Occupational Status and Health Transitions: The Processes of Aging Gracefully and Not So Gracefully

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Introduction

Empirical research has convincingly established that physically demanding jobs are related to lower levels of health. However, such results do not provide much information on either the reasons why health differs or the process by which such differences are generated. In particular we have little information regarding how occupation affects the timing of changes in health, especially transitions into and out of poor health. Information on these linkages could improve our understanding of the mechanisms that lead to the association between occupation and health. Towards this end, we examine how an individual's occupational history is related to the probability of *transitioning* between health states. Specifically, we focus on the difference in such transition probabilities between blue- and white-collar occupations, and we also consider differentials related to service occupations or non-employment although, for reasons discussed below, these receive less emphasis.

In analyzing the relationship between occupations and health, it is important to recognize, and allow for, the possibility that the transitions between health states need not be symmetric. For example, some occupations may be associated with relatively high probabilities of downward health transitions but without a corresponding increase in upwards transitions. Consider the extreme case of irreversible health changes. Occupationally influenced health investments to protect against or mitigate these shocks would not be observed to improve the level of health; instead they would slow or eliminate the decline. Alternatively, once an individual experiences a negative health shock his occupation may hinder his ability to offset negative health shocks with investment. Assuming that the effects of occupation on health are symmetric is unnecessarily restrictive. The estimation method employed below allows for such asymmetric effects.

In this analysis, we use data on males from the 1984 through 2007 waves of the Panel Study of Income Dynamics (PSID). Using the PSID data we create a five-year summary history of occupation and health status (at waves t, t-2 and t-4 for most of the analysis) and examine how this is related to health two years later (at wave t+2). Our results are consistent with prior research suggesting that the health of blue-collar workers deteriorates with age relative to white-collar workers. Interestingly, however, we are further able to show that this is a consequence of their having a greater probability of transitioning from very good to poor health, with little difference (or even a slight positive predicted effect) on the relative probability that they move from poor to very good health. Similarly, non-employment or service employment predicts relatively high rates of negative health transitions without offsetting increases in the relative probability of positive ones. Generally, these findings suggest that persons outside of white-collar occupations are more likely to experience health declines without corresponding increases in health improvements. These qualitative results are robust to several sensitivity analyses that we describe below and are unlikely to reflect differential patterns of errors in self-reports of health status.

Conceptual Issues and Previous Literature

In the original Grossman (1972) model health capital, individuals make health investments to optimize healthy time available to work and earn income. Similarly, health has been described as capital used in combination with or as a substitute for financial and traditional human capital to produce income by Muurinen and Le Grand (1985). Health *transitions* are a logical outcome to examine when considering such frameworks. Specifically, the stock of health capital at a point in time depends on health in the prior period, investment flows (that improve health ceteris paribus), predictable depreciation in the health stock and, once uncertainty is added to the model, stochastic shocks resulting from illness, accidents and so forth.

Occupational status could be related to health for several reasons. First, persons in highly paid occupations will have more ability to pay for health investments and greater incentives to undertake them, since periods of poor health impose higher opportunity costs. Second, occupations may have differential access to information related to health behaviors or methods of alleviating health problems. Third, peer effects may be important and these effects could differ across occupations due to variation in coworker characteristics. Fourth, the rate of health depreciation health depreciation is likely to be heterogeneous being particularly high, for example, in physically demanding jobs. Finally, the probability of stochastic health shocks will probably vary with negative shocks, for instance, especially common in occupations with high accident rates.

Several of these sources of occupational disparities could affect the probability of transitioning between health states differentially than the impacts on overall (average) health status. Most obviously, the negative health shocks caused by accidents will cause downward movements in health that could either be temporary or permanent (depending on the nature of the accident). Importantly, if such shocks are temporary, they will increase the volatility of health but need not induce any long-run difference in average status. In this case, both favorable and unfavorable health transitions will be relatively common in such occupations. Conversely, accidents that permanently reduce health will have asymmetric effects on health transitions –

increasing the probability of moving into worse health without a corresponding rise in health improvements.

Economists have recently started to examine empirically observed differences in health across occupations. Fletcher and Sindelar (2009) us an instrumental variables approach to show that entry into the labor force initiated with a blue-collar (rather than white-collar) job, is associated with significantly lower health at older ages – equivalent to a seven year increase in age in their OLS estimates and by an even greater amount in IV models.[1] However, mechanisms for this relationship are not examined: the maintained hypothesize that first occupation sets the trajectory of future job conditions, income, and consumption patterns, which affect health. Fletcher, Sindelar, and Yamaguchi (2009) provide evidence that cumulative exposure to more physical demanding jobs and harsh environmental conditions at work are cumulatively harmful to health: for example, a one standard deviation increase in the physical demands of the job is associated with a health decrement for nonwhite men equivalent to a two-year reduction in schooling or four additional years of age (with smaller effects for white males) Case and Deaton (2005) and Choo and Denny (2006) examine U.S. and Canadian cross-sectional data, providing evidence consistent with the possibility that health depreciates increases at a faster rate over the life course for individuals in manual labor occupations, suggesting that occupations not only have cumulative effects on health but also alter the trajectory of health over the life course.

However, the previous literature does not emphasize health status *transitions* but instead focuses on determinants of health status as a function of occupational status (and other characteristics) with or without controls for baseline health. For instance, Fletcher, Sindelar, and Yamaguchi (2009) estimate a model that examines how health status varies as a function of

[1] Baseline occupation is instrumented with the father's occupation and the proportion of workers in the state employed in blue-collar occupations.

physical job demands and environmental hazards, during the previous five years, controlling for health measured six years earlier. Using cross-sectional data, Case & Deaton (2005) and Choo & Denny (2006) estimate how average health varies across occupations over the life-course. However, these studies do not examine transitions between health states that might be correlated with occupation in ways that are both interesting and informative. For instance, blue-collar jobs might have relatively high rates of accidents that lead to large but temporary deteriorations in health. In this case, such workers might have relatively high probabilities of existing both good and poor health. Conversely, the accidents that cause health to permanently deteriorate might imply that they have high rates of exiting good but not poor health. Alternatively, downwards transitions in health might be relatively similar across occupations but some might have more difficulty returning to good health, resulting in a steepening of the long-term occupation-health gradient. The focus of our analysis is on examining how these (potentially asymmetric) health transitions vary across occupations.

Methodology

We estimate dynamic models that allow us to examine how occupational status differentially (and possibly asymmetrically) affects transitions from better to worse health and vice versa. Let h_t represent self-reported health status in year t for a given person; in most of our analyses we consider a binary indicator where h_t takes a value of one if the person reports being in "good," "fair," or "poor" health (we label this as "poor" health) and zero if the person reports being in "very good" or "excellent" health (we label this as "very good" health). Let h_{ave} be the person's average self-reported health status measured over some previous period (t, t-2 and t-4 in most of the analysis); let OCC_{ave} be a vector that represents occupational history over the same period; let X_t be a vector of observed (possibly time varying characteristics), and let ε_t be an error term. The basic model we estimate is then described by:

$$h_{t+2} = \delta h_{ave} + \theta OCC_{ave} + \gamma(OCC_{ave} \times h_{ave}) + \beta' X_t + \epsilon_{t+2}. \qquad (1)$$

In (1), the estimated values of δ, θ, and γ indicate how health at time *t*+2 is related to health and occupational histories.[2]

As with the models that have been estimated in previous studies, our specifications incorporate people's occupational histories. However, a distinguishing feature of our specifications is that they allow occupational status to have different associations with transitions into and out of bad health. In particular, for people who have experienced very good health in period *t* and over the previous measured period, the coefficients in θ describe how occupational status is associated with transitions into worse heath. Similarly, for people who have experienced bad health in period *t* and over the previous measured period, the coefficients in δ, θ, and γ describe how occupational status is associated with transitions into better health. The interpretations can be more complicated because h_{ave} ,which is an average of binary outcomes over several years, can take on values between zero and one.

We estimate (1) as a linear probability model throughout, for convenience and ease of interpretation.[3] The longitudinal design of the PSID implies that we will utilize multiple years of

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[2] X_t includes other determinants of health status, the most important being age. We also experimented with including age-occupation interactions, as discussed below.

[3] Preliminary analysis revealed similar patterns of coefficients and statistical significance when using a probit specifications, but the linear probability (LP) coefficients are easier to interpret, especially when including the occupation-health interactions (Ai and Norton, 2003). As a further check, we estimated LP and probit models corresponding to (1), but with only the main effects included (no occupation-health interactions). The predicted marginal effects from the probit were close to the coefficients of the LP model for most regressors. The largest difference seen is the difference in estimated marginal effects of health history on future health status. However, this difference is dependent upon whether the average marginal effects or marginal effects at the average values of covariates are calculated. Although different than the coefficient from the LP model, relative to the LP coefficient the average marginal effects suggest a weaker relationship between health history and future health while the marginal effects at the variable averages suggest a stronger effect. The two differing marginal effect calculations balance, above and below the estimate of the LP model.

data for most sample members. Therefore, we report robust standard errors that are clustered at the level of the individual.

Data

The data for our analyses come from the Panel Study of Income Dynamics. The PSID began surveying "heads" and "wives" of a nationally representative sample of 4,800 families in 1968, focusing on the economic and income behavior of the family.[4] The PSID has continued to follow these families over time and includes information on the children of the original cohort, and subsequent cohorts, after they have started independent households.[5]

In each survey since 1984, the PSID has asked heads and spouses about the present state of their general health, "Would you say your health in general is excellent, very good, good, fair, or poor?" Self-reported health status (SHS) has been shown to be a good predictor of subsequent mortality (Idler and Benyamini, 1997; Mossey and Shapiro, 1982) and correlated with other measures of morbidity (Manor, Matthews, and Power, 2001; Miilunpalo et al., 1997). While SHS has been known to suffer from a "justification" bias, resulting from lower reported health used to explain poor labor force outcomes (Currie and Madrian, 1999), it is not directly dependent upon the type of work and individual undertakes, like self-reports of health related work limitations. Furthermore, the relationship between self-rated health and mortality do not appear to vary between manual and non-manual workers (McFadden et al., 2009). With limitations of self-reported health in mind, we have chosen this measure of underlying health as the dependent measure of health for our study.

As we described earlier, we have dichotomized the SHS measure into "poor" health (SHS is good, fair, or poor) and "very good" health (SHS is excellent or very good). The dichotomized

[4] Family "heads" are defined as the primary financial contributor to a PSID family, but defaults to the male partner of a female primary financial contributor if the male is a husband or has cohabited with the "wife" for at least a year.
[5] Annually, 1968-1997; biennially, 1997-2007.

variable represents two health states that most individuals experience at some time in our sample of the PSID panel. We also perform sensitivity tests based on another, frequently used, definition of "poor" health, SHS is fair or poor.

The primary measure of a person's health history used in this analysis is the simple average of the dichotomized health variable over the preceding five years (i.e., the proportion of surveys over a preceding five years when the individual reported poor health). Because the PSID moved to a biennial survey after 1997, we create a measure that is equivalent across survey rounds and measures the proportion of the previous periods t, t - 2, and t - 4 that an individual's SHS was recorded in each of the dichotomized health states. For example, if an individual was observed in the "poor" health state in two of the three survey periods over the previous five years, the "poor" health history variable is equal to 0.667. We make the restriction that observations must include health information in these three periods, as well as the period of the dependent variable, t+2, for inclusion in our sample. As sensitivity tests, we also investigate alternative measures of health histories including a five year measure that includes all five years—includes periods t – 1 and t – 3 when available—as well as shorter three- and one-year health histories.

Our analysis focuses on how occupational status is associated with health transitions. Various questions regarding occupational status have been asked throughout the PSID. We consider the questions that were asked regarding the present main jobs (at the time of the surveys) of the heads and wives. Occupational information was created using 3-digit census occupational codes provided by the PSID. The occupational information was coded in 3-digit 1970 Census group definitions for the 1984 through 2001 waves and 3-digit 2000 Census group definitions for the 2003 and later surveys. In order to make this information uniform for all survey rounds, we have recoded the occupation codes to 1990 Census definitions for all years using the crosswalk provided by IPUMS-USA[6]. The occupations were subsequently defined as "blue-collar," "white-collar," or "service" following listings by the Bureau of Labor Statistics (2003). We also include a fourth category for people who were not employed at the time of the survey.[7]

To provide a more complete occupational history, we used the employment history information to create an annual occupation measures for individuals in the PSID after 1997. The retrospective work history information was examined to identify the occupation of individuals in the month one year prior to the survey month. For instance, to determine an individual's 1998 occupation we used the work history information to identify the occupation reported in the month one year prior to the 1999 interview.[8]

Recall that our multivariate analyses use measures, OCC_{ave}, that are averages over time. We created these averages by summing the occupational indicator variables over a preceding time period (i.e. 5 years) and dividing by the number of periods where an occupational state was observed in order to provide the proportion of observed periods where an individual was observed working in each occupation type. More specifically, we have created four variables equal to the proportion of observed periods spent in blue, white, service, and not employed occupational states over the previous 5 years and including the current period.

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[6] http://usa.ipums.org/usa/volii/documents/occ1990_xwalk.xls

[7] Appendix Table A broadly describes occupations included in the occupation categories. Twenty-six occupations are not within a defined occupation category. We have categorized these occupations within the classification that is subjectively appropriate. Many of the occupations have similar listings that were classified by the BLS and are, thus, included in the same classification. Occupations without a natural classification are subjectively classified by the authors. A list of the originally classless occupations and the resulting classifications is found in Appendix A.

[8] The retrospective information in the non-interview years (1998, 2000, 2002, 2004, and 2006) provides fewer occupational transitions than interview years. The lower proportion of transitions during the recalled employment history is consistent with seam effects, which have been found in the employment history of the PSID. However, the occupational measures during the non-interview years match the characteristics of occupational measures during interview years in the number of observations and proportion of individuals in each occupational state (Callegaro, 2007).

There are two notes of interest in constructing these categorical variables. First, the PSID identifies individuals who are serving in the Armed Forces. Although we could consider military service as a separate occupation, there are too few observations to make this feasible. Instead, we drop person-year observations for individuals who served in the Armed Forces during the 5-year occupational history window. Second, there are a small number individuals who report being unemployed or out of the labor force and still report an occupation. For consistency, we have coded these individuals as not-employed.

We include numerous other explanatory variables in our analyses that may be related with both health and occupational status. A key determinant of health is a person's age; we control for this using the person's age in years. To control for race, we include binary indicators for people who are black and who are non-black and non-white (the omitted category for these indictors is people who are white). To control for educational attainment, we use binary indicators for people who did not complete high school, people who completed high school or an equivalent but did not go on to college, people who completed some college but did not obtain a bachelor's degree, and people who obtained a bachelor's degree or higher credential. We distinguish between people who were married and unmarried at the time of the survey. We also include the log of the family's annual income in some analyses.

The PSID only conducts core interviews with one person in each household—either the head or the spouse. In some cases, this means that a person's health status is reported by the person's spouse. In most of our analyses, we include a binary indicator for such proxy reporting. In some sensitivity analyses, we also limit our samples to people who provided self-reports. In addition to these controls, our models also include a general set of time dummies for the survey years.

Our initial sample is restricted to males observed as a head of household after the PSID started collecting the self-reported health status information.[9] The sample is further restricted to individuals who are 30 to 59 years of age. The age restriction is allows us to examine occupational effects after individuals have had time to amass appreciable work histories, at 30 years of age, and before most individuals in the labor force retire, before age 60. Further restrictions arise from the requirement of 7 years of health information and non-missing values of covariates in the analysis. The final analysis includes 34,607 person-years of information from 5,611 individuals.

Table 1 displays the unweighted summary statistics for men in our PSID sample. The means indicate that 39% of the sample is in "poor health" in a given year and that, on average, over one third of the observations in the previous five years were observed in "poor health." The mean age in the sample is 42 and the mean age when individuals are in "poor health" is 44. Importantly, there are a significant proportion of observations in the occupation states, 39% blue-collar, 44% white-collar, 6% service jobs, and 11% unemployed or out of the labor force during a given year.

Table 2 displays information on the proportion of individuals ever observed in the differing occupation and health states. A significant number of individuals in the dataset were in each of the occupational categories at a point in time. Specifically, 63% of individuals were ever in a blue-collar occupation during an interview, 63% were ever in a white-collar occupation, 18% were ever in a service occupation, and 38% were not employed at one or more interviews. A considerable proportion of individuals in the data occupied the self-reported health states as

[9] We will add a separate analysis of females in future work. Previous work has found that similar effects for men and women with slightly stronger negative effects of manual jobs on the health of women (Case and Deaton, 2005; Fletcher, Sindelar, and Yamaguchi, 2009).
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well. Table 2 shows that 92% of individuals reported “very good” health in at least one survey. A lower, yet still substantial, proportion of individuals reported “poor” health in one or more survey rounds, 79%.

Not only do a significant proportion of individuals report the differing health states, they also transition between health states at significant rates. Table 3 displays the transition matrix for individuals in each health state from period *t* to two years later, *t+2*. In an average two-year period, just over one-fifth of the men who begin the period in “very good” health transition into “poor” health, and just over a quarter of those who begin the period in “poor” health transition into “very good” health. Because a substantially smaller proportion of the sample begins each period in “poor” health than in “very good” health, the transition patterns are consistent with a gradual worsening of health as time progresses and as the panel ages.

A concern in using the subjective self-reported health status variable is measurement error. This concern is increased when examining transitions between health states. If the variable or transitions in the variable’s state is noise then the information gleaned from examining health or movement between health states is weakened. To investigate the issue of a measurement error in SHS we present information about the health variable across varying ages. Figure 1 shows the mean of the self-reported health status over the 30-59 years age range. The mean increases to worse health gradually and nearly linearly over the time frame, conveying that average health worsens over time as expected. Figure 1 also displays the proportion of individuals reporting the dichotomized “poor” health category by age. The dichotomization appears to reflect the information from the SHS variable well. Together, the displays in Figure 1 imply that SHS and the dichotomized variable behave as expected over the life cycle and convey information relevant for this study.

In the absence of accidents or health shocks the model of health expects health to decline gradually over the life-cycle—Figure 1, the average health over the life-cycle, shows this gradual decline. However, there are two important notes: 1) SHS is not a continuous variable, as its mean is, but made up of ordinal categories; and, 2) that individuals may transition between states, better or worse, more frequently than desired due to changes in health. As seen in Table 3, there is significant movement between health states across all individuals in the PSID sample.

Table 4 lists estimated health status transition rates for our sample separately by occupational type. The first row in Table 4 lists the proportions of people within each occupational classification who make any transition at all. The estimates indicate many transitions occur. Transitions are most frequent among blue-collar workers, followed by service workers, followed by white-collar workers. People who are not working have the fewest transitions.

As with Table 3, we can also consider transitions from "very good" health to "poor" health and vice versa. The second and third rows of Table 4 list these transition rates separately by occupational status. Among those who are initially in "very good" health, non-workers are at the highest risk of transitioning to "poor" health, followed by blue collar workers and then by service workers. Non-workers are also the least likely to "recover" by making a transition from "poor" health to "very good" health, while white collar workers are the most likely to recover. The estimates from Table 4 suggest that occupational status may be related to both types of transitions. These descriptive results do not, however, account for other characteristics that may be associated with health and occupational status. In the next section, we report results from multivariate specifications that address this issue.

Results

In the following, we discuss the estimated effects of occupational history on the probability of transitioning into and out of "poor" health from a history of "very good" and "poor" health, respectively, as outlined in equation (2). The discussion of our initial specifications includes estimated effects all occupational types. However, the focus of the discussion of initial specifications and all discussions of sensitivity analyses compare differences in the probability of health transitions for men with a blue- versus white-collar employment history.

Interpreting results for occupations classified as service jobs and the non-employed is difficult. Service occupations make up a small proportion of employment observations, 6%, and it is not clear, to the authors, a common connection among the service occupation groups, listed in Appendix A, that affect health. Conversely, the occupations coded as blue-collar are more manually intensive than white-collar occupations and resemble the distinctions used by the previous economics literature (Case and Deaton, 2005; Choo and Denny, 2006; Fletcher and Sindelar, 2009).

The estimated effect for a 5-year history of non-employment difficult to interpret for two reasons. First, non-employment is highly endogenous to self-reported health for men in the sample age range (Currie and Madrian, 1999). Second, for observations with any observed non-employment in the previous five years, less than 5 percent are non-employed for more than half of the five year period. Because five years of unemployment is rare for the sample and, more generally, men 30 to 59 years in the United States, discussions in the text refer to effects of two non-employed years from a white-collar occupation rather than five years, as with blue-collar and service occupations.

Table 5 shows the coefficient estimates for the occupation, health, and age related variables for four specifications of equation (2). Specifications (1) – (3) vary based on the inclusion of controls for educational attainment and household income for the individual. We consider specification (1) our primary specification. It includes educational attainment, generally stable by age 30, the earliest observational period, and does not include household income, which is endogenous to occupational type. Specification (4) mimics the primary specification but adds interactions between the age variable and the employment histories. Explicitly, specification (4) allows for differing trajectories of health over the life-course as found by Case and Deaton (2005) and Choo and Denny (2006).

The main (uninteracted) occupational coefficients in specification (1) suggest that individuals with occupational histories in blue-collar and service jobs as well as the non-employed are more likely to be in "poor" health in period $t + 2$ than those with histories in white-collar occupations. These main effects represent the probability of transitioning into the "poor" health state given a 5-year history of "very good" health and a 5-year history in the respective occupational states relative to a white-collar employment history. Importantly, these are large estimated effects of 4.7, 3.0, and 5.2 percentage points for 5-year histories of blue-collar and service jobs and a 2-year spell of non-employment.

Looking in isolation at the occupation history and health history interaction terms in specification (1), we see that men with a history of blue-collar employment respond differently to a history of "poor" health than men with a history of white-collar work. However, looking at the coefficients of interactions in isolation is misleading as the true effect is the summation of the main occupational effects and the interaction terms. Therefore, we have produced the lower panel of Table 5, which presents the estimated probabilities of transitioning from "poor" to "very good" health relative to a white-collar work history. The predicted estimates of this primary specification suggest that given a history of "poor" health individuals with a history of blue-collar or service job employment do not differ significantly from men with a history of white-collar employment in the probability of exiting "poor" health. White-collar workers who experience two years of non-employment are estimated at a probability of 1.0 percentage point less likely to exit "poor" health relative to those who have worked in white-collar jobs during all of the previous five years. Therefore, given a history of "poor" health men who were employed in the previous five years in white-collar, blue-collar, or service jobs do not significantly differ in their probability of exiting the "poor" health state despite the fact that a high proportion of individuals do indeed move out of poor health as seen in Tables 3 and 4.

Specification (2), like specification (1), excludes the log of household income as a regressor but also drops the control variables for the individual's level of education. The exclusion of education as a regressor does not change the sign of any estimate but increases the estimated differences in probability of entering "poor" health from "very good" health between the white-collar workers and all other occupational states. The probability of exiting "poor" health, however, remains indistinguishable between white-collar and blue-collar or service job histories; non-employed spells maintain a lower probability of exiting "poor" health than fully employed white-collar workers.

Simple comparisons of means, not shown, demonstrate that men in white-collar occupations have a higher level of average education than blue-collar or service workers. As education is correlated with occupational type, the difference in estimates between specification (1), controlling for education, and specification (2) is not surprising. The positive correlations between education and health (Grossman and Kaestner, 1997) and education and white-collar employment explain the change in estamated effects of occupation between specifications (1) and (2). Because the general implications of the model do not change when excluding education as a covariate, we follow the previous empical economics literature and control for education in all other specifications.

Specification (3) controls for educational attainment, like specification (1), but adds the log of total household income in period *t* as a control variable.[10] When the log of household income is included as a regressor additional to educational attainment, the estimated relative probabilities of entering "poor" health are similar to the main specification. For men with a history of "very good" health, the estimates still suggest a history of blue-collar employment increases the probability of "poor" health in period *t*+2 by more than 4 percentage points relative to white-collar employment. Similarly, the estimated difference for men with a work history in service jobs is relatively close to the original estimate at an increase of 2.5 percentage points in the probability of entering "poor" health. As for exiting "poor" health, there are still no statistically significant differences between men with blue-collar or service occupational histories and white-collar histories. Futhermore, the prior estimated difference between men who with a work history of white-collar employment versus non-employment of exiting "poor" health disappears, suggesting that income may play an notable role in health investment remediating "poor" health. This change in the estimate is reported with caution, however, given that non-employment is related to very low or zero personal earned income production and there is likely to be high marginal returns to additional income at low levels. Together, these two points bring uncertainty to our confidence in interpreting the predicted probability for the

[10] In results not shown, we have also used the mean of total household income averaged over the 5-year period without a substantive change in results.

relationship between occupation and health for movement into a five year history of non-employment.

Specification (4) ammends the primary specification by adding interactions between the employment history variables and the linear age trend. This interaction allows for differing trajectories of health across occupational types over the age range. Case and Deaton (2005) and Choo and Denny (2006) have shown evidence of differing health trajectories for manual and non-manual job types in cross-sectional U.S. and Canadian data sets. However, when we include the age and occupation interactions in our model we do not find statistically significant differences in the age trajectories.[11]

Sensitivity Tests

Table 6 displays the estimated relative probability of transitioning into and out of "poor" health for workers with a history of blue-collar versus white-collar employment. The first specification, (1), is a restatement of the estimates from the primary specification of Table 5, which includes measures of health over the previous five years during periods *t*-4, *t*-2, and *t* and controls for the individual's level of education but not household income in the list of covariates.

The first sensitivity test, presented in specification (2) of Table 6, uses an alternately defined 5-year health history variable. The health history variable used in specification (2) includes all available survey rounds—i.e. when the annual information was collected the health histories also include periods *t*-1 and *t*-3, but these periods are omitted when not available. The estimates with all available health information closely resemble those of the original health history definition.

[11] Additional investigation of alternative cut-points for the dichotomized SHS variable indicates that occupation age interactions may be significantly related to health transitions. Future work will further examine differing occupationally related age trajectories across SHS.

Defining a health state as five years in “poor” health is rather restrictive. If an individual is in “poor” health for a full five years it may be the case that the health persistence is too strong to identify any differences across occupational types. To investigate differing health histories Table 6 displays two specifications that use shorter health history measures. The first measures the proportion of the previous three, rather than five, years in “poor” health, specification (3). The second alternative health history definition, used in specification (4), simply measures health in the current period, t. Conditioning on a shorter and shorter histories of health, blue-collar workers are increasingly likely to transition into “poor” health relative to white-collar workers. This effect is, likely, directly due to the loss of health history information. Blue-collar work is correlated with worse health over the span of the dropped health history periods and this correlation is reflected in the larger difference in probabilities of “poor” health transitions. However, there is still no signficant difference in probability of exiting “poor” health between blue- and white-collar work histories given less restrictive, shorter histories of “poor” health.

The change in relative probability of transitioning into but not out of “poor” health provides evidence against one concern of this study, occupationally related measurement error in self-reported health status. If the level of measurement error in self-reported health, uninformative movement between health categories, is greater for individuals in blue-collar occupations then we expect to see greater probabilities of transitioning between better *and* worse health states when we condition on shorter measures of health history for this group. The fact that we see a greater probability of transitioning into “poor” health but no change in the probability of transitioning out of “poor” health when the shorter health history measures are used suggests that differences in the probability of transitions are not simply due to the correlation of measurement error in the health variable with occupational types.[12]

Specification (5) of Table 6 shows results when the SHS is dichotomized at a different point on the scale. Rather than dividing categories into groups that include “Excellent and Very Good” SHS versus “Good, Fair, and Poor” SHS, specification (2) places only “fair and poor” SHS only in the “poor” health state. The alternative dichotomization represents a poorer health state that has also been frequently used and found to be predictive of mobidity and mortality (for example see Adams et al., 2003). When the worse definition of “poor” health is used, the probability of entering “poor” health relative to having a white-collar work history for a blue-collar work history is reduced to 1.46 percentage points from 4.65 percentage points but is statistically different from zero at the 0.01 level of signficance. Again, the difference in probability of exiting a history of “poor” health under the new definition remains small and insignficant.

Specification (6) of Table 6 alters the dependent variable from the primary specification, (1). Rather than looking at a transition into or out of “poor” health in period t+2, the new dependent variable extends the future time period to allow for transitions in either period t+2 or t+4. The additional time to switch health states increases the differences between white-collar and blue-collar work histories in the probability of entering “poor” health from “very good” health. Yet, there is still no dicernable difference between the probability of exiting “poor” health for men with blue- and white-collar work histories.

[12] Using the same principle, the estimates do not suggest that occupationally related measurement error was driving either the estimates for the service job or non-employment effects on health.

Conclusion

In this paper, we use longitudinal data on men's health and occupational histories from the PSID to examine how occupational status is associated with both decrements and improvements in health. Previous literature indicates that differing occupations affect individuals' levels of health differently. Given that individuals' levels of health do not simply decline gradually over the life-course but show significant movement into better as well as worse health, we have estimated a model that identifies the relationship between occupational history and the probability of transitioning between better and worse health for a sample of working age men in the U.S. The results consistently show that a recent, five year, history of blue-collar employment is related to a four percentage point increase in the probability of transitioning into the "good", "fair", or "poor" SHS health states, from "excellent" or "very good" relative to white-collar employment. However, there are no indications that a blue-collar work history affects the probability of transitioning out of the worse health states any differently than a history of white-collar employment.

A series of sensitivity analyses show that the results are robust. Furthermore, the analyses provide confidence that differences in health transitions between occupational types are not the result of occupationally related measurement error. In particular, we estimate two specifications that shorten the health histories from which individuals are modeled to transition, from five years to three and one year histories. Conditioning on shorter health histories excludes information on health stability. Estimated probability differences between blue- and white-collar workers transitions into poorer health increase when conditioning on shorter health histories. However, the shorter health history models do not show increasing occupational differences in the probability of exiting "poor health. This finding suggests that the estimated differences are not the result of greater measurement error in reported health for blue-collar than white-collar workers.

Like previous studies, education and income are found to be positively related to health, but do not eliminate occupational effects on health. Future work will examine other health and occupation correlates to further examine robustness and possible mechanisms for our findings.

Our study does have important caveats that should be considered when interpreting the results. First, the model does not attempt to discern causal effects from endogenous effects. Endogeneity is a problem if workers with a history of blue-collar employment are more likely to have faster health declines than those in white-collar occupations for reasons that are not occupationally related or observed. The inclusion of additional covariates and, potential, use of instrumental variables in future work will further examine the consequences of endogeneity. Second, our dichotomization of self-reported health status limits our findings to a subjectively chosen threshold. Because our primary point of dichotomization reflects a well-balanced point on the self-reported health status scale (see Tables 1 and 2), we are potentially losing information regarding movement into and out of more extreme health states.

References

Adams, P., M. Hurd, D. McFadden, A. Merrill, and T. Ribeiro. (2003). “Healthy, wealthy, and wise? Tests for direct causal paths between health and socioeconomic status.” *Journal of Econometrics* 112, no. 1: 3-56.

Ai, Chunrong and Edward Norton. (2003) “Interaction Terms in Logit and Probit Models.” *Economics Letters*. 80: 123-129.

Case, Anne and Angus Deaton. (2005). “Broken down by work and sex: How our health declines.” In *Analyses in the economics of aging*, ed. David A. Wise:185-205: Chicago: University of Chicago Press.

Chao, Elaine L. and Kathleen P. Utgoff. (2003). “National Compensation Survey: Occupational Wages in the United States, January 2001.” US Department of Labor – Bureau of Labor Statistics, Bulletin 2552.

Choo, Eugene and Michael Denny. (2006).” Wearing out--the decline in health.” 28 pages: University of Toronto, Department of Economics, Working Papers.

Currie, Janet and Brigitte C. Madrian. (1999). “Health, health insurance and the labor market.” In *Handbook of labor economics. Volume 3c*, ed. Orley Ashenfelter and David Card:3309-3416: Handbooks in Economics, vol. 5. Amsterdam; New York and Oxford: Elsevier Science, North-Holland.

Fletcher, Jason M. and Jody L. Sindelar. (2009). “Estimating causal effects of early occupational choice on later health: Evidence using the psid.” NBER Working Paper #15256.

Fletcher, Jason M., Jody L. Sindelar, and Shintaro Yamaguchi. (2009). “Cumulative effects of job characteristics on health.” NBER Working Paper #15121.

Grossman, Michael. (1972). “On the concept of health capital and the demand for health.” *Journal of Political Economy* 80, no. 2: 223-55.

Grossman, Michael and Robert Kaestner. (1997). "Effects of education on health." In *The social benefits of education*, ed. Jere R. Behrman and Nevzer Stacey:69-123: Economics of Education series. Ann Arbor: University of Michigan Press.

Idler, Ellen L. and Yael Benyamini. (1997). "Self-Rated Health and Mortality: A Review of Twenty-Seven Community Studies." *Journal of Health and Social Behavior*. Vol. 38(1): 21-37.

Manor, Orly, Saron Matthews, and Chris Power. (2001). "Self-rated health and limiting longstanding illness: inter-relationships with morbidity in early adulthood." *International Journal of Epidemiology*. Vol. 30(3): 600-607.

McFadden, Dan. (2005). "Comments on case and deaton 'broken down by work and sex: How our health declines'." In *Analyses in the economics of aging*, ed. D. Wise:205-212. Chicago: University of Chicago Press.

McFadden, E., R. Luben, S. Bingham, N. Wareham, A.-L.Kinmonth, and K.-T. Chaw. (2009) "Does the association between self-rated health and mortality vary by social class?" *Social Science & Medicine* 68. no. 2: 275-280.

Miilunpalo, Seppo, Ilkka Vuori, Pekka Oja, Matti Pasanen, and Helka Urponen. (1997). "Self-Rated Health Status as a Health Measure: The Predictive Value of Self-Reported Health Status on the Use of Physician Services and on Mortality in the Working-Age Population." *Journal of Clinical Epidemiology*. Vol. 50(5): 517-528.

Mossey, J.M. and E. Shapiro. (1982). "Self-rated health: A predictor of mortality among the elderly." *American Journal of Public Health* 72, no. 8: 800-808.

Muurinen, Jaana-Marja and Julian Le Grand. (1985). "The economic analysis of inequalities in health." *Social Science & Medicine* 20, no. 10: 1029-1035.

Table 1: Sample Means of Selected Variables

Health	
"Poor" health (period *t*)	0.386 (0.006)
"Poor" average (*t*, *t*-2, *t*-4)	0.364 (0.005)
Occupation	
Blue-collar	0.386 (0.007)
White-collar	0.444 (0.007)
Service job	0.063 (0.003)
Not employed	0.107 (0.003)
Race	
White	0.707 (0.007)
Black	0.261 (0.007)
Other race	0.032 (0.002)
Age	
Age	42.3 (0.096)
Age given "Poor" health	43.7 (0.136)
Education	
Less than HS	0.136 (0.005)
HS graduate	0.366 (0.008)
Some college	0.228 (0.007)
Bachelor's degree	0.270 (0.007)
Household Characteristics	
Married	0.86 (0.004)
Household income	70894.00 (997.00)

Note: Table shows the average values of selected characteristics for a sample of 30-59 year old men in the Panel Survey of Income Dynamics, 1988-2005. "Poor" health is defined as self-reported health status in "Good", "Fair", or "Poor" health (versus "Very Good" or "Excellent" health). Occupational groups match 1990 3-digit census occupational codes to occupational classifications used by the Bureau of Labor Statistics (2003). Household income is deflated to 2000 dollars. The sample includes 34,607 person-years from 5,611 individuals. Clustered standard errors are in parentheses.

Table 2

Proportion of Men Ever Observed in Specified Occupations or Health States

Occupation		**Health**	
Blue-collar	0.626	Good Health	0.921
	(0.006)	(SHS = Excellent, Very Good)	(0.004)
White-collar	0.625	Poor Health	0.789
	(0.006)	(SHS = Good, Fair, Poor)	(0.005)
Service job	0.181		
	(0.005)		
Not Employed	0.379		
	(0.006)		

Note: Table shows the proportion of PSID men, aged 30 to 59 years, ever observed in the defined occupational and health states (between 1984 and 2005). Clustered standard errors are in parentheses. Health states are defined by dichotomizing self-reported health status. Occupational groups match 1990 3-digit census occupational codes to occupational classifications used by the Bureau of Labor Statistics (2003).

Table 3. Two-Year Health Status Transitions

	"Very Good" (*t*+2)	"Poor" (*t*+2)	Total
"Very Good" (*t*)	79%	21%	61%
sample size	16,893	4,359	21,252
"Poor" (*t*)	27%	73%	39%
sample size	3,605	9,750	13,355

Note: Table shows the health transitions between period *t* and *t*+2 for 5,611 PSID men, aged 30 to 59 years in 1988-2007. Health states are defined by dichotomizing self-reported health into "Very Good" (self-reported “Excellent” or “Very Good” health) and "Poor" (self-reported “Good”, “Fair” or “Poor” status).

Table 4

Two-Year Health Transitions by Occupational Status

Health Transition	Blue-collar	White-collar	Service	Not employed
Health Transition Occurs	0.268	0.207	0.236	0.188
	(0.005)	(0.005)	(0.012)	(0.008)
Transition to "Poor" Health	0.258	0.157	0.223	0.296
Conditional on "Very Good" health in *t*	(0.007)	(0.005)	(0.015)	(0.015)
Transition to "Very Good" Health	0.280	0.340	0.253	0.138
Conditional on "Poor" health in *t*	(0.008)	(0.010)	(0.017)	(0.008)

Note: Table shows the proportion of 30 to 59 year old men changing health status between periods *t* and *t*+2. Data are from the 1988 to 2007 waves of the Panel Survey of Income Dynamics. Health states are defined by dichotomizing self-reported health into "Very Good" (self-reported Excellent or Very Good health) and "Poor" (self-reported Good, Fair or Poor status).

Table 5. Multivariate Estimates on the Probability of "Poor" Health

	(1)	(2)	(3)	(4)
Blue-collar Occupation	0.0465***	0.0742***	0.0417***	0.0367***
	(0.009)	(0.008)	(0.009)	(0.012)
Service Occupation	0.0299*	0.0515***	0.0247	0.0155
	(0.016)	(0.016)	(0.016)	(0.022)
Not employed	0.1299***	0.1534***	0.0979***	0.1383***
	(0.025)	(0.025)	(0.025)	(0.028)
"Poor" Previous Health	0.7193***	0.7275***	0.7151***	0.7203***
	(0.012)	(0.012)	(0.012)	(0.012)
Blue-collar×"Poor"	-0.0611***	-0.0606***	-0.0615***	-0.0646***
	(0.017)	(0.016)	(0.017)	(0.017)
Service×"Poor"	-0.0211	-0.0221	-0.0232	-0.027
	(0.028)	(0.028)	(0.028)	(0.029)
Not employed×"Poor"	-0.0785***	-0.0739**	-0.0740***	-0.0717**
	(0.029)	(0.029)	(0.029)	(0.030)
Age	0.0029***	0.0029***	0.0032***	0.0025***
	(0.000)	(0.000)	(0.000)	(0.001)
Blue-collar*Age				0.0009
				(0.001)
Service*Age				0.0014
				(0.002)
Not employed*Age				-0.0008
				(0.001)
Additional Controls				
Education	Yes	No	Yes	Yes
Household Income	No	No	Yes	Yes
Transition to Better Health Status				
Blue-collar	0.0146	-0.0135	0.0198	0.0278
	(0.0141)	(0.0133)	(0.0141)	(0.0189)
Service	-0.0088	-0.0294	-0.0015	0.0115
	(0.0217)	(0.0215)	(0.0218)	(0.0327)
Not employed (2 years)	-0.0103***	-0.0159***	-0.0048	-0.0133*
	(0.0029)	(0.0028)	(0.0030)	(0.0052)

Note: Table displays coefficient estimates from linear probability models where the dependent variable is "poor" health in period t+2. The data are for males from the 1988-2005 waves of the Panel Survey of Income Dynamics. "Poor" health is defined as "Good, Fair, or Poor" self-reported health status. "Poor Previous Health" refers to the average probability of being in poor health during periods t, t-2, and t-4. Occupational histories are defined over annual measures from period t to t-4. "Transition to Better Health Status" is the estimated difference in probability of transitioning from "poor" into "very good" health relative to white-collar workers. All models also include controls for race, marital status, proxy respondents, and a vector of survey year dummy variables. Robust standard errors, clustered by individual, are shown in parentheses.

Table 6. Predicted Difference in Probability of Health Transitions for Blue-collar Workers Versus White-collar Occupations

Econometric Specification	Transition to Worse Health Status	Transition to Better Health Status
(1) Main Model	0.0465*** (0.009)	0.0146 (0.0141)
(2) Health History included in all available years	0.0417*** (0.009)	0.0146 (0.0138)
(3) Health History in *t* & *t*-2 Only	0.0539*** (0.010)	0.0062 (0.0143)
(4) Health History in *t* only	0.0645*** (0.011)	-0.0060 (0.0153)
(5) Restrictive Definition of "Poor' Health	0.0146*** (0.0043)	0.0115 (0.0403)
(6) Health Transition in t+2 or t+4	0.0789*** (0.0135)	-0.0165 (0.0191)

Note: Table shows the difference in predicted probability for transitions into or out of "poor" health for men with a 5-year history of blue-collar work versus an equal period in white-collar occupations. The sample includes 34,607 person-years from 5,611 men aged 30-59 in the 1988-2005 waves of the Panel Study of Income Dynamics. Predicted effects are estimated from linear probability models. The main specification corresponds to the model estimated in column (1) of Table 5. Transitions are between "poor" and "very good" health defined, respectively as "poor", "fair" or "good" versus "very good" or "excellent" self-reported overall health, except for model (5), where "good" self-reported health is included in the "very good" health category. Model (2) includes health history variables in years t-1 and t-3 in all years these are available (they are excluded in the main specification, since this information is not provided when year t is later than 1997. Models (3) and (4) measure health history over a shorter time period and model (6) measures health transitions that occurring in either t+2 or t+4. Robust standard errors, clustered by individual, are shown in parentheses.

Figure 1

Health Status by Age

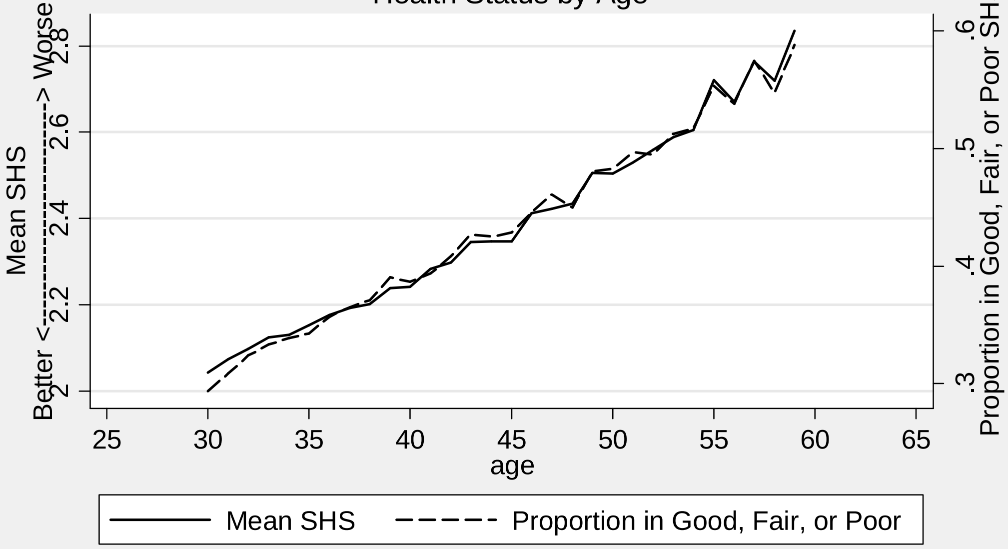

Figure shows the average values of self-reported health status information for a sample of 30 to 59 year old men in the Panel Study of Income Dynamics, 1988-2005. The sample includes 34,607 person-years from 5,611 men.

Appendix A: Occupational Classifications

White-collar

Professional Specialty and Technical Occupations (043-235)
Executive, Administrative, and Managerial Occupations (003-037)
Sales Occupations (243-285)
Administrative Support Occupations (303-348, 353, 356-389)
Classified by the Authors
- Other Telecom Operators (349)
- Postal Clerks, Excluding Mail Carriers (354)
- Mail Carriers, Postal Service (355)
- Managers, Farms, Except Horticultural (475)
- Managers, Horticultural Specialty Farms (476)

Blue-collar

Precisions Production, Craft, and Repair Occupations (503-529, 534-547, 553-654, 656-658, 666-669, 675-699)
Machine Operators, Assemblers, and Inspectors (703-714, 723-724, 726-729, 734-736, 738-748, 753-777, 783-800)
Transportation and Material Moving Occupations (803-859)
Handlers, Equipment Cleaners, Helpers, and Laborers (483-487, 489-489, 864-889)
Classified by the Authors
- Farmers, Except Horticulture (473)
- Horticultural Specialty Farmers (474)
- Supervisors, Farm Workers (477)
- Farm Workers (479)
- Graders and Sorters, Agricultural Products (488)
- Hunters and Trappers (499)
- Miscellaneous Electrical and Electronic Equipment Repairers (533)
- Not Specified Mechanics and Repairers (549)
- Miscellaneous Precision Metal Workers (655)
- Miscellaneous Precision Woodworkers (659)
- Miscellaneous Precision Apparel and Fabric Workers (674)
- Miscellaneous Metal, Plastic, Stone, and Glass Working Machine Operators (715)
- Miscellaneous Metal and Plastic Processing Machine Operators (725)
- Miscellaneous Woodworking Machine Operators (733)
- Miscellaneous Textile Machine Operators (749)
- Machine operators, not specified (779)

Service Jobs

Protective, Food, Health, Cleaning, and Personal Service (413-469)
Classified by the Authors
- Launderers and Ironers (403)
- Cooks, private Household (404)
- Housekeepers and Butlers (405)
- Child Care Workers, Private Household (406)
- Private Household Cleaners and Servants (407)

NOTE: Groups are based on 1990 3-digit Census occupation codes in parentheses. Blue-collar, white-collar, and service job classifications are based on the work of Chao and Utgoff (2003) except for occupations "Classified by the Authors," which were classified for use in this paper only.