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SOCIOECONOMIC STATUS AND HEALTH ACROSS GENERATIONS AND OVER THE LIFE COURSE

Occupational Status and Health Transitions

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Abstract

We use longitudinal data from the 1984-2007 waves of the Panel Study of Income Dynamics to examine how occupational status is related to the health transitions of 30-59 year-old U.S. males. A recent history of blue-collar employment predicts a substantial increase in the probability of transitioning from very good into bad self-assessed health, relative to white-collar employment, but with no evidence of a difference in movements from bad to very good health. Service work is also associated with a higher probability of transitioning into bad health and possibly with a lower probability of recovery. These findings suggest that blue-collar and service workers "wear out" faster with age because they are more likely than their white-collar counterparts to experience negative health shocks. There is also evidence that this partly reflects differences in the physical demands of jobs.

KEYWORDS: occupation, health transitions, PSID

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INTRODUCTION

Empirical research shows that jobs in physically demanding occupations are related to lower levels of health than jobs in other occupations but provides little indication about why health differs across occupations or about how such differences are generated. A particular gap in our knowledge involves understanding how occupations might affect the timing of transitions into and out of poor health. With this in mind, we examine how a person's occupational history is related to the probability of *transitioning* between health states. Specifically, we focus on how health transitions are related to employment in blue-collar, white-collar, and service occupations; we also consider differentials related to the physical demands of occupations.

Occupational status could have asymmetric effects on health transitions—for example, some occupations may be associated with relatively high probabilities of downward movements in health but without corresponding increases in the probabilities of health improvements. Consider the extreme case of an irreversible change, such as the loss of a limb or organ. Occupationally-influenced health investments might protect against or mitigate the likelihood of such shocks but have no effect on health once those shocks occur. Alternatively, once a person experiences a negative but reversible health shock, his occupation may hinder or enhance the ability to offset the initial deleterious effects.

A better understanding of occupation-related asymmetries in health transitions may improve our ability to model how the work environment is related to the production of health capital and be useful for designing policies to retain or restore health. For example, if occupational differences in health deterioration over the life cycle are dominated by the frequency of negative shocks, rather than the recovery from such shocks, policy interventions should probably focus on primary prevention (e.g. the elimination of accidents and other health related shocks) in high-risk occupations. Conversely, if there are substantial occupational differences in rates of recovery from initial deleterious events, policies might focus on bolstering the availability of convalescent services and therapies in slow-recovering occupations.

Our analysis specifically allows for these types of asymmetries. We use data on men's occupational and health histories from the 1984 through 2007 waves of the Panel Study of Income Dynamics (PSID) to create summary histories of occupation and health status over a five-year window and examine how these are related to health two years later. Consistent with prior research, the health of blue-collar workers is found to decline with age faster than that of white-collar workers. Importantly, we show that this is a consequence of blue-collar employees having a greater likelihood of transitioning from very good to bad health but with no difference in the relative probability of moving from bad to very good health. We find similar asymmetric associations when examining work histories on the basis of physical demands—workers with more physically demanding jobs face greater risks of negative health transitions but do not have different chances of health improvements.

Different patterns appear for histories of nonemployment and jobs in service occupations. Both are associated with higher risks of negative health events than white-collar work. However, nonemployment and, in some specifications, service employment are also correlated with lower probabilities of recovery. Taken together, our results indicate that downwards health transitions figure prominently in the negative relationship between non-white-collar occupations and health status. For nonemployment and service work, negative associations with rates of health improvement may also be important.

Conceptual Issues and Previous Literature

In models of health capital, individuals make investments to optimize healthy time available to work and earn income, and health capital can be combined with or used as a substitute for financial and traditional human capital (Grossman, 1972; Muurinen and Le Grand, 1985). This framework is also informative when considering health *transitions*, because the stock of health capital at a point in time depends on health status in the prior period, investment flows, predictable depreciation in the health stock, and stochastic shocks resulting from illness or accidents.

Health capital models identify several pathways through which occupational status may be related to health. First, occupational differences in pay may affect the resources available for investments, as well as the incentives to engage in them. Higher earnings have income effects, leading to greater investments in health. They also have substitution effects—periods of poor health impose larger opportunity costs for high-wage than low-wage workers, but high wages simultaneously increase the time costs of engaging in health-improving behaviors. Second, differences in access to information related to health behaviors or methods of alleviating health problems may be correlated with occupations. Occupational status could play a causal role in explaining these disparities or might be correlated with other determinants (like education or income) that are of fundamental importance. Peer effects could also matter and differ across occupations due to variation in coworker characteristics. Third, the rate of health depreciation is likely to be heterogeneous. For example, workers in physically demanding jobs may wear out faster; however, sedentary jobs can also pose health risks (Lakdawalla *et al*., 2005). Finally, the incidence of stochastic health events, such as accidents and injuries, may vary across occupations.

These sources of occupational disparities could have different effects on health transitions than on overall (average) health status. Most obviously, health shocks due to accidents cause downward movements in health that could either be transitory or permanent (depending on the nature of the injury). Work-related accidents are a plausibly important cause of occupational differences in health transitions because they are common. Data from the National Health Interview Survey show that 24 percent of injuries to 25-64 year-olds occur while working, making jobs the most common source for injuries in this age group (Bergen *et al.*, 2007, p. 123).

Shocks from accidents, if temporary, increase the volatility of health but need not change long-run average status. In this case, occupations with high accident rates will be characterized by large frequencies of both favorable and unfavorable health transitions. Conversely, accidents that permanently reduce health will have asymmetric effects, increasing negative transitions without a corresponding rise in health improvements.

Economists have recently started to examine how occupational status and health are related. Fletcher and Sindelar (2009) find that entering the labor force in a blue-collar (rather than white-collar) job is associated with significantly worse health at older ages—equivalent to the average effect of a seven-year increase in age (for persons 30 and older) in OLS models and by an even greater amount in IV specifications. The mechanisms for this correlation are not examined, but the maintained hypothesis is that the first occupation sets the trajectories of future job conditions, income, and consumption, which determine health. Fletcher *et al.* (2011) provide evidence that exposure during the previous five years to physically demanding jobs and work-related environmental hazards harms health: a one standard deviation increase in physical demands 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. Cross-sectional analyses for the U.S. (Case and Deaton, 2005) and Canada (Choo and Denny, 2006) indicate that health depreciates faster with age for individuals in manual than non-manual jobs, suggesting that occupations have cumulative effects on health and alter its trajectory over the life course.

Prior research does not examine how occupational status is related to health transitions, the study of which is interesting in its own right and potentially informative for understanding differences in age-related health gradients. As discussed, blue-collar jobs are likely to have relatively high rates of accidents. These could result in large but temporary deteriorations in health—implying relatively high probabilities of both entering and exiting poor health—or permanent health decrements, so that blue-collar workers disproportionately transition into but not out of poor health. Alternatively, downwards health mobility might be similar across occupations, but with blue-collar workers having more difficulty restoring good health. We examine whether there are occupational disparities in these (potentially asymmetric) health transitions, rather than on explaining the sources of any such differences, although we provide some indication of the role played by the physical job demands. A more explicit analysis of mechanisms represents an important topic for future research. We also investigate one health measure (self-assessed overall health status), and it would be useful for subsequent analyses to examine other health indicators. For instance, we hypothesize that health depreciation will be high in physically demanding jobs. However, this might be less true for outcomes such as obesity, where some forms of physical activity might be protective (Lakdawalla *et al*., 2005).

METHODOLOGY

We estimate dynamic models that allow us to examine how occupational status may be differentially and asymmetrically associated with transitions between better and worse health. Let h_t represent self-reported health status in year t for a given person. Most of our analyses consider a binary indicator where h_t takes a value of one if the person reports being in "good," "fair," or "poor" health (which we label below as "bad" health) and zero if the person states he is in "very good" or "excellent" health (denoted as "very good" health). h_{ave} is the average of self-reported health measured over some previous period (t, t–2 and t–4 in most of the analysis); OCC_{ave} represents either occupational history over the five-years ending in period t or particular characteristics of that history; X_t is a vector of observed and possibly time-varying personal characteristics; and ε_t is an error term that encompasses unobserved characteristics. The basic model we estimate is 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), estimated values of δ, θ, and γ indicate how health at time t+2 is related to the person's recent health status and occupational history.

Models that incorporate occupational histories have been estimated in previous studies; however, our specifications further allow occupational status to have different associations with transitions into and out of bad health. For people with a recent history of very good health, θ describes how occupational status is associated with downwards health transitions. For those with a recent history of bad health, combinations of θ and γ indicate how occupational status is associated with movements into better health.[1] The interpretations can be more complicated

[1] Specifically, the difference in the probability of transitioning from bad to very good health for a five-year history in occupation type *j,* rather than occupation type *k,* is $\theta_k - \theta_j + \gamma_k - \gamma_j$.

because h_{ave}, which averages health status over several years, can take values between zero and one. Similarly, OCC_{ave} can take a variety of values, but we will focus on the effects of one-unit changes corresponding, for example, to differences between persons in blue-collar and white-collar occupations during all previous periods over which occupational status is measured.

We estimate (1) as a linear probability model throughout, for convenience and ease of interpretation.[2] The longitudinal design of the PSID provides the health and occupational history information needed to estimate the model. Because the survey includes multiple observations for most sample members, we report robust standard errors clustered at the individual level.

The dynamic nature of the model partially addresses concerns related to the potential endogeneity of work and health. Examining the effects of occupational histories on *subsequent* health transitions decreases the possibility of reverse causality, because future health outcomes do not cause *prior* occupational choices. Moreover, the model conditions on health status over the time period that occupational history is measured, diminishing (but not completely eliminating) potential biases caused by health selection into occupational types. Specifically, the model compares individuals across occupations conditional on their health histories.

The estimates could still be biased, however, if self-reports of health are correlated with people's occupations. For instance, when indicating overall health status, people may compare themselves to others in their occupation. Thus, conditional on a given level of objectively measured health, persons in occupations with relatively poor average health may report themselves to be healthier than their counterparts in occupations with better average health. Previous studies have identified state-dependent thresholds in health reporting, but the biases appear to be related to age, sex, and country of origin, rather than socioeconomic characteristics such as income and education (Jürges, 2007; Groot, 2000; Lindeboom and van Doorslaer, 2004; Sadana *et al*., 2000; van Doorslaer and Jones, 2003). Moreover, because our analysis focuses on health transitions, all time-invariant reporting disparities will be accounted for. We also conduct sensitivity analyses that vary the time period over which health histories are measured and obtain evidence that our main findings are unlikely to be caused by occupation-specific differences in the size of random reporting errors.

[2] A preliminary analysis revealed similar patterns of coefficients and statistical significance when using probit specifications, but the linear probability coefficients are easier to interpret, especially when including the occupation-health interactions (Ai and Norton, 2003).

DATA

Our data on men's health and careers come from the Panel Study of Income Dynamics, which began surveying "heads" and "wives" of a national sample of 4,800 families in 1968, focusing on economic and demographic behavior.[3] The PSID has followed these families, including original sample members and their children when they establish independent households. Interviews were conducted annually through 1997 and biennially thereafter.

Since 1984, the PSID has asked heads and spouses: "Would you say your health in general is excellent, very good, good, fair, or poor?" Self-reported overall health status (SHS) is a widely used summary measure that predicts subsequent mortality (Idler and Benyamini, 1997; Mossey and Shapiro, 1982) and is correlated with indicators of morbidity (Manor *et al.*, 2001; Miilunpalo *et al.*, 1997). The measure has many advantages, but also limitations. One shortcoming, which is relevant for studies of employment outcomes, is that SHS may suffer from "justification" bias, in which health problems are reported to justify poor labor market outcomes (Currie and Madrian, 1999). However, this bias is unlikely to depend strongly upon occupation, and the relationship between SHS and objective health measures (like mortality) does not appear to vary between manual and non-manual workers (McFadden *et al*., 2009).

We dichotomize SHS into "bad" health (SHS is good, fair, or poor) and "very good" health (SHS is excellent or very good). Nearly all of our sample is observed to be in very good or excellent health at least once. The use of "good" health as a cut-off means that many of our sample members are also observed in the lower health category; however, the results in our analysis are robust to using "fair" health as the dividing line.

We measure a person's health history as a simple average of the binary health indicator over the preceding five years (i.e., the proportion of surveys when the person reported "bad" health). To accommodate the PSID change to biennial surveying after 1997, our primary measure averages data from t, t–2, and t–4 (ignoring data from t–1 and t–3 that are available in some but not all years). For example, if the person reported bad health in two of the three survey periods, the health history variable would equal 0.667. As sensitivity tests, we investigated several alternative health history variables including one that contained data for all five years—incorporating periods t–1 and t–3 when available—as well as measures based on shorter three- and one-year histories. These changes did not alter our main results and are discussed below.

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[3] Family "heads" are defined as the primary financial contributor to a PSID family, but this 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.

Occupational status and the physical demands of occupations are obtained using the reported occupation of the main job held by the household head at the time of each interview and one year earlier in the years when biennial surveys were conducted. The PSID records 3-digit occupation codes, and these were reclassified, using procedures detailed in Appendix A, to distinguish between "white-collar," "blue-collar" and "service" occupations, as well as periods of nonemployment. "White-collar" occupations mostly include office jobs, including managers and professionals. The "blue-collar" occupations generally include production work and tend to be more physically demanding. "Service" occupations include some physically demanding jobs, such as protective service workers, but also positions with fewer physical demands, such as personal service workers. Blue-collar and service workers generally enjoy less autonomy than white-collar workers.

The occupations within these broad categories are not homogeneous. For example, the white-collar category includes sales occupations, which might occur outside an office or involve little autonomy, and the blue-collar category includes machine operators, who might have few physical demands. Because of these issues, we also consider alternative classifications that have been used in previous research. In some specifications, we follow Fletcher and Sindelar (2009) by considering differences between blue-collar employees and all other workers (i.e., not distinguishing between white-collar and service jobs). In others, we follow Case and Deaton (2005) by considering managers and professionals as one category and combining the remaining white-collar jobs with service occupations in another.

A more direct way to describe the conditions of employment is in terms of specific job attributes, rather than occupational groups. The core PSID interviews do not ask about these characteristics; however, it is possible to map occupations to attributes typical of them. We do this for one especially relevant characteristic—the physical demands of the job. Using data from the Dictionary of Occupational Titles and methods described in Appendix A, occupations were classified on a five-point scale of increasing physical demands, where one indicates "sedentary" jobs and five indicates positions requiring "very heavy work." Consistent with expectations, occupation-based physical demands were highest in blue collar jobs and lowest in white-collar jobs, with service employment intermediate between the two. Using the five-point scale, physical demands averaged 2.9, 2.5 and 1.6 for blue-collar, service, and white-collar workers in our sample.[4]

[4] The physical demands variable should be interpreted cautiously because the measure is ordinal rather than cardinal, because it averages across jobs within a three-digit occupational category, and because occupational characteristics change over time.

For most analyses, we average the relevant measures of occupational status or characteristics over the preceding five years. For example, a person's recent history of blue-collar work is measured as the proportion of the previous five years that the person was employed in a blue-collar occupation. Similarly, the physical demand measures are averaged over the last five years. In sensitivity analyses, we averaged over shorter time periods but did not see differences in the main patterns of results.

Occupational mobility is common in our sample. Twenty-one percent of those in a blue-collar occupation at time *t* were in another broad occupation or nonemployed two years later, as were 15 percent, 30 percent and 36 percent of those in white-collar jobs, service occupations, and nonemployment. This mobility provides variation for our analysis and suggests that we are not simply capturing the effects of initial jobs described in Fletcher and Sindelar (2009).

Our multivariate analyses include other relevant explanatory variables. A key determinant of health is age, which we measure in years. Our main models include linear controls for age, but including a quadratic age specification does not alter the results. To account for racial differences in health, we include binary indicators for being black and for being neither black nor white (the reference group is white men). Educational differences are captured with binary indicators for not completing high school, graduating high school (or getting a GED) but without attending college, attending college but without obtaining a bachelor's degree, and completing a bachelor's degree or more education. We further distinguish between men who were married and unmarried at the time of the survey and include a general set of year dummy variables to account for trends in economic, social, health, and policy conditions. The log of the family's annual income is also included in some analyses.

Another issue arising in the PSID is that each year's reports come from one respondent, so that wives may sometimes be reporting the health status of their husbands. Our analyses include a binary indicator for such proxy reporting. We have also conducted analyses that exclude proxy responses, with no substantial change in the results.

We use information for men from the 1984 to 2007 waves of the PSID. Because of the need to measure health and occupational histories, the observations in our analyses are limited to men whose health outcomes (the year *t*+2 measures) were reported in the 1991 to 2007 waves and whose recent health histories, occupational histories, and other background information (the year *t* and earlier data) could be ascertained. We further restricted the observations to heads of households, aged 30 to 59 years at year *t* (the 1989-2005 waves). The lower end of the age restriction allows us to examine occupational effects for individuals who had time to amass appreciable work histories. The upper age threshold stops the analysis before most people retire but after many have experienced at least some bad health—73 percent of our sample reports bad health at least once during the observation period. We exclude person-year observations from even PSID interview years to remove overlaps in the dependent variable and to treat observations before and after the PSID switched to biennial surveys—in 1997—consistently.[5] Furthermore, we do not include individuals added with immigrant supplement to the PSID in 1990 as these individuals were subsequently dropped after 1995. We exclude women because the data are sometimes reported differently for them than for men.[6] The absence of women from our analyses is a significant limitation, and an important topic for future research.

The PSID includes 33,631 person-year observations for 7,659 men that meet the sample inclusion criteria. From this potential sample, we excluded 4,255 person-year observations because they did not have health information for the period *t*+2. We further deleted 5,139 person-years without sufficient health history information, 73 person-years without sufficient occupational history information, 530 person-years with recent service in the armed forces, and 336 person-years with missing data for the supplemental covariates. The resulting analysis sample includes 23,298 person-year observations from 5,351 men.

Observations are not excluded completely at random. Specifically, compared to those analyzed, the excluded person-year observations were 2.4 years younger, on average, were in slightly worse health (41% in bad health compared to 38%), had lower family incomes ($55,000 compared to $74,000), and were less educated (20% with a bachelor's degree compared to 28%).

Descriptive Analyses

Table 1 lists the variable means for the full analysis sample and for men with specified health histories and transitions between *t* and *t*+2. Thirty-eight percent of the person-year observations occurred in years when the men reported being in bad health. When considering recent health histories (the average from *t*, *t*–2, and *t*–4), the proportion of these years in bad health averages 36 percent. This slight drop from the average for contemporaneous health status is consistent with gradual age-related deterioration in health. White-collar employment is most common (44 percent of observations), followed by blue-collar work (38 percent), nonemployment (11 percent) and service jobs (7 percent). The demographic composition reflects the oversampling of poor households in the PSID, resulting in over-representation of black men. Also, males who are neither black nor white

[5] Models that include even year observations, when these are available, yield similar results.
[6] For example, the information for men is always reported in the questions for heads. Information for women may come from either the "head" or "spouse" question, depending on the person's living arrangements.

Table 1. Sample Statistics of Selected Variables

	Full sample	Health (t, t+2) Very good, very good	Very good, bad	Bad, bad	Bad, very good
Number of person-year obs.	23,298	11,425	2,907	6,495	2,471
Proportion of full sample	1.000	0.490	0.125	0.279	0.106
Health					
"Bad" health in period t	0.385	-	-	1.000	1.000
	(0.006)	-	-	-	-
Recent history of bad health (proportion of years t, t–2, and t–4 in bad health)	0.364	0.081	0.246	0.821	0.608
	(0.006)	(0.002)	(0.005)	(0.004)	(0.005)
Occupation in period t					
Blue-collar	0.380	0.332	0.449	0.413	0.433
	(0.007)	(0.009)	(0.011)	(0.011)	(0.012)
White-collar	0.445	0.552	0.406	0.291	0.396
	(0.007)	(0.009)	(0.011)	(0.010)	(0.011)
Service job	0.070	0.066	0.070	0.077	0.071
	(0.003)	(0.004)	(0.005)	(0.005)	(0.006)
Not employed	0.105	0.050	0.075	0.219	0.099
	(0.003)	(0.003)	(0.005)	(0.009)	(0.006)
Physical demands (Employed only)	2.221	2.105	2.296	2.391	2.30
	(0.005)	(0.014)	(0.017)	(0.018)	(0.018)
Individual Characteristics					
White	0.710	0.801	0.656	0.597	0.655
	(0.007)	(0.008)	(0.011)	(0.013)	(0.012)
Black	0.251	0.168	0.304	0.356	0.300
	(0.007)	(0.007)	(0.011)	(0.012)	(0.011)
Other race	0.039	0.032	0.040	0.047	0.045
	(0.002)	(0.003)	(0.004)	(0.004)	(0.004)
Age	42.8	41.7	42.7	44.9	42.7
	(0.097)	(0.129)	(0.158)	(0.162)	(0.172)
Less than high school	0.126	0.058	0.142	0.228	0.152
	(0.005)	(0.004)	(0.008)	(0.011)	(0.009)
High school graduate	0.365	0.322	0.395	0.412	0.404
	(0.008)	(0.009)	(0.011)	(0.013)	(0.012)
Some college	0.231	0.245	0.235	0.208	0.224
	(0.007)	(0.009)	(0.010)	(0.011)	(0.010)
Bachelor's degree	0.278	0.375	0.228	0.152	0.220
	(0.007)	(0.011)	(0.010)	(0.009)	(0.010)
Married	0.859	0.881	0.855	0.822	0.856
	(0.005)	(0.005)	(0.007)	(0.009)	(0.008)
Household income ($)	73,628	87,689	67,268	53,902	67,943
	(1,111)	(1,849)	(1,192)	(1,006)	(1,398)

Notes: Table shows the average values of selected characteristics for 30-59 year old men from the 1989-2005 odd-year waves of the PSID (n=23,298). Clustered standard errors are in parentheses.

are under-represented because the PSID does not fully account for the growth in this group that has occurred since the original (1968) sample construction. The average age is 43 years, and more than five-sixths of the observations are of married men. The sample includes a range of educational attainments.

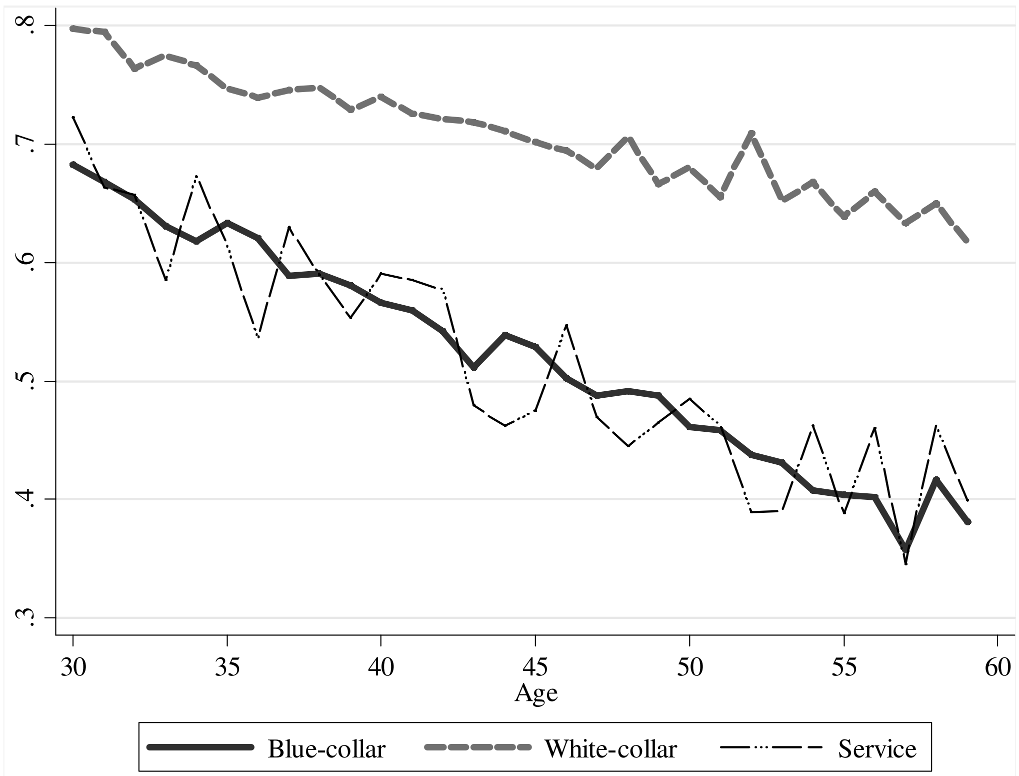
Considering health status in periods *t* and *t*+2, approximately half of the observations represent continuations of very good self-reported health (11,425 out of 23,298), just over a quarter come from continuations of bad health, leaving around a quarter that represent transitions between the health states during the two-year period. In particular, there were 2,907 transitions from very good health to bad health, which implies a transition rate of 20 percent, and 2,471 transitions from bad health to very good health, which implies a transition rate of 28 percent.

Several occupational associations are also apparent in Table 1. Men with recent histories of blue-collar work are under-represented in continuations of good health but over-represented in other health patterns. In contrast, white-collar workers are over-represented in the observations with continuations of very good health and under-represented in those with continuations of bad health. The composition of service workers does not vary substantially across groups, although there is some under-representation (over-representation) in continuations of very good (bad) health. These same patterns are more pronounced for nonemployed men. Workers continuing in very good health had the least physically-demanding recent job histories; those continuing in bad health had the most physically-demanding employment histories.

Figure 1 displays the proportion of men in our sample who report being in very good health conditional on the current occupation. As expected, the proportion of men in very good health declines with age for all occupational groups. The figure also reinforces the stylized fact that men in more physical occupations (blue-collar and service) are in worse health on average than men with less physical jobs (white-collar) and that this health differential increases with age.

Figure 2 shows the transition rates for men in very good health (top panel) and bad health (bottom panel) conditional on current occupation and age. Not surpisingly, transitions from very good to bad health increase with age while movements into improved health become less common. While Table 1 showed that blue-collar workers are over-represented in the sample of men who transition from bad to very good health, Figure 2 demonstrates that this is due to the overrepresentation of blue-collar workers in bad health at time *t*. More specifically, Figure 2 suggests that when conditioning solely on health and age in period *t*, blue-collar and service workers move from very good to bad health more frequently, than white collar workers, but transition from bad to very good health somewhat less often. The descriptions of health and health transitions in Figures 1 and 2 do not, however, condition on other important observable characteristics

Figure 1. Proportion of Men in 'Very Good' Health by Age and Occupation



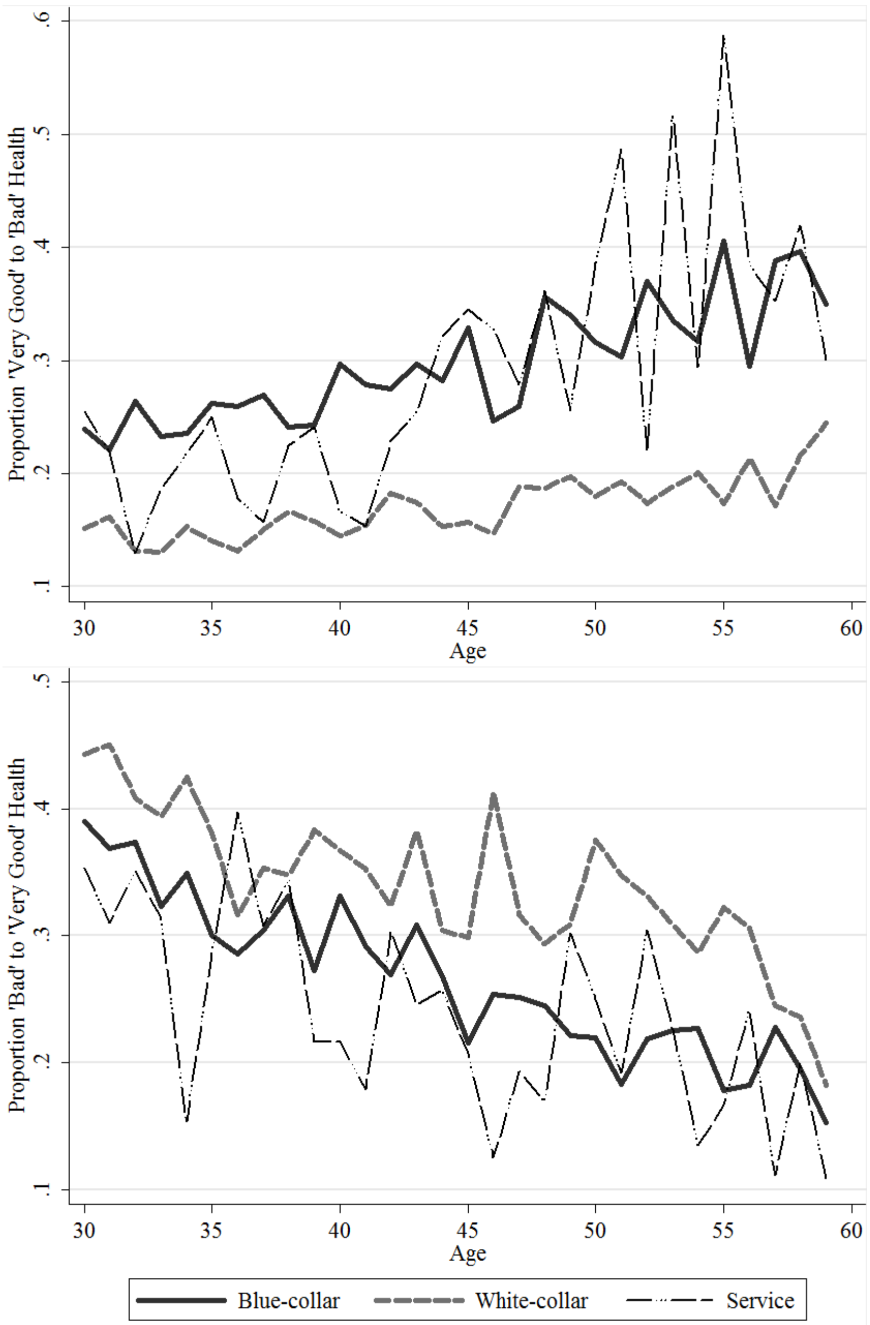
Notes: Figure shows the proportion of men aged 30 to 59 years reported to be in "very good" health by occupational status. Data are from the 1989-2005 odd-year waves of the PSID.

that are correlated with health, such as race, marital status, or educational status. Therefore, in the next section, we re-examine these relationships using multivariate models that account for possible confounding influences of other observed characteristics.

MULTIVARIATE RESULTS

Table 2 presents the results of four linear probability specifications estimating how occupational history is related to the probability of transitioning into and out of bad health. The models all control for recent health history, occupational history, interactions of the health and occupational histories, as well as for age, race, marital status, and general year effects. However, for brevity, we only report the coefficients for health, occupation, and age. All columns except the second also control for educational attainment. The third also includes household income. The last column adds occupation-specific age profiles.

Figure 2. Proportion Transitioning Health States by Age and Occupation



Notes: Figures show the proportion of men in 'very good' health (top figure) and 'bad' health (bottom figure) who transition to the alternate health state in period *t*+2 by current occupational status. Data are from the 1989-2005 odd-year waves of the PSID.

Table 2. Selected Results from Linear Probability Models of the Probability of "Bad" Health

	(1)	(2)	(3)	(4)
Recent history of bad health	0.713***	0.722***	0.709***	0.715***
	(0.013)	(0.013)	(0.013)	(0.013)
Blue-collar occupation	0.041***	0.069***	0.036***	0.026**
	(0.010)	(0.009)	(0.010)	(0.014)
Service occupation	0.032**	0.053***	0.026	-0.013
	(0.016)	(0.016)	(0.016)	(0.023)
Not employed	0.103***	0.123***	0.070***	0.118***
	(0.027)	(0.027)	(0.027)	(0.031)
Blue-collar occupation ×	-0.052***	-0.052***	-0.052***	-0.057***
recent history of bad health	(0.018)	(0.018)	(0.018)	(0.019)
Service occupation ×	-0.017	-0.020	-0.020	-0.034
recent history of bad health	(0.030)	(0.030)	(0.030)	(0.032)
Not employed ×	-0.056*	-0.050	-0.054**	-0.047
recent history of bad health	(0.032)	(0.032)	(0.031)	(0.033)
Age	0.003***	0.003***	0.003***	0.002***
	(0.000)	(0.000)	(0.000)	(0.001)
Blue-collar × age				0.001
				(0.001)
Service × age				0.004
				(0.002)
Not employed × age				-0.001
				(0.001)
Additional Controls				
Education	Yes	No	Yes	Yes
Household income	No	No	Yes	No

Notes: Table displays results from linear probability models where the binary dependent variable equals one for a person in "bad" health in period t+2. The models were estimated using 23,298 person-year observations on 5,351 men from the 1989-2005 odd-year waves of the PSID. All models control for race, marital status, proxy respondents, and general year effects. Robust standard errors, clustered by individual, are shown in parentheses.
*Significant at .10 level. **Significant at .05 level. ***Significant at .01 level.

Coefficients on the uninteracted occupation variables indicate conditional associations of occupational status with transitions from very good to bad health. The corresponding associations of occupational status with moves from bad to very good health, can be determined by combining the coefficients on recent occupational history and the occupation-health interaction term. Specifically, the difference in the probability of transitioning from a history of bad health in t, t–2, and t–4 to very good health in t+2 for men with a five-year history of blue-collar, service, or nonemployment, compared to a five-year history of white-collar

Table 3. Predicted Transition Probabilities by Occupational History

	(1)	(2)	(3)	(4)
		Transition to bad health		
White-collar occupation	0.129	0.111	0.136	0.128
	(0.006)	(0.005)	(0.006)	(0.006)
Blue-collar occupation	0.170***	0.180***	0.172***	0.171***
	(0.007)	(0.007)	(0.007)	(0.008)
Service occupation	0.160**	0.164***	0.161	0.169**
	(0.015)	(0.015)	(0.015)	(0.016)
		Transition to very good health		
White-collar occupation	0.158	0.167	0.155	0.157
	(0.011)	(0.111)	(0.011)	(0.011)
Blue-collar occupation	0.168	0.150	0.172	0.170
	(0.009)	(0.009)	(0.009)	(0.009)
Service occupation	0.144	0.134	0.149	0.150
	(0.021)	(0.021)	(0.021)	(0.022)
Additional Controls				
Education	Yes	No	Yes	Yes
Household income	No	No	Yes	No

Notes: Table displays the predicted probability of transitioning from a history of bad or very good health for a man with a five year history of white-collar, blue-collar, and service employment. Results are from linear probability models where the binary dependent variable equals one for a person in "bad" health in period $t+2$. All models control for race, marital status, proxy respondents, and general year effects. The predicted probability sets the value of each non-occupational and health covariate equal to its mean value. Statistical tests indicate a difference from the predicted value for a history of white-collar employment. The models were estimated using 23,298 person-year observations on 5,351 men from the 1989-2005 odd-year waves of the PSID. Robust standard errors, clustered by individual, are shown in parentheses.
*Significant at .10 level. **Significant at .05 level. ***Significant at .01 level.

employment, is the additive inverse of the sum of the occupation coefficient and the occupation-health interaction coefficient.

For ease of interpretation, Table 3 presents results from Table 2 as conditional expectations of transition probabilities following a consistent history of very good health (top panel) or bad health (bottom panel) for individuals with five-year histories of white-collar, blue-collar, and service jobs. When estimating these conditional probabilities, all non-health and non-occupational covariates were set to their mean values.

The estimates show an important asymmetry in the relationship between occupation history and health transitions. The top panel of Table 3 indicates that the expected probability of transitioning across health states significantly differs between white-collar and other workers. The first column, which controls for education but not income, indicates that otherwise similar men whose recent experience has been entirely in blue-collar work have an expected probability of transitioning into bad health that is 4.1 percentage points higher than men whose recent experience has been entirely in white-collar work. Work in service occupations is associated with a 3.2 percentage point increase in the probability of transitioning to bad health. Conversely, as shown in the bottom panel of the table, the probabilities of exiting bad health do not differ significantly with occupational status.[7]

The results are largely robust to altering the set of regression controls. The difference in probabilities of downwards health transitions becomes stronger for blue-collar and service workers, relative to those in white-collar jobs, when education is excluded (column 2), and the relative likelihood of moving from bad to very good health also falls for these groups. These findings suggest that some of the occupational differences in health transitions are due to educational disparities, probably because schooling provides protection against downwards movements in health (Grossman and Kaestner, 1997; Cutler and Lleras-Muney, 2008, Cawley and Ruhm, 2012). We follow the previous empirical economics literature and control for education in all other specifications, implying that most of our results show the role of occupation net of any such differences.

The log of total household income in period *t* is added as a control in third column of Tables 2 and 3.[8] Although this reduces the estimated occupational differences, men with a history of blue-collar employment are still 3.6 percentage points more likely to move from very good to bad health than their white-collar counterparts. Service employment is also associated with an increased chance of transitioning to bad health, though the coefficient is marginally insignificant. There are also no statistically significant occupational differences in transitions from bad to good health. In general, these results indicate that differences in income account for some of the occupational disparities in health transitions, but that most of them, especially for blue-collar workers, remain.

[7] Nonemployed men are estimated to be more likely to transition downward in health and less likely to transition upward in health than white-collar workers. However, the estimated effect of nonemployment is difficult to interpret because it is highly endogenous to self-reported health for men in the sample age range (Currie and Madrian, 1999) and because, conditional on experiencing some nonemployment in the previous five years, fewer than 5 percent of men were not working more than half the time.

[8] Controlling for total household income averaged over the 5-year period does not substantively change the results.

Finally, specification (4) allows the health trajectories to differ with age across occupational types. The occupation-age interactions are never statistically significant (see Table 2) and the predicted health transition probabilities do not significantly differ from simpler specifications, suggesting that little is lost by assuming that the main effects of occupation on health are age-independent.

SENSITIVITY TESTS

We estimated our models using a variety of alternative specifications of health and occupational histories. All of these included controls for age, race, marital status, proxy reporting, education, and year effects, but not income or occupation-age interactions. Thus, they replicate the specifications from the first column of Table 2. Like Table 3, Table 4 summarizes estimates from models showing the expected probability of transitioning from a history of very good health (columns 1-3) or bad health (columns 4-6) to the opposite health state in period t+2.

We begin our sensitivity analyses with alternative specifications of the health status measures. The first two rows in Table 4 list results from models that use shorter histories of health than our principal measure. In previous specifications, we combined several years of health data into a single summary variable to reduce the noise associated with the wave-to-wave measures. This, however, introduces two potential problems. On the one hand, the health reports from prior years may themselves introduce noise, if they are measured too far in the past to be relevant for the health transitions examined. On the other hand, we would be suspicious of correlations that stem mainly from the components of the health histories that were measured several years in the past. To address these concerns, we estimated models with health histories based on the data from periods t and t–2 (row 1) and solely from data based on period t (row 2). Using shorter health histories mostly strengthens our findings. The estimated probability differential between blue-collar work and a history of white-collar work for negative health transitions is 5.0 percentage points in row (1) and 6.0 percentage points in row (2). The estimated association between service work and negative health transitions remains statistically different from white-collar work and is of similar magnitude as in the primary specification. The models continue to show no significant difference between blue-collar and white-collar work in the likelihood of health improvements; however, there is now evidence that service workers are less likely to transition from bad to very good health.

Our next specification, shown in row 3, uses more of the available health data than our principal measure. Recall that the principal health history measure averages reports from periods t–4, t–2, and t, but not t–3 or t–1, even when those data are available. The model in row 3 incorporates a health history that uses all

Table 4. Occupational Status and Predicted Probability of Health Transitions in Alternative Specifications

	Transition to bad health			Transition to very good health		
	(1)	(2)	(3)	(4)	(5)	(6)
	White-collar	Blue-collar	Service	White-collar	Blue-collar	Service
Alternative specifications for health information						
(1) Health history in *t* and *t*−2 only	0.149	0.198***	0.178*	0.226	0.231	0.186*
(2) Health history in *t* only	0.188	0.248***	0.223*	0.332	0.328	0.281*
(3) Health history included for all available years	0.118	0.156***	0.144*	0.130	0.143	0.111
(4) Health transition in *t*+2 or *t*+4	0.215	0.284***	0.282***	0.291	0.266	0.218**
(5) Bad health defined as "fair" & "poor" health	0.034	0.045***	0.062***	0.213	0.247	0.167
Alternative specifications for occupational information						
(6) Occupational history in *t*, *t*−1 and *t*−2 only	0.130	0.170***	0.154	0.157	0.172	0.155
(7) Occupational history in *t* only	0.135	0.167***	0.147	0.155	0.171	0.163

(8) Blue-collar vs. all other occupations (service omitted)	0.133	0.169***		0.155	0.170	
(9) Service defined to include non-professional white-collar occupations	0.125	0.170***	0.148**	0.161	0.169	0.148
(10) Occupational status replaced by index of physical demands	0.141	0.159**	0.153**	0.168	0.163	0.165

Notes: Table displays the predicted probability of transitioning from a history of bad or very good health for a man with a five year history of white-collar, blue-collar, and service employment. Results are from linear probability models where the binary dependent variable equals one for a person in "bad" health in period t+2. All models control for race, marital status, proxy respondents, and general year effects. The predicted probability sets the value of each non-occupational and health covariate equal to its mean value. Statistical tests indicate a difference from the predicted value for a history of white-collar employment. The models were estimated using 23,298 person-year observations on 5,351 men from the 1989-2005 odd-year waves of the PSID. Robust standard errors, clustered by individual, are shown in parentheses.
*Significant at .10 level. **Significant at .05 level. ***Significant at .01 level.

the available time periods between t–4 and t. This yields almost no change in the results. Workers with a five-year history of blue-collar work are 3.8 percentage points more likely to transition from very good to bad health than workers with a five-year history of white-collar work. Workers with five-year histories of service work are estimated to be 2.7 percentage points more likely to make this transition than white-collar workers. The estimated associations of blue-collar and service work with health recoveries are not statistically different from those for white-collar work.

In row 4, we respecify our dependent health outcome variable, rather than our independent health history variable, to consider health transitions that occur between period t and either t+2 or t+4. The reason behind changing the observational window for the outcome is similar to that used when changing the window for the health history variable—to address concerns about the possible noise in reported health status. In this respecification, blue-collar and service work continue to be associated with higher expected probabilities of negative health transitions, and service work is estimated to be negatively associated with the relative likelihood of health recoveries.

In the fifth row of Table 4, we specify "bad" health more stringently to include only those who report "fair" or "poor" SHS, rather than also including the "good" category. Even with the stricter definition, blue-collar and service workers face a higher estimated risk of negative health transitions than white-collar workers, although the size of the differential falls. The attenuated coefficients are consistent with fewer transitions occuring under the stricter SHS criterion. The estimated associations of blue-collar and service work and health recoveries remain statistically indistinguishable from white-collar workers. However, this occurs mainly because of a loss in precision (the associations are estimated for a smaller pool of people who are "at risk" of transitioning to good health).

In the remaining rows of Table 4, we report results using alternative occupational history measures and contrasts. Rows 6 and 7 list results from models that use three- and one-year histories, respectively, rather than the five-year histories from our principal specifications. These alternatives are intended to address the already mentioned concerns about longer observational windows possibly introducing irrelevant information. In each model, we continue to find that blue-collar work has a significantly higher association with negative health transitions than white-collar work. The differentials with respect to service work, however, become weaker and statistically insignificant.

In row 8, we compare blue-collar employment to a reference category that combines both service and white-collar occupations. A similar contrast was used by Fletcher and Sindelar (2009) in their study of initial occupations. This has almost no effect on the results for blue-collar work, probably because of the low incidence of service work in our sample. The ninth row presents estimates from a model that combines service, sales, and administrative workers into a single occupational category, so that the reference group is restricted to professional and managerial workers. Once again, this yields no substantive changes.

The model estimated in the final row of Table 4 replaces the occupational history variables with the five-year average of the index of physical demands in each individual's occupation. These results show expected transition probabilities conditional on a five-year employment history with the average physical demands found in white-collar, blue-collar, and service jobs, respectively. Average physical demands of blue-collar and service occupations in our sample are 1.3 and 0.4 units greater than those of white-collar occupations. More physically demanding occupations are associated with relatively high probabilities of transitioning from very good into bad health but without a corresponding difference for moves from bad to very good health. Based on the results in row 10, the higher physical demands of five years of employment in the average blue-collar job increase the estimated probabilty of transitioning to bad health by 1.8 percentage points relative to the average white-collar job. This calculation suggests that physical demands account for over two-fifths of the differential between blue-collar and white-collar workers in movements from very good to bad health.

CONCLUSION

We use longitudinal data from the Panel Study of Income Dynamics to examine how men's occupational status is asociated with health and health transitions. Previous research indicates that health varies by occupation and that this heterogeneity increases with age. However, because health does not simply decline over the life-course—with both health decrements and improvements occurring frequently—we estimate models that identify relationships between occupational history and the probabilities of transitioning between both better and worse health for U.S. working-age males.

The results show that a recent (five-year) history of blue-collar employment predicts a four-to-five percentage point increase in the probability of moving from very good ("very good" or "excellent") into bad ("poor," "fair," or "good") self-assessed health, relative to white-collar employment. Conversely, there are no indications that blue-collar work differentially affects the probability of transitioning out of worse health. In most of our analyses, service work is also associated with a higher probability of transitioning from very good to bad health, while in some specifications, service work is also associated with a lower probability of transitioning to very good health (i.e., recovering). Education and income are positively related to health, as in previous studies, but their inclusion does not eliminate the observed occupational effects.

The findings regarding the associations for blue-collar workers are robust to a series of sensitivity analyses and do not appear to reflect errors in the reporting of self-assessed health. In particular, we estimate specifications that shorten the measured health histories from five years to either three years or one year. Conditioning on shorter health histories should increase measurement error, because the averaging occurs over fewer years, and is likely to then increase the likelihood of reporting error based health transitions. Consistent with this, we do see a rise in the relative probability that blue-collar and service workers transition into poorer health when using shorter occupational histories. However, there is no corresponding indication that they are more likely to move from bad to very good health, as the differential reporting error explanation would predict. Additionally, we test differing occupational groupings and an alternative occupational characteristic (physical demands). All results suggest that blue-collar workers, or those in more physically demanding jobs, relatively often transition into worse health, without detectable differences in the probability of health improvements.

These findings suggest that blue-collar and service workers "wear out" faster with age because they experience more negative health shocks than their white-collar counterparts. There is no consistent evidence that blue-collar workers have greater difficulty in recovering from given shocks, but nor is there a strong indication that they regain health more quickly or completely following them. Future research could fruitfully examine mechanisms underlying this occupational heterogeneity. An obvious possibility is that blue-collar and service workers are more prone to accidents or job-related physical traumas than white-collar workers. Indeed, our analysis suggests that differences in physical job demands can account for around two-fifths of the heterogeneity in the health transition rates of blue-collar versus white-collar workers.

Several caveats should be kept in mind when interpreting our results. Most importantly, endogeneity could be problematic if workers with histories of blue-collar or service employment have faster health declines than those in white-collar occupations for reasons that are correlated with but not caused by the occupation of employment or if individuals switch occupations because of a change in health status. In future research, the inclusion of additional covariates and the use of instrumental variables methods or other identification strategies would be helpful for examining the consequences of such occupational selection. Second, we cannot say what characteristics of occupations cause the health transition patterns to differ, beyond our exploratory analysis of the role of physical demands. Third, dichotomization of self-reported health status limits our findings to a subjectively chosen threshold and implies that we potentially lose information about movements into or out of more extreme health states. However, this concern is substantially mitigated by the robustness of the results to the use of alternative thresholds for distinguishing between better and worse health. Finally, during an era when female employment rates are approaching those of males, and the occupations in which they work are becoming increasingly diverse, an extension of this research to consider the role of women's occupational status is needed.

APPENDIX A: OCCUPATIONAL CLASSIFICATIONS

The PSID provided 3-digit 1970 Census group definitions for the 1984 through 2001 waves and 3-digit 2000 Census group definitions thereafter. To make this information uniform for all survey rounds, we recoded the occupation codes to 1990 Census definitions for all years using the crosswalk provided by IPUMS-USA (http://usa.ipums.org/usa/volii/documents/occ1990_xwalk.xls). The occupations were subsequently defined as "blue-collar," "white-collar," or "service" following listings provided by Chao and Utgoff (2003). Twenty-six occupations were not included in the BLS list; we have categorized these occupations within the classification that is subjectively appropriate (see Table A-1). In addition to the occupational classifications, we included a fourth category for men who were not employed at the survey date.

There are two notes of interest in constructing these categorical variables. First, the PSID identifies individuals serving in the armed forces but does not indicate their occupation while in military service. Because there were too few observations to classify military service as a separate occupation, we dropped person-year observations for individuals serving in the armed forces during the 5-year occupational history window. Second, a small number individuals report being unemployed or out of the labor force but still indicate an occupation. For consistency, we coded these individuals as not-employed.

Our main occupation variables represent average values for the five years t–4, t–3, t–2, t–1, and t. In the years up to 1997, we used information on the occupation of the primary job at the time of the interview for all these periods. In later years, when the PSID interviewed biennially, we used available retrospective work history information to identify the occupation of individuals in the month one year prior to the survey month to obtain the measures for periods t–3 and t–1. For instance, an individual's 1998 occupation is defined as that reported in the month one year prior to the 1999 interview.[9] If data were missing for any years between t–4 and t (after including the constructed values just discussed), averaging took place over the period for which the data were available.

[9] The retrospective information in the non-interview years (1998, 2000, 2002, 2004, and 2006) provides fewer occupational transitions than interview years. A 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, occupational measures during the non-interview years match the characteristics of those during interview years in the terms of the number of observations and proportion of individuals in each occupational state (Callegaro, 2007).

Table A-1. Classification of Occupations

White-collar

Professional Specialty & Technical Occupations (043-235), n = 5850
Executive, Administrative, & Managerial Occupations (003-37), n = 6975
Sales Occupations (243-85), n = 2334
Administrative Support Occupations (303-48, 353, 356-89), n = 1767
Classified by the authors:
- Other Telecom Operators (349), n = 1
- Postal Clerks, Excluding Mail Carriers (354), n = 138
- Managers, Farms, Except Horticultural (475), n = 109

Blue-collar

Precisions Production, Craft, & Repair Occupations (503-29, 534-47, 553-654, 656-58, 666-69, 675-99), n = 6451
Machine Operators, Assemblers, & Inspectors (703-14, 723-24, 726-29, 734-36, 738-48, 753-77, 783-800), n = 1927
Transportation and Material Moving Occupations (803-59), n = 3059
Handlers, Equipment Cleaners, Helpers &Laborers (483-87, 489, 864-89), n=1870
Classified by the authors:
- Farmers, Except Horticulture (473), n = 420
- Farm Workers (477,479), n = 310
- Graders and Sorters, Agricultural Products (488), n = 4
- Miscellaneous Electrical and Electronic Equipment Repairers (533), n = 4
- Not Specified Mechanics and Repairers (549), n = 317
- Miscellaneous Woodworking Machine Operators (733), n = 5
- Miscellaneous Textile Machine Operators (749), n = 63
- Machine operators, not specified (779), n = 869

Service Jobs

Protective, Food, Health, Cleaning, and Personal Service (413-69), n = 2438
Classified by the authors:
- Mail Carriers, Postal Service (355), n = 164
- Housekeepers and Butlers (405), n = 141
- Private Household Cleaners and Servants (407), n = 8

Notes: 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. The numbers of observations, n, refer to person-year observations between 1984 and 2005.

We merged information on the physical demands of occupations using data from the Dictionary of Occupational Titles (DOT): Revised Fourth Edition (1991), which provides a five point ordinal measure of the physical demands for 12,742 occupations. The demands are listed as Sedentary, Light Work, Medium Work, Heavy Work, and Very Heavy Work (see http://www.occupationalinfo.org /appendxc_1.html#STRENGTH).

We matched the physical demand characteristics of DOT occupations to the Census occupational codes by assigning the five measures to integers, one to five, increasing in physical demands. The DOT occupations and physical demand scores were then matched to Occupational Employment Statistics (OES) codes provided by the Bureau of Labor Statistics (BLS Crosswalk Center) and averaged over the DOT occupations within each OES occupation. Finally, physical demands by OES occupation were weighted according to 1997 estimates of the number of individuals employed in each of the OES occupations (BLS, 2010) and matched to the 1990 Census occupation codes for person-years in our PSID data set.

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