marginal utility of any additional consumption from the disability benefit (b) is lower, and thus more likely to be exceeded by the cost of applying (c), which could include time costs, forgone income if one leaves the labor market or works less than possible in order to meet income eligibility requirements, the cost of lawyers and appeals, or related costs of applying for DI. Equation (4) implies that the benefit is quite valuable to individuals with low incomes and little retirement savings.

In contrast, consider the case where $H \geq \underline{H}_j$, so that an individual is able to work (since health still exceeds the threshold required to maintain employment). Furthermore consider individuals for whom $U_D > U_R$, (i.e., individuals without substantial retirement savings or unearned income) to focus on the incentives provided by the DI program to drop out of the labor force. Here the decision depends on

$$(5) \qquad U_D - U_W = u(r+y) - u(wHK+y) + p(H)\,[\,u(b+r+y) - u(r+y)\,] + (\alpha_L - \alpha_W)\,H - c$$

This shows that low health (or a health decline) affects the decision to apply for DI in three ways. First is the loss of labor market productivity, from the earnings wHK. Second is the increased probability of acceptance, $p(H)$. Third, the marginal effect of health on utility (the α's) may be smaller in leisure than at work. If work is more physically or mentally demanding on average than leisure, having better health would be more important for work than for leisure ($\alpha_L < \alpha_W$) and thus ($\alpha_L - \alpha_W$) is negative.[1] All three channels imply a negative relationship between health and the probability of applying.

This model is useful for distinguishing between the perspective that disability benefits are increasingly used as unemployment insurance for low-skill workers, and the perspective that the program is well targeted to individuals with health problems. If the efficiency wage (w) drops due to macroeconomic conditions, or human capital falls (perhaps because K is defined in a relative sense and there are fewer high school drop-outs, for example), the probability of applying increases due to these labor market incentives. Similarly if the benefits level or the overall acceptance probability increase, individuals are more likely to choose D over W regardless of their health. Program targeting, on the other hand, relates specifically to the shape of the function p. The more sharply p declines over some range of H, the better the targeting is in terms of health.

[1] The opposite could also be true. Provided this term is not sufficiently large and in the opposite direction, our results would still hold.

At the extreme, suppose the screening process works perfectly, so that only individuals who truly cannot have any substantial gainful activity are accepted. In terms of the model this means p is defined by a threshold $\underline{H}^*$ such that

$$p(H) = 1\{H < \underline{H}^*\}.$$

Hence nobody would apply if $H_i > \underline{H}^*$. Moreover suppose $\underline{H}^* = \min\{\underline{H}_j\}$ for all jobs j, given the definition of substantial gainful activity. Hence nobody could work if $H_i < \underline{H}^*$, and their only choice would be between retirement and applying for DI. This choice is determined by equation (4), which involves retirement benefits and unearned income, but not earnings (or earnings potential, as captured by human capital). Thus if we had perfect measures of health and potential income in retirement, this extreme version suggests that earnings potential should have no effect on the probability of applying for DI. In addition, the closer the relationship between health status H and the probability of a DI application getting accepted, the more important health factors will be relative to economic factors.

This simple framework yields several empirical implications that we will test. The probability of DI application receipt should decline with measures of own earnings (including wage earnings and other compensation like health insurance benefits). Second, the probability of DI application should decline with measures of unearned income, which includes other sources of household income, but also non-financial sources of income like health insurance benefits provided by a spouse. In the context of our goal of understanding differences in DI application/receipt by demographics like education and race, the framework above suggests that educational groups or racial groups that have lower levels of human capital, on average, will have higher rates of applying for disability, since their earnings will be lower. However, the model also suggests that careful controls for earnings should then explain at least part of differences in DI application/receipt across education and race groups. Our framework also suggests that changes in H may have different effects for individuals with different levels of education since they have, on average, different levels of human capital, and because they work in different occupations which may have very different health requirements. Thus, the framework implies that differences in DI application/receipt rates across education or race groups may be smaller if one controls for differences in the health demands of one's occupation (physical and mental demands).

3. Data and Empirical Approach

We analyze labor force status and the decision to apply for DI empirically using data from the Health and Retirement Study (HRS). The HRS has biennial data on health status, labor force participation, and disability application and receipt for a sample of over 18,000 people aged 52 to 64. We use these data to study the immediate and long-term impact of health shocks over 15 years (1994-2008), a period in which the application to DI climbed from 9 to 12 percent of 52-64 year olds (Figure 1). We relate the transition to application for disability benefits following a health shock to three sets of variables: basic demographic controls such as age, gender, race, and education; health capital measures such as indicators for the type of health shock, the pre-shock level of health, and the physical and mental requirements of the pre-shock job; and labor force measures such as wages and the income/benefits of other family members.

With survey weights, the HRS reflects the non-institutionalized population. We focus on the labor force status of adults aged 52 to 64. We focused on the 6,693 men and 8,707 women observed between the ages of 50 and 62 in at least one wave (a baseline wave) and 52 to 64 in the next wave (Table 1). Of these, we further restricted the sample to 4,733 male and 4,517 female respondents who reported full time work in their baseline interview and who were not applying for or receiving DI. Finally, after excluding those with missing information on DI application/receipt and other key variables (i.e. the health measures described below, along with education), the sample included 4,096 men and 3,756 women, yielding 16,442 observations (person-waves at 4 or more years from baseline).

To define a health shock, we follow the methods used by Smith (1999) to define major and minor health shocks. The HRS asks respondents at baseline, "Has a doctor ever told you that you have/had _______" where the blank ranges from conditions like cancer or chronic lung disease, to a heart attack, congestive heart failure, to arthritis. In subsequent waves, respondents are asked about new diagnoses since the last interview. In each wave, we create a variable for a new major health shock equal to 1 if a respondent reports having any of the following: heart disease, lung disease, cancer, stroke, or a psychiatric diagnosis, and zero otherwise. Note that individuals who previously reported these conditions would have a value of zero for this variable, since the health condition was not "new". Similarly, we created a variable for a new minor health shock if respondents reported a new diagnosis of arthritis, hypertension, or diabetes. Using these definitions, Table 1 summarizes characteristics of the 50-64 year old population in the HRS, the subset of full time workers (defined as above), and a subset of 596 males and 482 female workers that experienced a new major health shock, and for whom we had observations at least 4 years after baseline. With the definition of health shocks above, 8.1 percent of adults aged 50-62 experience a new major health shock over a two-year period. When restricted to full-time workers at baseline, the rate of new health shocks falls to 6.6 percent. Among the 3.2 percent of full-time workers we observe who apply for DI within a four-year period, one-third of these applicants have had one of the major health shocks we identify during that period.

The HRS also reports in detail regarding limitations faced by survey respondents based on questions about Activities of Daily Living (ADLs; questions regarding whether a respondent needs assistance with dressing, bathing, walking, standing) and Instrumental Activities of Daily Living (IADLs; questions regarding whether a respondent needs assistance with activities like balancing a check book, grocery shopping, meal preparation) and questions regarding other functional limitations, (based on seven questions regarding whether a respondent has difficulty walking a block, sitting down, getting out of a chair, lifting, stooping, and similar functions). Among adults who were full time workers at baseline, limitations are rare: adults average 0.047 ADL limitations, 0.026 IADL limitations, and 0.96 functional limitations (Table 1).[2] One advantage of the longitudinal nature of the HRS is our ability to control for baseline health status using prior reports of the above conditions, as well as prior reports of limitations.

The rich information on functional status will also help us to assess how a given health shock may differ in severity across people. For example, if less educated individuals are less likely to see a doctor when a condition begins to bother them, or receive less good care when they access the system, a given health shock may be more severe by the time they report a physician diagnosis. Similarly, for a given health condition, the decline in health (or rise in limitations) may be greater for individuals from less educated groups. The presence of questions regarding activity limitations will help us to examine whether and/or how these differences in severity may explain differences in the response to a health shock across educational groups. We also can see how different types of limitations affect a respondent's probability of applying for disability.

Empirical Specifications

[2] The most common functional limitation is difficulty stooping.

We estimate linear regressions for whether an individual is applying for or receiving SSDI/SSI in a future wave. With time measured in years and biennial interviews, then for some baseline year *t* the future outcomes are assessed in years *t*+2, *t*+4, etc. All samples are restricted to individuals who are not currently applying for or receiving DI, meaning that the regressions may be understood as discrete-time hazard functions specified as linear probability models.

For the preliminary analysis we include all full-time workers ($FT_t = 1$) who are aged 50 to 62 in the year *t* and under 65 in the year when DI status is assessed (year *t*+*k*). We first estimate regressions with only basic demographic controls and then add our complete set of health and economic variables. Intuitively, these specifications are

$$\Pr(DI_{i,t+k} = 1 \mid FT_{it} = 1, DI_{it} = 0) = \delta_1 demog_{it} + \delta_t \tag{6}$$

for the model with demographics only and

$$\begin{aligned}\Pr(DI_{t+k} = 1 \mid FT_t = 1, DI_t = 0) = \beta_1 demog_{it} + \beta_2 Hshock_{i,t+2} + \beta_3 Hstock_{it} + \beta_4 hhold_{it} \\ + \beta_5 job_{it} + \beta_6 earnings_{it} + \beta_7 unearned\ income_{it} + \beta_t\end{aligned} \tag{7}$$

for the full model that includes human capital and labor supply effects. The demographic controls (*demog*) are education (dummies for < high school, some college, college degree or more), race (dummies for black non-Hispanic, other nonwhite race, and Hispanic ethnicity) and single year of age dummy variables. The health shocks (*Hshock*) are a set of indicators for whether each diagnosis occurred between year *t* and *t*+2. We also estimate versions with a single indicator for any major shock and another indicator for any minor shock, rather than the individual diagnosis dummies. The stock measures (*Hstock*), also referred to as "wave t health," include indicators for existing diagnoses in year t, as well as three variables that capture the ADLs, IADLs and functional limitations described above. Rather than allowing individual ADLs, IADLs or functional limitations to count equally towards the probability of disability, we include the factor scores of 3 primary factors from a principal components factor analyses (described below) of all 15 limitation measures.

We measure three types of labor market variables: job characteristics, earnings, and unearned income. Job characteristics, or those factors which influence the likelihood that individual health exceeds the threshold H_j in our conceptual framework, include indicators regarding whether the individual's job at time t requires frequent physical activity, stooping/kneeling or similar mobility requirements, heavy lifting, the need for good eyesight, and whether the job is "high stress", and dummies for industry, and occupation. We measure earnings, or wHk in our conceptual framework, using indicators for quintiles of own earnings and indicators for own HI coverage for self and spouse. We do this to reflect both cash earnings (which will reflect a combination of one's human capital, health status, and wages faced at that point in time) and non-cash compensation. Unearned income variables, or y in our conceptual model, include quintiles of other family income, whether a spouse provides health insurance coverage, and retiree health insurance. The coefficients δ_t and β_t represent year dummies to capture the role of the business cycle.

Although household composition was not directly addressed in our model, evidence suggests the importance of controlling for household members in models of labor force exit among older adults, as, for example couples tend to make retirement decisions jointly (Coile 2004). Furthermore, nonworking or college-bound household members may represent additional financial obligations, which modify the probability of leaving the labor force. Household characteristics included in the regression are marital status (single, married with working spouse relative to all others), indicators for the number of household residents (two unmarried adults, 3-

4 household members, >4 household members versus a married couple household), the age difference between spouses, and Census region.

To examine the differential response to a health shock, we restrict the sample to individuals who have experienced a major health shock between years t and t+2. These regressions include the same variables as the full models above, with the exception that one of the health shock indicators is omitted (heart disease).[3]

For supplemental analyses, we further extend the models in equation (7) to include measures of the severity of the shock that occurred between years t and t+2. These measures include the number of hospitalizations between t and t+2 (1, 2, or 3+), the limitation factor scores in t+2 or t+4, the respondent's regular use of prescription drugs in t+2 or t+4, and the respondent's self-reported expectation about the probability of living to age 75 (on a scale from 1 to 100), also from year t+2 or t+4. In all cases, the regressions are estimated separately by gender and by the time period for the transition (as indicated by the subscript k). All standard errors are clustered on the individual.

Factor Analyses on ADLs, IADLs and Functional Limitations

To best use the rich information on activity and functional limitations in the HRS, we conducted principal components factor analysis on the 15 questions in the HRS regarding limitations in activities of daily living, instrumental activities of daily living, and functional limitations. We found that three factors explained about half of the variance in these measures. The factors are naturally correlated. To reduce the correlation, we performed an oblique transformation of the factors. The result is three factors, shown in Figure 2, which tend to cluster

[3] Because people can have more than one condition, we can in principle include dummy variables for all of the health shocks. The occurrence of multiple major health shocks is rare, however.

on functional limitations (factor 1), ADLs (factor 2), and IADLs (factor 3). We use these as independent variables in our regressions of disability application.

4. Results

Figure 3 describes the age profile of disability application/receipt between ages 52 and 64. Over these ages, application rates climb from about 8 to 12 percent and they do so for both men and women. However, this trend is swamped by exit from the labor force, with males who are neither working nor applying for DI growing from 10 percent at age 52 to over half by age 64. Women experience similar growth in the share in the "other" category, although they start out with more women in this group (about one-quarter of women at age 52). Table 1 displays some basic characteristics of older adults in the HRS, our full-time workers sample (those working full time at the baseline interview), and the sample of full-time workers who later experience a major health shock. Looking across the table, there are predictable differences: 62 percent of full time workers have attended college, but only 53 percent of the workers experiencing a health shock continued school after their high school degree. One thing that stands out is the similarity in characteristics of the average full-time worker and the sample of workers who experience a health shock. Workers with and without a health shock are equally likely to work in services occupations. Average earnings are remarkably similar for the average full-time worker, compared with those who have a health shock during the study period. One other notable trend in Table 1 is the transition from full-time work at time t to no work (and no application for DI benefits) at time t+2. Nearly 13.2 percent of all full-time workers make this transition, while the share is higher, 18.5 percent, among workers with a health shock between time t and t+2.

We explore these labor force transitions further in Table 2, which provides additional information regarding transitions into different labor force states across waves. Not surprisingly, the diagonal elements in this transition matrix are the most likely. About 80 percent of full-time workers remain working full-time 2 years later. Also, workers who report having started the DI application process, nearly always—over 90 percent of the time—remain in this applying/receiving DI state. Part-time work is the one exception to this rule. Only 28 percent of male workers who were part time at t remain there at t+2, with 40 percent transitioning to full time work, 28 percent moving to the other (non-working) states and 3 percent applying for or receiving DI. For men, part-time work appears to be more temporary as male workers either return to full-time work or transition out of the labor force. Among women, just over half of part-time workers remain there from t to t+2, with 20.6 percent transitioning to full-time work, 26 percent transitioning to the other non-work state, and 1.8 percent applying for/receiving DI.

Tables 3a and 3b display results of our descriptive models of DI application/receipt among full-time workers (independent of having had a health shock or not), drawn from equations 6 and 7. These models present baseline differences in DI application across demographic groups, and examine how much of these differences can be explained by health and labor market characteristics. Table 3a reports disability transitions for men between t and t+4; table 3b is the equivalent for women. In each case, we start with the model including only demographics, and then add additional variables.

The models with just demographics show strong gradients in DI application by education for both men and women. Compared to high school graduates, college grads are 2 to 3 percentage points less likely to apply for DI depending on gender. Male workers with Hispanic ethnicity are 3 percentage points less likely to apply for or receive DI compared with non-Hispanic workers. Among women, blacks are nearly 3 percentage pointes more likely to apply for or receive DI relative to non-Hispanic whites. Given the mean incidence of a new DI application/receipt (between t and t+4) of 3.2 percent, these effects are very large.

The next column shows the impact of including two dummy variables, for having a major or minor health shock between *t* and *t*+2. These models suggest that a modest share of the education gradient in DI application/receipt (less than 10%) stems from differences in the propensity to have a health shock. The third column adds the other health indicators as of time *t.* Baseline health of workers explains a bit more of the education gradient. For example, the coefficient on having a college degree is 20 to 25 percent lower (depending on gender) in models with health shocks and health at time t, compared with the basic model. The fourth column includes labor force indicators that reflect the relative generosity of work in comparison to DI. These additions do not materially influence the race or health status coefficients, but they do eliminate the negative effect of a college degree on DI application/receipt. None of these variables influence the racial gap in DI application. If anything, holding health and labor market characteristics constant, the relative probability that older black adults apply for or receive DI increases. On balance, the labor market and household variables we include better explain education gradients in DI application than the health shocks. Of course, the issue we started with is how the health shock interacts with requirements on the job and the relative return to work versus DI, a topic we return to below.

Before examining these results, however, we consider the longer-run impact of health shocks on DI applications and receipts. Table 4 shows how the Disability Insurance application response to a new health shock varies over different time horizons out to 8 years.[4] The results are from regression similar to those in column 4 of Table 3. Lumping together all the major shocks and (separately) the minor shocks, these tables suggest that DI application rates continue to rise 4 and 6 years after a new health shock, although there is little difference when comparing 6 and 8 years beyond a shock. For example, within 2 years of a major shock, DI application/ receipt is around 5 percentage points higher than for those without a new shock, but by 6 years out, application/receipt rates are 9 to 11 percentage points higher. Because the patterns are similar 4 years after a health shock compared with 6 or 8 years after a shock, and because the sample size falls drastically when we restrict to individuals observed at baseline and 6 or more years later, we present our regressions for the transition onto DI in 2 and 4 years.

Heterogeneity in the Application Decision

Tables 5a and 5b present our primary models of DI application and receipt among workers experiencing a health shock at some point during our study period. Among the sample of full time workers who experience a health shock, column 1 of table 5 shows that education gradients in DI application and receipt are even more pronounced than in the overall population. College educated workers are 4 to 8 percentage points less likely to apply for DI within 4 years of a new health shock, regardless of gender. While the 4 percent reduction in the two-year transition to DI for the better educated is not statistically significant, the education dummies as a whole are statistically significant for females, and for both genders in models of four-year transitions. Racial differences in DI application or receipt are also large in this sample, especially for men. Black males are 10 percentage points more likely to apply for DI within 2

[4] The models shown here compare slightly different samples (there are fewer observations as we include more follow-up years), but restricting models to a smaller, but constant, sample of workers yields similar qualitative results.

years of a new health shock than their white peers, and this racial gap is even larger when comparing DI application rates within 4 years of a new health shock. The R^2 on models with demographics alone suggest we explain 4 to 17 percent of the variation in DI application/receipt with just demographics.

The next column includes measures of health capital and the relative return to DI. The addition of these detailed measures can explain 20 to 46 percent of the variation in DI application/receipt, depending on gender and the time horizon (t+2 versus t+4). The type of health shock a person experiences plays a role in the likelihood someone will apply for DI. A new stroke signals a significant increase in disability applications, especially after the initial 2 year period. The magnitude is about 15 percent for both men and women, though only the result for men is statistically significant. Pre-existing diagnoses of heart disease and lung disease appear to be important determinants of DI receipt for women, as are prior diagnoses of diabetes and psychiatric disorders for men. Somewhat surprisingly, there were no consistent patterns in the way baseline scores from the three limitation factors related to the probability of DI application or receipt.

Conditioning on individuals who experience a major health shock, earnings and income variables also contribute to the probability of DI application. Among males, those who have health insurance policies that cover a spouse, and those who worked in blue-collar occupations are significantly more likely to apply for DI than others. Among, female workers, those with own health insurance were substantially more likely to apply for DI (by about 11-12 percentage points compared to a mean application rate of about 7 percent). There was no consistent pattern of DI application related to health insurance coverage or source among men.

After controlling for health and labor market related variables, the education gradients shrink substantially for men. For example, the coefficient on college education falls by 43 percent, and the education variables are no longer statistically significant. This is less true among our sample of women, although the standard errors increased as we added health and labor supply variables for women.

One reason health shocks may be more significant for the less educated is that a given health shock may be more significant for them, or because the same magnitude shock has a different impact for people with different job requirements. We test this in the next column of the table, including measures of physical functioning after the health shock. It is clear that the severity of the shock matters for the DI decision. Having a shock accompanied by 3 or more hospital admissions, or experiencing functional limitations, ADLs or IADLs makes once substantially more likely to apply for DI. However, controlling for severity of these health shocks does not seem to affect the role of demographic variables in the models. Regardless of the controls, once we restrict to workers with a health shock, race effects for males are very large, as are education effects for females. In contrast, the pre-shock job requirements are not related to the DI application decision. In our richest models, including measures for the severity of the health shock, we explain 41 percent of the variation in DI transitions for males and over 61 percent for females. Rich economic and health measures are crucial in models of the DI application decision, and further research can refine these measures to best understand which ones are most important. However, important differences in application across demographic groups remain. Additional theories and information are needed to understand why groups respond so differently to similar health conditions.

5. Conclusions

For workers over the age of 50, the onset of new health conditions and the rate of new applications for DI rise rapidly and unevenly across different groups in the population. In this paper, we focus on the disability application response of workers, both overall and restricted to workers who experienced a new health shock, defined as the new diagnosis of a major or minor health condition. We focused on these transitions in order to increase our understanding of differences in disability application across demographic groups. We modeled disability application/receipt following a health shock as a function of demographics like education, race and ethnicity. Demographic differences in DI application or receipt are large in a sample of workers; high school dropouts are about 6 percentage points more likely to apply for DI than workers with a college degree. However, differences in the onset of new health conditions do not explain these gradients, even though a new major health condition raises the probability of application by 5 to 10 percentage points. The addition of labor market variables attenuated but did not eliminate education gradients. The onset of a major health condition is a pre-cursor to DI application, but it leaves an enormous amount of variation in DI application unexplained.

In a sample of older workers experiencing a new health shock, demographic differences in DI application or receipt were even greater. Following our conceptual framework, we expanded our regression models to include individuals' health stock, or pre-existing health conditions and functional limitations, which are important components of health capital, and labor market characteristics to reflect the relative benefits of work versus applying for DI, which are implied by common models of labor supply. We then examined how demographic differences changed in richer models of DI application that included health and labor market details, as well as the importance of detailed health and labor market characteristics as determinants of DI application or receipt. With a rich set of controls for health stocks, the severity of health shocks, and labor market factors, we could explain 40 to 60 percent of the variation in DI application among workers after experiencing a health shock. However, among workers experiencing a health shock, these health and labor supply characteristics did not explain sharp education gradients for females nor racial differences for males in DI application.

We can draw several conclusions from our findings, however. First, the nature of a health shock matters in DI application: new male stroke victims are more likely to apply for DI within four years compared with workers who experience heart disease. Prior health conditions such as diabetes or psychiatric disorders, for men, and heart and lung disease, for women, also predict DI application. Measures of the severity of health shocks over time, and in particular hospitalization, were important predictors of DI application/receipt, but severity of health shocks did not explain demographic effects such as differences in application rates by race or education. As a group, labor market variables are important determinants of the DI decision, but further work is needed to understand which factors in particular matter most, as some factors such as earnings and income mattered less than one might guess based on theories of labor supply. A true understanding of differences in DI application/receipt across demographic groups requires rich models of both health status and economic factors over time.

References

Autor, David H. and Mark G. Duggan, "The Rise in the Disability Rolls and the Decline in Unemployment." *Quarterly Journal of Economics,* 118:1, February 2003: 157–206.

Autor, David H. and Mark G. Duggan, "The Growth in the Disability Insurance Roles: A Fiscal Crisis Unfolding," *Journal of Economic Perspectives* 20(3), Fall 2006: 71-96.

Bound, John and Richard Burkhauser. 1999. "Economic Analysis of Transfer Programs Targeted at People with Disabilities," in *Handbook of Labor Economics*, Orley Ashenfelter & David Card (ed.). Elsevier, pp. 3417-528.

Board of Trustees, Federal Old-Age and Survivors Insurance and Federal Disability Insurance Trust Funds. 2011 "The 2011 Annual Report of the Board of Trustees of the Federal Old-Age and Survivors Insurance and Federal Disability Insurance Trust Funds," Washington D.C.: Government Printing Office.

Coile, Courtney C. 2004, "Retirement Incentives and Couples' Retirement Decisions." *Topics in Economic Analysis & Policy* 4(1): article 17.

Grossman, Michael. 1972. "On the Concept of Health Capital and the Demand for Health," *Journal of Political Economy* 80(2): 223-55.

Smith, James, 1999, "Health Bodies and Thick Wallets: The Dual Relation between Health and Economic Status," *Journal of Economic Perspectives* 13(2): 145-166.

Figure 1: Labor Force Status of Older Adults 1994-2008

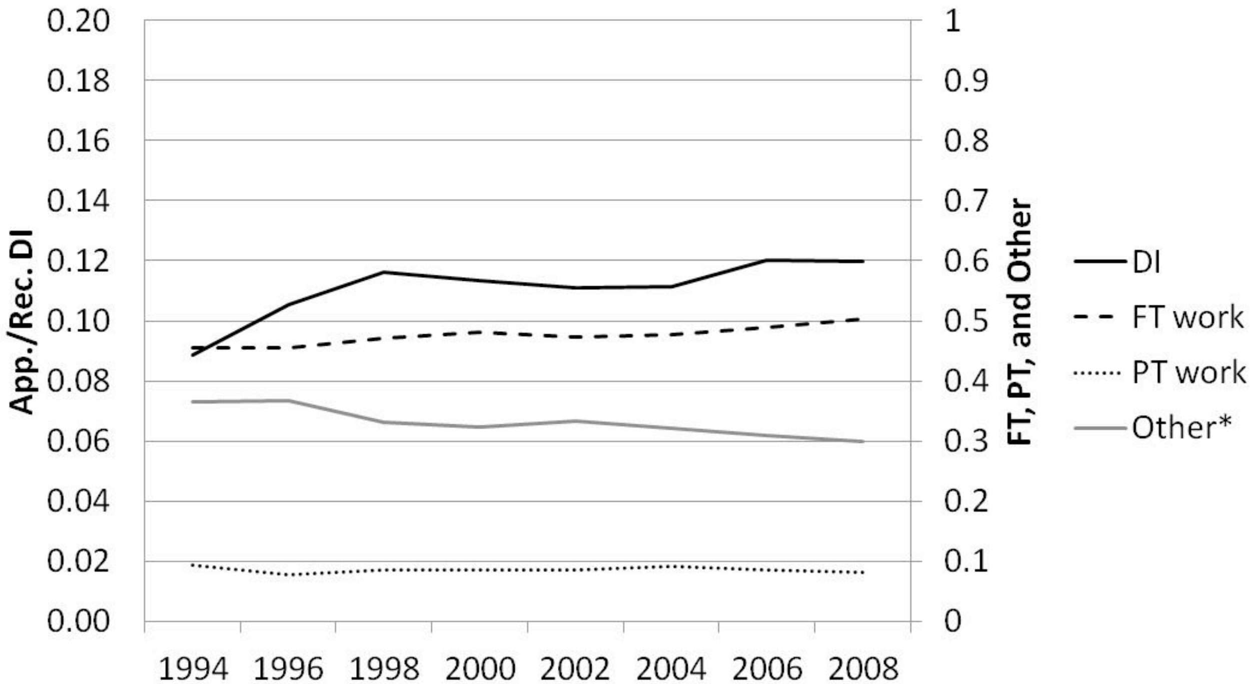
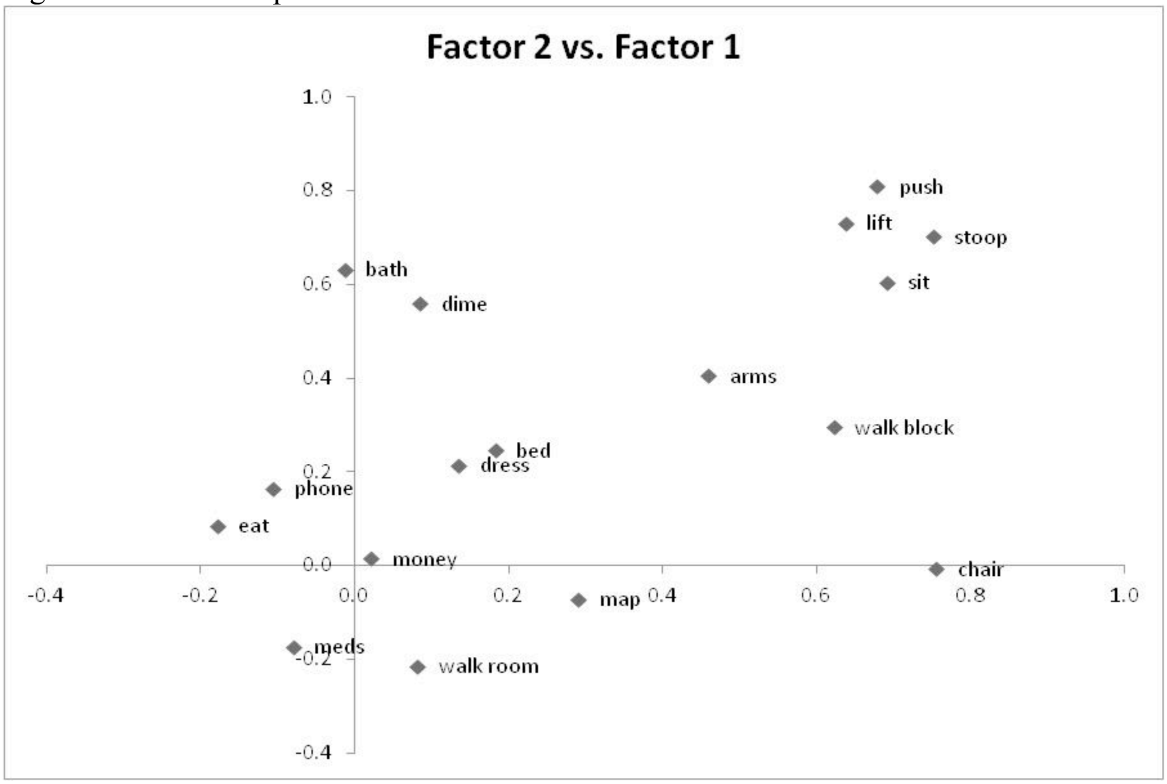


Figure based on calculations of adults aged 52-64 in the HRS. *Other includes individuals who are retired, unemployed, or otherwise out of the labor force, excluding anyone who is applying for or receiving DI.

Figure 2: Relationship of Limitation Factors to Each Other



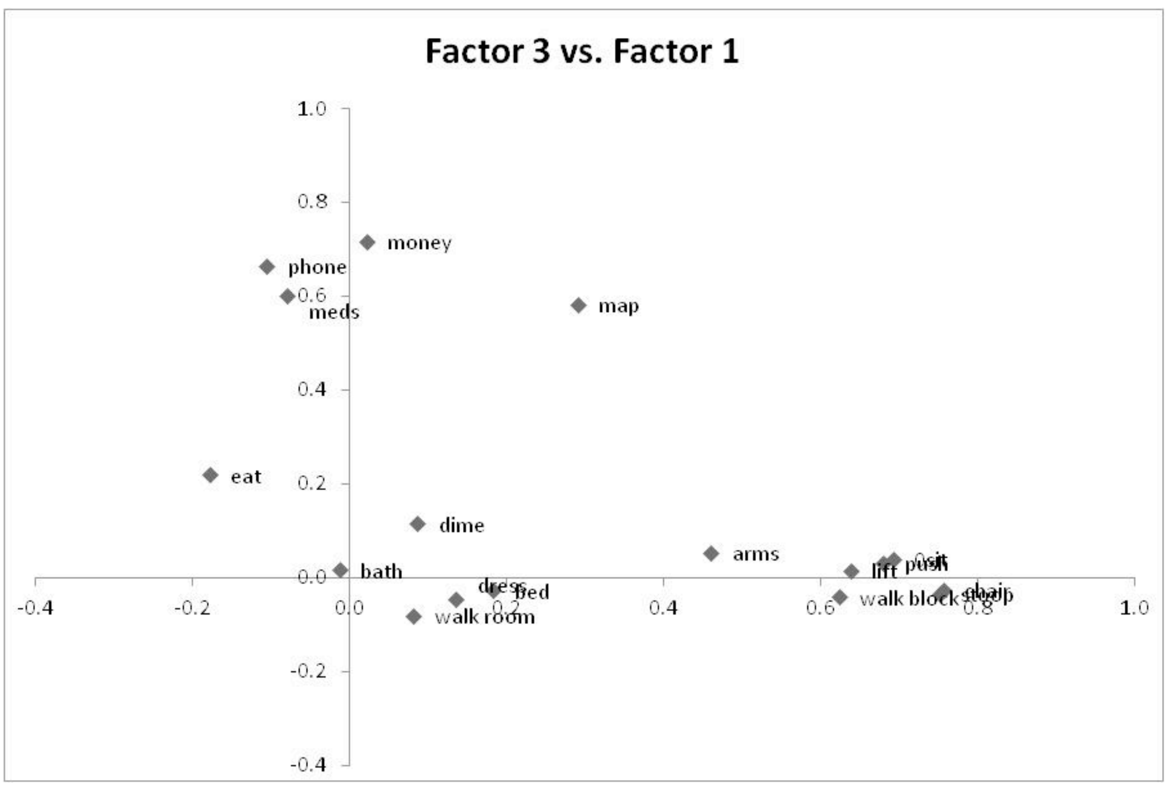


Figure shows factors based on 17 limitation questions (ADLs, IADLs and functional limitations).

Figure 3a: Labor Force Status of Older Adults in the HRS - Males

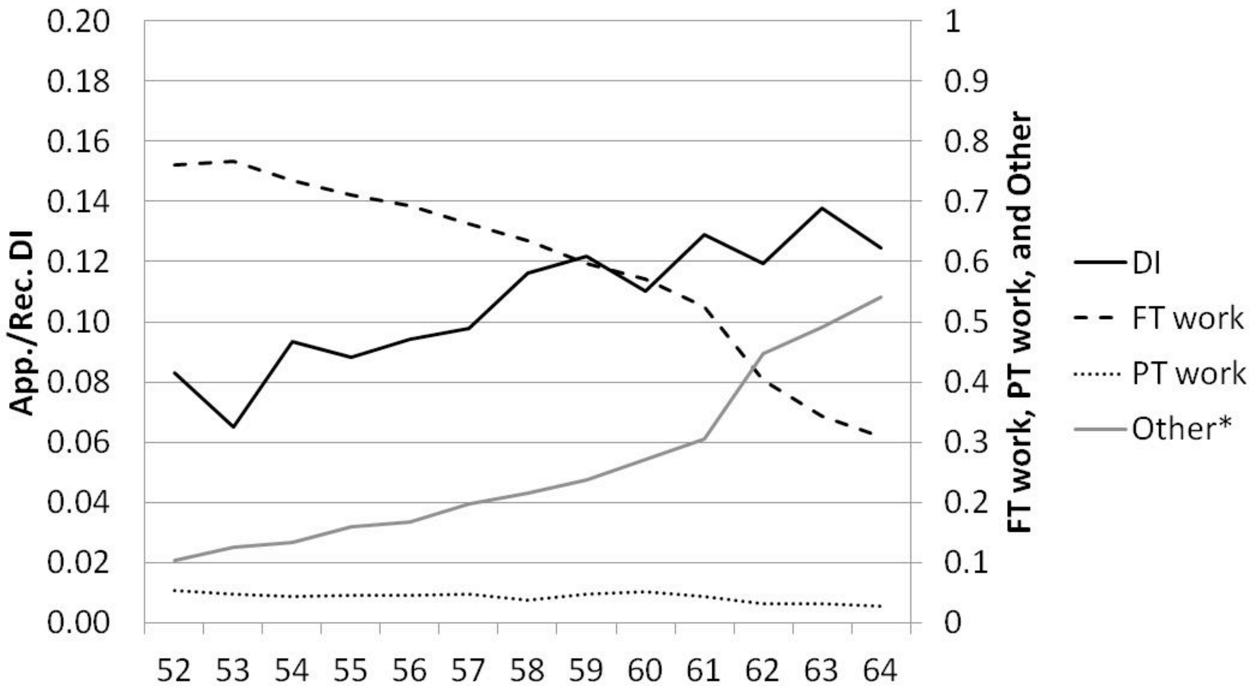


Figure 3b: Labor Force Status of Older Adults in the HRS - Females

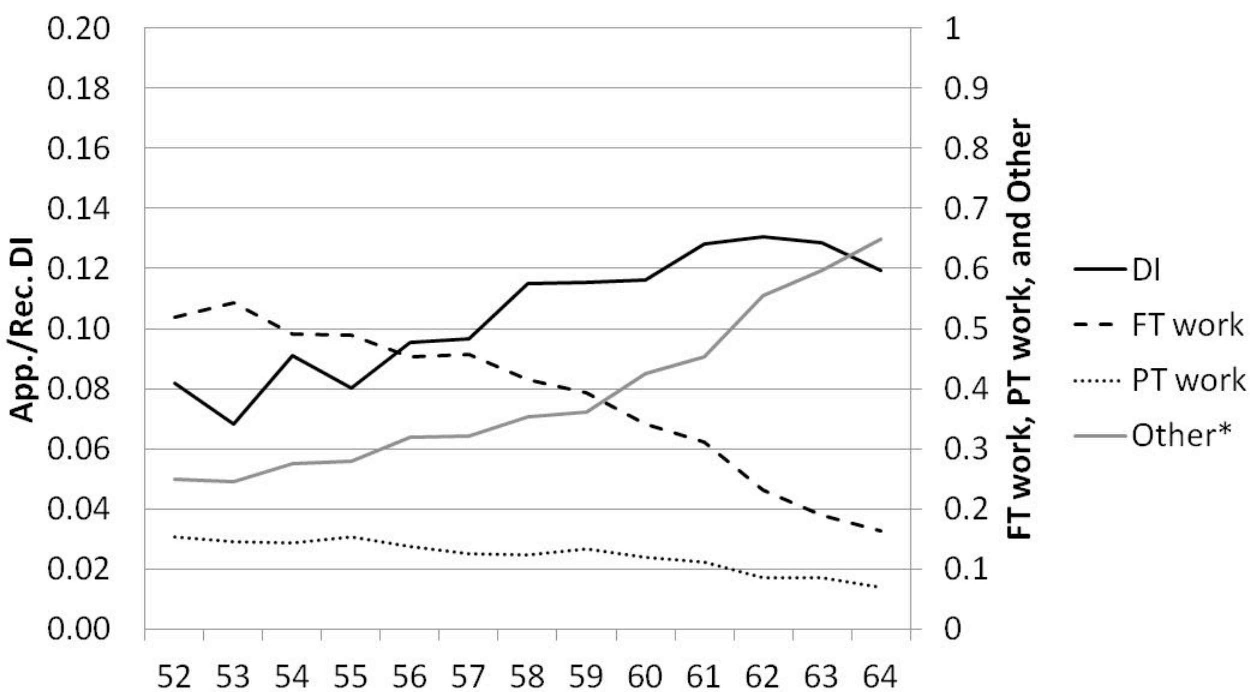


Figure based on calculations the HRS. *Other includes individuals who are retired, unemployed, or otherwise out of the labor force, excluding anyone who is applying for or receiving DI.

Table 1: Sample Means from HRS Data, Selected Variables

		Not applying for or receiving DI in year t	
Variable	**Ages 50-62 in year t**	**& full-time work in year t**	**& major shock t to t+2**
N= # of observations (person waves)*	**44,903**	**16,442**	**1,140**
# of unique HRS respondents	15,400	7,852	1,087
Demographics (year t)			
Age	56.5	57.8	58.6
	(3.29)	(2.70)	(3.27)
Male	0.477	0.528	0.552
Black	0.102	0.129	0.094
Hispanic	0.078	0.073	0.056
Single	0.255	0.220	0.225
Education:			
Less than high school	0.170	0.134	0.143
High School graduate	0.323	0.248	0.269
At least some college	0.239	0.327	0.264
Four years of college or more	0.267	0.291	0.263
Health Status (year t, unless indicated)			
ADL limitations (0-5)	0.183	0.047	0.077
IADL limitations (0-3)	0.064	0.026	0.038
Other functional limitations (0-7)	1.468	0.961	1.259
Major health shock between waves[a]	0.081	0.066	1.0
Minor health shock between waves[b]	0.127	0.122	0.194
Job Characteristics (year t)			
Earnings (among workers)	$43,125	$45,075	$43,425
High stress	0.414	0.477	0.677
Lots of physical effort	0.223	0.469	0.349
Occupation in current job:			
Blue collar	0.147	0.259	0.281
Services[c]	0.076	0.113	0.114
Labor Force / DI Status (year t+2)			
Working full-time	0.502	0.806	0.693
Working part-time	0.084	0.049	0.059
Not working, no SSI/SSDI benefits	0.312	0.132	0.185
Applying for SSI/SSDI	0.016	0.005	0.022
Receiving SSI/SSDI	0.090	0.009	0.041

Note: The data are from the HRS, 1994-2008.. *Person waves reflect the number of waves for which we observe individuals 4 or more years from baseline (year t). Means and standard deviations are calculated using survey weights. [c]A major health shock includes lung disease, heart disease, a psychiatric disease, cancer, or stroke.[b]A minor health shock includes high blood pressure, diabetes, or arthritis. [c]Services occupations include household, cleaning, or building services, protection, food preparation, health services, and personal services, as defined in the 1980 Census classification of occupations.

Table 2: Labor Force / DI Transition Probabilities

2a.	**Status in year t+2**				
Status in year t	**Full time**	**Part time**	**Other***	**App./rec. DI**	**Total**
Males					
Full time	0.820	0.029	0.138	0.013	1.000
Part time	0.404	0.285	0.280	0.030	1.000
Other*	0.116	0.029	0.800	0.055	1.000
App./rec. DI	0.003	0.000	0.034	0.964	1.000
Females					
Full time	0.778	0.071	0.138	0.013	1.000
Part time	0.206	0.514	0.263	0.018	1.000
Other*	0.064	0.060	0.840	0.037	1.000
App./rec. DI	0.002	0.004	0.045	0.950	1.000

2b.	**Status in year t+4**				
	Full time	**Part time**	**Other***	**App./rec. DI**	**Total**
Males					
Full time	0.718	0.029	0.224	0.029	1.000
Part time	0.398	0.208	0.333	0.061	1.000
Other*	0.137	0.033	0.734	0.096	1.000
App./rec. DI	0.000	0.003	0.062	0.937	1.000
Females					
Full time	0.669	0.080	0.220	0.030	1.000
Part time	0.222	0.396	0.344	0.038	1.000
Other*	0.078	0.068	0.794	0.060	1.000
App./rec. DI	0.001	0.003	0.073	0.922	1.000

* Other status includes retired, unemployed, or out of the labor force.

Table 3a: Linear Regressions for Applying for or Receiving DI in Wave *t*+4, among Full-time Workers in Year *t*: Males

Independent Variable	(1)	(2)	(3)	(4)
Education				
< 12 years	**0.0336****	**0.0327****	**0.0303****	**0.0269****
	(0.0135)	(0.0134)	(0.0133)	(0.0136)
13-15 years	**-0.0178****	**-0.0175****	**-0.0157****	**-0.0090**
	(0.0074)	(0.0073)	(0.0073)	(0.0077)
16+ years	**-0.0309*****	**-0.0303*****	**-0.0234*****	**-0.0072**
	(0.0066)	(0.0065)	(0.0066)	(0.0089)
Race and ethnicity				
Hispanic ethnicity	**-0.0318*****	**-0.0310*****	**-0.0259****	**-0.0295*****
	(0.0098)	(0.0099)	(0.0100)	(0.0110)
Black race	**0.0189**	**0.0195***	**0.0220***	**0.0220***
	(0.0120)	(0.0118)	(0.0116)	(0.0122)
Other race	**0.0160**	**0.0151**	**0.0060**	**0.0088**
	(0.0195)	(0.0197)	(0.0192)	(0.0188)
Health shock				
Major health shock		**0.0565*****	**0.0529*****	**0.0537*****
		(0.0128)	(0.0126)	(0.0126)
Minor health shock		**0.0103**	**0.0069**	**0.0066**
		(0.0069)	(0.0072)	(0.0073)
Wave t health	No	No	Yes	Yes
Labor market variables	No	No	No	Yes
Household characteristics	No	No	No	Yes
N	7091	7091	7091	7091
R^2	0.0191	0.0270	0.0500	0.0645

See text for details of Wave t health variables, labor market variables, and household characteristics.

Table 3b: Linear Regressions for Applying for or Receiving DI in Wave *t*+4, among Full-time Workers in Year *t*: Females

Independent Variable	**(1)**	**(2)**	**(3)**	**(4)**
Education				
< 12 years	**0.0445*** **	**0.0437*** **	**0.0363** **	**0.0311** **
	(0.0145)	(0.0139)	(0.0140)	(0.0147)
13-15 years	**-0.0039**	**-0.0040**	**-0.0038**	**0.0010**
	(0.0081)	(0.0080)	(0.0078)	(0.0080)
16+ years	**-0.0222*** **	**-0.0203*** **	**-0.0174*** **	**-0.0094**
	(0.0062)	(0.0061)	(0.0062)	(0.0073)
Race and ethnicity				
Hispanic ethnicity	**-0.0054**	**-0.0041**	**-0.0019**	**0.0000**
	(0.0117)	(0.0113)	(0.0115)	(0.0116)
Black race	**0.0289** **	**0.0295** **	**0.0319** **	**0.0312** **
	(0.0128)	(0.0126)	(0.0127)	(0.0123)
Other race	**-0.0168** **	**-0.0151** **	**-0.0174** **	**-0.0163* **
	(0.0068)	(0.0068)	(0.0081)	(0.0090)
Health shock				
Major health shock		**0.0929*** **	**0.0799*** **	**0.0755*** **
		(0.0199)	(0.0190)	(0.0184)
Minor health shock		**0.0110**	**0.0148**	**0.0126**
		(0.0092)	(0.0089)	(0.0089)
Wave t health	No	No	Yes	Yes
Labor market variables	No	No	No	Yes
Household characteristics	No	No	No	Yes
N	6429	6429	6429	6429
R^2	0.0158	0.0341	0.0743	0.0907

See text for details of Wave t health variables, labor market variables, and household characteristics.

Table 4: Effect of Health Shocks over Time

	Males		Females	
Effect of new diagnosis from t to t+2 on DI application or receipt in year:	**Major shock**	**Minor shock**	**Major shock**	**Minor shock**
t+2	**0.0470*****	**0.0004**	**0.0489*****	**0.0035**
	[0.0090]	[0.0041]	[0.0112]	[0.0040]
t+4	**0.0537*****	**0.0066**	**0.0755*****	**0.0126**
	[0.0126]	[0.0073]	[0.0184]	[0.0089]
t+6	**0.0922*****	**0.0157**	**0.1085*****	**0.0329****
	[0.0228]	[0.0121]	[0.0282]	[0.0149]
t+8	**0.0986*****	**0.0079**	**0.0758***	**0.0110**
	[0.0308]	[0.0157]	[0.0413]	[0.0205]

Note: Each row shows estimates from a different regression model, estimated separately by sex.