

What Explains Educational Disparities in Older Adults' Propensity to Work?

Richard W. Johnson
Urban Institute

Nadia S. Karamcheva
Congressional Budget Office

Although older Americans' employment has surged over the last 20 years, less-educated adults are much less likely to work at older ages than their better-educated counterparts. Using data from the Health and Retirement Study linked to job demands information derived from the Occupational Information Network, this study identifies those factors driving educational differences in old-age employment. The results show that self-reported health and work-restricting health conditions account for almost half of the employment gap. Job demands and other job characteristics, including the presence of difficult working conditions, also account for a significant share of the gap.

INTRODUCTION

Retirement patterns have shifted significantly over the past quarter century, as the trend of ever-earlier retirement has been replaced by delayed withdrawal from the labor force (Quinn, Cahill, & Giandrea, 2011). Whereas men born between 1933 and 1937 retired at much younger ages, on average, than those born 20 years earlier, the early Baby Boom generation that followed (born between 1943 and 1947) generally retired later; more than 40 percent of early Boomers had not retired by age 65, compared with only 20 percent of those born 10 years earlier, and the early Boomers' median retirement age was one-half year higher (Johnson, Butrica, & Mommaerts, 2010). The growth in women's labor force participation over the past several decades has translated into delayed retirement for women as well. Between 1993 and 2016, labor force participation rates at ages 65 to 69 increased 13 percentage points for men and 11 points for women (US Bureau of Labor Statistics, 2016).

Previous research has identified several factors that might have contributed to the reversal of the retirement trend (Blau & Gilleskie, 2001; Blau & Goodstein, 2010; Burtless, 2013; Friedberg & Webb, 2005; Gustman & Steinmeier, 2000; Mermin, Johnson, & Murphy, 2007; Schirle, 2008). For example, recent Social Security reforms raised the financial gains from working longer by boosting the full retirement age, increasing the bonus for delaying Social Security benefit take up past the full retirement age, and eliminating the retirement earnings test on work past the full retirement age.¹ Changes in employer practices have also made work more lucrative at older ages. Employers have shifted away from traditional defined benefit pension plans that generally penalize work at older ages to defined contribution retirement plans that reward continued employment throughout a career. In addition, erosion in employer-sponsored retiree health insurance made leaving the workforce before age 65, when Medicare coverage

begins, more costly for employees who received health benefits at their workplace. The rising educational attainment of older adults may have improved employment prospects at older ages, especially in less physical occupations. Finally, the increase in women's employment and the growth in dual-earning couples may have encouraged men to work longer so they could retire at the same time as their generally younger wives.²

The trend in delaying retirement is significant because working longer tends to bolster retirement income security. Munnell and Sass (2008) argue that additional years in the labor market promote income security not just by raising current earnings, but also by helping people avoid the Social Security benefit reductions associated with early claiming and by generating more time to accumulate savings through defined contribution retirement plans. Butrica, Smith and Steuerle (2006) estimate that working an additional five years would raise average annual retirement incomes by about one-half for workers overall and would nearly double annual retirement incomes for low-income workers.

However, retirement ages have not increased equally among all groups, and less-educated older adults are falling behind. Increased labor force participation among older adults is concentrated predominantly among people with the most education, while those with less education are more likely to retire early (Bosworth & Burke, 2012; Munnell & Sass, 2008). Among men born between 1940 and 1944, for example, 56 percent of high school dropouts and 53 percent of those with only a high school diploma claimed Social Security retirement benefits at age 62—the earliest possible age—compared with 38 percent of those with a bachelor's degree and 33 percent of those with an advanced degree (Haaga & Johnson, 2012). In addition, poverty rates among less-educated older adults are much higher than the poverty rates of their more educated counterparts (O'Brien et al., 2010). Less-educated older adults will further jeopardize their retirement income security if they continue to retire early, falling behind their better-educated counterparts and exacerbating late-life income inequality (Crystal, Shea, & Reyes, 2016).

This study examines the educational gap in employment at older ages and identifies factors that explain it. We use parametric linear decomposition methods and related applications developed for limited dependent variable models to estimate the portion of the gap that arises from educational differences in health status, job characteristics, household income and wealth, spousal employment, and demographic characteristics.

An important contribution of our research is the inclusion of detailed job and occupational demands among the explanatory factors. We link household survey data on older adults from the Health and Retirement Study (HRS) to the US Department of Labor's Occupational Information Network (O*NET) dataset to formulate a more "objective" measure of older workers' job demands, which we use in conjunction with more standard self-reports. The rich information in the O*NET dataset has been used recently to analyze changes in occupational demands over time (Johnson, Mermin & Resseger, 2011), as well as to examine the influence of occupations and job characteristics on workforce departure and retention (McFall et. al, 2015).

By including both "objective" and self-reported job demands in the analysis, this article extends the existing literature on retirement determinants and quantifies the relative importance of various factors. Previous studies have shown that factors that make work less appealing, such as poor health or work-limiting health conditions, encourage earlier retirement (e.g., Bound et al., 1999; French, 2005; McGarry, 2004). More recently, Munnell, Sanzenbacher and Rutledge (2015) find that health shocks are the most important drivers of earlier-than-planned retirement. Earlier research has also shown that job characteristics can influence work at older ages. Workers in physically demanding jobs and those in stressful occupations retire earlier than other workers (Filer & Petri, 1988; Hayward et al., 1989; Holder, 1988; Hurd & McGarry, 1993). In contrast, workers in cognitively demanding jobs tend to retire later, possibly because those jobs provide the autonomy and intellectual stimulation that makes work satisfying (Hayward et al., 1989).

However, health status and job characteristics are both correlated with education, partly explaining the relationship between schooling and retirement and thus making it difficult to explain what most accounts for early retirement among less-educated older adults. For example, less-educated workers are also more likely than others to hold physically demanding jobs (Johnson, Mermin, & Resseger, 2011). It

is also well known that health problems are especially prevalent among low-socioeconomic-status adults (e.g., Adler & Ostrove, 1999; Mackenbach et al., 2008; Smith, 2004; Williams & Collins, 1995; Williams et al., 2010). This paper sheds light on the relative importance of these factors in explaining observable educational differences in work propensities at older ages.

Our results show that self-reported health status and health conditions account for nearly half of the employment gap between older adults with no more than a high school diploma and those with at least a bachelor's degree. Job demands and other job characteristics also account for a significant share of the gap. These findings have important implications for Social Security, disability, and employment policy.

DATA

This article uses data from the HRS, supplemented by job demand information from O*NET. The HRS is a large nationally representative longitudinal survey of Americans ages 51 and older and their spouses. Conducted by the University of Michigan for the National Institute on Aging, the survey began in 1992 and re-interviewed respondents every two years. The baseline sample included 12,652 respondents born between 1931 and 1941 (who were ages 51 to 61 in 1992). The HRS periodically refreshes the sample, adding in 1998 respondents born between 1942 and 1947, adding in 2004 respondents born between 1948 and 1953, and adding in 2010 respondents born between 1954 and 1959. The latest available data when we began our study was collected in 2010, when the HRS completed interviews with 22,039 respondents.

The HRS is particularly useful for studies of work and retirement. It collects rich information on employment, demographics, socioeconomic factors, self-reported health and medical conditions, income, assets, and debt, as well as information on job characteristics such as required physical and mental effort, stress, perceived age discrimination, and work satisfaction.

Our key outcome of interest is employment, which we measured by creating a dummy variable indicating whether respondents were currently working for pay. Our analysis focused on adults ages 55 to 70, because some workers begin to retire at age 55 and most workers have retired by age 70.

We used HRS data to create measures for gender, age, race, marital status (whether currently married or partnered), education, health status, income, and wealth. Education is summarized by four categories: not high school graduate, high school graduate, some college but not a bachelor's degree, and bachelors' or advanced degree. The empirical analyses distinguish between older adults with no more than a high school diploma and those with at least a bachelor's degree. The HRS asks respondents to describe their overall health as excellent, very good, good, fair, or poor; we created dummy variables identifying those who reported fair or poor health and those who reported better health. The HRS also asked respondents whether they have ever been diagnosed with various health conditions, including high blood pressure, diabetes, cancer, lung disease, heart problems, stroke, psychological problems, and arthritis. We created a health conditions measure equal to the number of reported conditions. Finally, we created a measure of nonemployment income, equal to household income excluding the individual's earnings, and per capita household net worth, equal to per capita total household wealth minus per capita total household debt. Total household wealth includes financial assets (checking and savings accounts, certificates of deposit, stocks, bonds, IRA accounts and other), real estate, and property vehicles, and total household debt includes outstanding mortgages, debt on vehicles and other debt. We expressed income and wealth in constant 2010 dollars, adjusted by the change in the consumer price index.

Self-Reported Job Demands

Employed HRS respondents provide information about the characteristics of their current jobs. The survey asks whether jobs require lots of physical effort, lifting heavy loads, stooping, kneeling, or crouching, or having good eyesight; whether it involves a lot of stress; and whether it requires intense concentration, people skills, or computer use. In addition, respondents report whether they believe their employer gives preference to younger workers in terms of promotion and whether their employer would let older workers move to a less demanding job with less pay if they wished, which we summarize as job

flexibility. They are also asked about how much they enjoy their work, whether they think their job requires them to do more difficult things than it used to, and whether they feel pressure to retire before 65.

In the descriptive and multivariate analyses we measure these self-reported job characteristics with dummy variables that equal 1 if respondents report that these job features are present “most or all of the time,” or if they “agree or strongly agree” with the survey’s statement. We also include respondents’ self-assessment of whether their employer gives younger people preference over older people in decisions about promotions. In the empirical specifications we include job demands for the current job for employed respondents and for the most recent job for respondents who are not employed.

Occupational Information Network Database

We supplemented the self-reported job characteristics information in the HRS with a more “objective” measure of job demands derived from O*NET, which is a comprehensive database of job characteristics produced by the National Center for O*NET Development, under the sponsorship of the Employment and Training Administration at the US Department of Labor. We matched this information to our HRS respondents using detailed occupational codes available in a restricted-access version of the HRS.

The data is collected from job incumbents or occupational experts and updated annually, by surveying a broad range of workers from each occupation. We used the version 17 release data from 2010. The file contains information on 974 occupations and 277 “descriptors,” a standardized set of variables defining key features of each occupation. Next we applied the methods described in Johnson, Mermin and Resseger (2011) to group 56 specific job characteristics into 14 broad categories of physical demands, nonphysical demands, and workplace conditions (Table 1).

O*NET assigns each job attribute a score between 1 and 5, where one indicates that the attribute is not important to job performance and five indicates that it is extremely important. We classified each occupation as involving one of the 14 job demands if the O*NET score for any of the underlying detailed characteristics equaled or exceeded 4, indicating that the requirement was very or extremely important to job performance. In addition we created four O*NET indexes, relating to physical demands, cognitive demands, social- and stress-related demands, and working conditions, by summing the corresponding detailed indicators for job demands and working conditions for each occupation. We include these O*NET indexes, rather than the indicators for each detailed job demand or working condition, in the multivariate regression and decomposition analysis.

DESCRIPTIVE STATISTICS

Table 2 compares the characteristics of adults ages 55 to 70 in 1998 and 2008.³ Women make up about 53 percent of the sample in both years, and more than 70 percent of the sample is married or partnered (72.3 in 1998, 71.2 in 2008). Educational attainment in this age group improved considerably over the 10-year period. Between 1998 and 2008, the share of adults ages 55 to 70 without a high school diploma dropped from 24.7 to 14.8 percent, while the share with a bachelor’s or advanced degree increased 8 percentage points (from 20.7 to 28.7 percent). In addition, the employment rate rose 6.4 percentage points over the period, from 50.5 to 56.9 percent.

These trends are evident among both men and women. Whereas men ages 55 to 70 are more likely to be in a coupled household than their female counterparts, have more education on average, and are more likely to be employed, educational attainment and employment rates increased for both men and women in this age group between 1998 and 2008. In 2008, 62.6 percent of men ages 55 to 70 were employed, compared with 58.4 percent in 1998. For women, the corresponding rates are 51.6 percent in 2008 and 43.5 percent in 1998. The share without a high school diploma fell 10.1 percentage points among men and 9.7 percentage points among women, whereas the share with a bachelor’s degree or more increased 7.0 percentage points among men and 8.7 percentage points among women.

TABLE 1
O*NET JOB DEMAND CATEGORIES

Job Demand	Job Demand
<p>High General Physical Demands</p> <ul style="list-style-type: none"> Dynamic Strength Explosive Strength Static Strength Stamina Trunk Strength Bending or Twisting of the Body Kneeling, Crouching, Stooping, or Crawling Reaction Time Gross Body Equilibrium <p>High or Moderate General Physical Demands</p> <ul style="list-style-type: none"> <i>High General Physical Demands</i> Handling and Moving Objects Significant Time Standing Significant Time Walking and Running Performing General Physical Activities Making Repetitive Motions <p>High Flexibility and Dexterity</p> <ul style="list-style-type: none"> Arm-Hand Steadiness Extent Flexibility Finger Dexterity Manual Dexterity <p>High or Moderate Flexibility and Dexterity</p> <ul style="list-style-type: none"> <i>High Flexibility and Dexterity</i> Handling or Controlling Objects or Tools <p>Difficult Working conditions</p> <ul style="list-style-type: none"> Cramped Work Space, Awkward Positions Exposed to Contaminants Exposed to Hazardous Conditions Exposed to Hazardous Equipment Exposed to Whole Body Vibration Works Indoors, Not Environmentally Controlled Works Outdoors, Exposed to the Weather Works Outdoors, Covered Distracting or Uncomfortable Noise Levels Exposed to Very Hot or Cold Temperatures 	<p>Vision</p> <ul style="list-style-type: none"> Depth Perception Far Vision Near Vision <p>High Cognitive Ability</p> <ul style="list-style-type: none"> Deductive Reasoning Inductive Reasoning Mathematical Reasoning Originality Written Expression Thinking Creatively Complex Problem Solving Judgement and Decision Making Use of Scientific Rules or Methods <p>High or Moderate Cognitive ability</p> <ul style="list-style-type: none"> <i>High Cognitive Ability</i> Getting Information Processing Information Writing Letters or Memos Making Decisions and Solving Problems Active Learning Critical Thinking <p>Computer Use</p> <ul style="list-style-type: none"> Interacting with Computers Using Electronic Mails <p>Dealing with Unpleasant or Angry People</p> <p>Interpersonal Skills</p> <ul style="list-style-type: none"> Establishing, Maintaining Interpersonal Relations Social Perceptiveness <p>High Stress</p> <ul style="list-style-type: none"> Frequent Conflict Situation High Level of Competition <p>High or Moderate Stress</p> <ul style="list-style-type: none"> <i>High Stress</i> Time Pressure <p>Updating and Using Relevant Knowledge</p>

TABLE 2
DEMOGRAPHIC CHARACTERISTICS OF ADULTS AGES 55 TO 70 IN 1998 AND 2008 (%)

	All		Male		Female				
	1998	2008	1998	2008	1998	2008			
Female	53.1	52.4	0.0	0.0	100.0	100.0			
Married or partnered	72.3	71.2	81.9	78.7	***	63.7	64.3		
Education									
Not a high school graduate	24.7	14.8	***	24.6	14.5	***	24.8	15.1	***
High school diploma only	35.1	31.2	***	31.0	27.5	***	38.8	34.5	***
Some college, not bachelor's degree	19.4	25.0	***	18.4	24.7	***	20.3	25.2	***
Bachelor's degree or more	20.7	28.7	***	25.9	32.9	***	16.2	24.9	***
Employed	50.5	56.9		58.4	62.6	***	43.5	51.6	***
Race									
White	87.5	86.7	*	88.7	87.9		86.4	85.6	
African American	9.9	10.0		8.7	8.9		11.0	11.0	
Other	2.6	3.3	**	2.6	3.2		2.6	3.4	
<i>Number of observations</i>	<i>11,030</i>	<i>8,259</i>		<i>5,033</i>	<i>3,513</i>		<i>5,997</i>	<i>4,746</i>	

Source: Authors' calculations from the HRS.

Note: Significance * p<0.1, ** p<0.05, *** p<0.01 relates to t-test for comparison of means between the two categories. Person-level weights were used.

Table 3 further illustrates the changes in labor force participation that occurred over the 10-year period. A larger share of older adults worked in 2008 than 1998 across all education groups, except among those who did not complete high school—for them the employment rate dropped 0.9 percentage points. The fastest growth in employment occurred among college graduates, whose employment rate increased 7.6 percentage points over the period, followed by those with only some college (3.1 percentage point growth) and those with only a high school diploma (2.4 percentage point growth).

TABLE 3
PERCENTAGE OF ADULTS AGES 55 TO 70 EMPLOYED, BY EDUCATION, 1998 AND 2008

	All		Men		Women				
	1998	2008	1998	2008	1998	2008			
Education									
Not a high school graduate	36.6	35.7	44.1	46.4	30.0	26.2	*		
High school diploma only	49.8	52.2	*	59.0	54.8	*	43.3	50.4	***
Some college, not bachelor's degree	56.3	59.4	*	63.1	63.8		50.8	55.5	**
Bachelor's degree or more	62.9	70.5	***	68.0	75.3	***	55.6	64.7	***
All	50.5	56.8	***	58.4	62.6	***	43.5	51.6	***
<i>Number of observations</i>	<i>11,009</i>	<i>8,228</i>		<i>5,026</i>	<i>3,498</i>		<i>5,983</i>	<i>4,730</i>	

Source: Authors' calculations from the HRS.

Note: Significance * p<0.1, ** p<0.05, *** p<0.01 relates to t-test for comparison of means between the two categories. Person-level weights were used.

The education gap in employment increased between 1998 and 2008. Adults ages 55 to 70 with at least a bachelor's degree were 26.3 percentage points more likely to work in 1998 than those who did not complete high school, and they were 34.8 percentage points more likely to work in 2008. Women in all

education groups, with the exception of those without a high school diploma, were significantly more likely to work in 2008 than 10 years earlier. Among men, by contrast, only college graduates made significant gains in employment over the period. In 2008, men without a high school diploma and those with some college who did not earn a bachelor's degree were just as likely to be employed as their counterparts 10 years earlier, and those with only a high school diploma were 4.2 percentage points less likely to be employed.

Our empirical models examine how well various characteristics can explain educational differences in work at older ages. We hypothesize that less-educated adults might stop working because they are in poor health, are more likely to suffer from various health conditions, are more likely to hold jobs that are physically demanding or feature poor working conditions, or have employers that provide little flexibility in terms of reducing their workload as they age. Before estimating empirical models and comparing the explanatory power of these factors, we examine how individuals with different levels of education compare in terms of health outcomes and job characteristics.

Table 4 compares gender, race, marital status, and health status in 2008 for adults ages 55 to 70 with no more than a high school diploma and those who attended college. Compared with the more-educated group, those with no more than a high school diploma are more likely to be female, less likely to be white, and less likely to be married or partnered, and on average they have worse health. Only 7.3 percent of these less-educated adults described their health as excellent, compared with 15.6 percent of those who attended college. Overall about one-third of them (33.4 percent) described their health status as very good or excellent, while more than one-half (54.5 percent) of the better-educated group described their health that way. Similarly, less-educated older adults were more than twice as likely to report poor health as those with more education (11.0 versus 4.6 percent). Older adults with no more than a high school diploma are also more likely to have been diagnosed with high blood pressure, diabetes, lung disease, heart problems, psychiatric problems or arthritis, or a stroke. All of these differences are statistically significant at the 99 percent confidence level. The only health condition that does not differ significantly between the two education groups is cancer.

According to their own reports, less-educated older adults who are working are much more likely to hold jobs that require lots of physical effort "all or most of the time" (45.9 versus 23.8 percent) (see Table 5). Less-educated older adults are also significantly more likely to hold jobs that require lifting heavy loads (21.6 versus 9.9 percent) or stooping, kneeling or crouching (23.0 versus 12.0 percent). However, they are less likely to be in stressful jobs (54.2 versus 63.6 percent), or jobs that require intense concentration (76.2 versus 83.3), computer use (39.1 versus 66.4), or strong people skills (83.5 versus 89.9). Less-educated older workers are only slightly more likely than better educated adults to report feeling pressure to retire before 65 (14.5 versus 10.8 percent), and they are less likely to report that their job has become more difficult over time (45.1 versus 52.2). No statistically significant differences exist between the two groups in terms of whether they enjoy going to work, whether their employer would allow them to move to a less demanding job if they wished (job flexibility), or whether their employer prefers younger workers when it comes to promotions.

Older workers with limited education also differ significantly from their more-educated counterparts in the type of objective job demands they face in their current occupation. As Table 6 reports, 7.9 percent of older workers who did not attend college are in occupations with high general physical demands, and nearly one-half (49.7 percent) hold jobs with high or moderate physical demands, much more than the corresponding shares for older workers with at least some college education. More than one-third of workers with no more than a high school diploma hold jobs that require high or moderate flexibility and dexterity, compared with only 14.1 percent of those who attended college. Difficult working conditions are about twice as common among older workers with less education than among their better-educated counterparts.

TABLE 4
DEMOGRAPHIC AND HEALTH CHARACTERISTICS OF ADULTS AGES 55 TO 70,
BY EDUCATION, 2008

		All	No More than a High School Diploma	Attended College	
Female (%)		52.4	56.4	49.0	***
Race (%)	White	86.7	83.6	89.3	***
	Black	10.0	12.2	8.2	***
	Other	3.3	4.2	2.5	***
Married or partnered (%)		71.2	68.1	73.8	***
Self-reported health (%)	Excellent	11.8	7.3	15.6	***
	Very good	33.0	26.1	38.9	***
	Good	30.7	31.5	29.9	
	Fair	17.0	24.1	11.0	***
	Poor	7.5	11.0	4.6	***
Health conditions	High blood pressure (%)	51.3	56.7	46.6	***
	Diabetes (%)	18.9	22.9	15.4	***
	Cancer (%)	10.6	10.3	10.9	
	Lung disease (%)	8.8	12.3	5.9	***
	Heart problems (%)	17.7	20.2	15.6	***
	Stroke (%)	4.7	6.1	3.5	***
	Psychiatric problems (%)	19.9	21.9	18.2	***
	Arthritis (%)	52.9	59.4	47.3	***
	Average number of conditions	1.85	2.10	1.64	***
<i>Number of observations</i>		8,173	4,237	3,936	

Source: Authors' calculations from the HRS.

Note: Significance * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ relates to t-test for comparison of means between the two categories. Person level weights were used.

On the other hand, limited education is negatively correlated with the chances of facing substantial cognitive demands or stress on the job. Eighty-five percent of the better-educated group held jobs that required high or moderate levels of cognitive ability, compared with 63.7 percent of those with no more than a high school diploma. More-educated workers are significantly more likely to need interpersonal skills at their job, to use a computer on their job, and to update and use knowledge. A larger proportion of older workers who attended college held highly stressful jobs than those who did not attend college, although the educational difference in the share holding highly or moderately stressful jobs is relatively small.

MODELING STRATEGY

We use a reduced-form approach to model the probability of being employed as a function of demographic and socioeconomic characteristics. We especially focus on the impact of education, health status, and job characteristics. Our sample consists of HRS respondents born between 1931 and 1941—the original HRS cohort—whom we follow from ages 55 to 70, pooling data from all available waves. The estimation also uses matched occupational information from O*NET. We estimate the following equation:

$$y_{it}^* = E_{it}\beta_1 + H_{it}\beta_2 + J_{it-1}\beta_3 + X_{it}\beta_4 + \varepsilon_{it} \quad (1)$$

$$y_{it} = 1[y_{it}^* > 0]$$

TABLE 5
**PERCENTAGE OF WORKERS AGES 55 TO 70 AT JOBS WITH SPECIFIED SELF-
 REPORTED CHARACTERISTICS, BY EDUCATION, 2008**

Self-Reported Job Characteristics	All	No More than a High School Diploma	Attended College	
Physical effort	32.1	45.9	23.8	***
Lifting heavy loads	14.3	21.6	9.9	***
Stooping, kneeling or crouching	16.2	23.0	12.0	***
Good eyesight	89.5	88.9	89.8	
Stress	60.1	54.2	63.6	***
Intense concentration	80.6	76.2	83.3	***
People skills	87.5	83.5	89.9	***
Computer usage	87.5	39.1	66.4	***
Job increased in difficulty	49.6	45.1	52.2	***
Preference given to younger workers	14.4	15.0	13.9	
Pressure to retire	12.2	14.5	10.8	*
Job flexibility	38.0	37.1	38.6	
Enjoy work	90.2	89.8	90.5	
<i>Number of observations</i>	<i>3,841</i>	<i>1,624</i>	<i>2,217</i>	

Source: Authors' calculations from the 2008 wave of the HRS.

Note: Significance * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ relates to t-test for comparison of means between the two categories. The dummy categories indicate the job characteristic applies "most or all of the time". Person-level weights are used.

in which y_{it}^* denotes individual i 's propensity to work at time t . If we assume the error term ε_{it} is normally distributed, we can estimate equation (1) as a probit. The variable E_{it} denotes education, H_{it} denotes health status, J_{it} denotes job demands, and X_{it} denotes age and other sociodemographic controls. The job demands measures refer to the current job for respondents currently employed and the most recent job for those who are not currently employed. The estimation excludes respondents who lack full working histories between ages 55 and 70 and who never worked before age 55.

Decomposition Method

To identify those factors that account for much of the difference in employment rates between education groups, we use the decomposition techniques developed by Oaxaca (1973) and Blinder (1973), which are widely used in social science research. This method decomposes the observable differences between two groups into explained and unexplained portions and enables us to simulate one group's outcomes if it possessed the characteristics of the other group. It is particularly useful for quantifying the separate contributions of various factors. In our analysis, we are particularly interested in the role of self-reported health, medical conditions, self-reported job characteristics, occupational demands, and wealth and income differences.

We measure how much of the mean outcome difference R can be accounted for by differences in the predictors, as described in equation (2):

$$R = E(Y_A) - E(Y_B) \tag{2}$$

TABLE 6
PERCENTAGE OF WORKERS AGES 55 TO 70 IN JOBS WITH SPECIFIED OBJECTIVE DEMANDS, BY EDUCATION, 2008

Job Demands	All	No More than a High School Diploma	Attended College	
General physical demands				
High	4.4	7.9	2.2	***
High or moderate	35.8	49.7	27.4	***
Flexibility and dexterity				
High	2.0	3.2	1.4	
High or moderate	22.7	36.7	14.1	***
Vision	4.8	5.5	4.4	*
Cognitive ability				
High	31.6	11.7	43.7	***
High or moderate	77.0	63.7	85.0	***
Computer use	51.8	30.0	65.1	***
Interpersonal skills	33.5	19.5	42.1	***
Dealing with unpleasant people	9.2	8.0	9.9	
Stress				
High	12.6	5.7	16.7	***
High or moderate	45.8	39.7	49.4	***
Updating and using knowledge	24.5	10.1	33.3	***
Difficult working conditions	27.6	40.6	19.8	***
<i>Number of observations</i>	4,156	1,747	2,409	

Source: Authors' calculations from the 2008 wave of the HRS matched with 2010 O*NET.

Note: Significance * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ relates to t-test for comparison of means between the two categories. Person-level weights are used.

where $E(Y)$ denotes the expected value of the outcome variable for each of the two groups A and B. Assuming a linear model $Y_k = X_k' \beta_k + e_k$, $k \in \{A, B\}$ and a mean zero error $E(e_k) = 0$, we can express the mean difference as

$$R = E(Y_A) - E(Y_B) = E(X_A)' \beta_A - E(X_B)' \beta_B \quad (3)$$

Adding and subtracting $E(X_B)' \beta_B$ from both sides results in the popular “two-fold” decomposition that separates the outcome differential into an “explained” portion (attributable to differences in characteristics between the two groups) and the “unexplained” portion (attributable to differences in coefficients, including the intercept):

$$R = [E(X_A) - E(X_B)]' \beta_A + E(X_B)' (\beta_A - \beta_B) \quad (4)$$

The estimation of the components of the two-fold decomposition in the linear case is straightforward and can be obtained by least squares estimation on the two group-specific samples. Based on these estimates, the decomposition is computed as:⁴

$$\hat{R} = \overline{Y}_A - \overline{Y}_B = (\overline{X}_A - \overline{X}_B)' \widehat{\beta}_A + \overline{X}_B' (\widehat{\beta}_A - \widehat{\beta}_B) \quad (5)$$

Equation (5) can be used in the aggregate to compute the share of the total difference in the first moments that can be attributed to differences in characteristics and the share that can be attributed to differences in coefficients. The linearity of the model also makes it straightforward to compute the contribution of each variable to the total difference, that is, the detailed decomposition. However, if the outcome is binary, such as employment, and the coefficients are derived from the probit or logit model, the coefficients cannot be used directly in equation (5) to derive the detailed decomposition. Instead, we apply the nonlinear decomposition techniques developed by Yun (2004) and Fairlie (2005) and present those results alongside the linear model.

A more general way to write equation (5) is:

$$\hat{R} = \overline{Y}_A - \overline{Y}_B = [\overline{F(X_A \beta_A)} - \overline{F(X_B \beta_A)}] + [\overline{F(X_B \beta_A)} - \overline{F(X_B \beta_B)}] \quad (6)$$

where $Y = F(X\beta)$ and the dependent variable is a function of a linear combination of independent variables, but the function F itself is not necessarily linear. The Blinder-Oaxaca decomposition is a special case of equation (6). At the aggregate level, equation (6) can be used to calculate the total “explained” and “unexplained” portion as described above. To derive the detailed decomposition, however, one needs a method to properly weigh the contribution of each variable to the characteristics and coefficient effects. Intuitively, the Fairlie (2005) method consists of creating a match between the observations in the two groups and calculating the contribution of each variable to the total difference as the change in the average predicted probability as a result of replacing the group A distribution of a variable with the group B distribution, while holding the distributions of the other variables constant.⁵ For example, the contribution of variable X^1 can be expressed as:

$$\frac{1}{N_B} \sum_{i=1}^{N_B} F(\hat{\beta}_A^0 + \hat{\beta}_A^1 X_{Ai}^1 + \dots + \hat{\beta}_A^M X_{Ai}^M) - F(\hat{\beta}_A^0 + \hat{\beta}_B^1 X_{Bi}^1 + \dots + \hat{\beta}_A^M X_{Bi}^M) \quad (7)$$

where $(\beta_k^0, \beta_k^1, \beta_k^2, \dots, \beta_k^M)$, $k \in \{A, B\}$ is the vector of coefficients. By construction, and because of the nonlinearity, this method is path dependent, so the ordering of the variables can affect the calculated contribution to the gap. Following Fairlie (2005)’s suggestion, we address this issue by using many simulations and randomizing the ordering.

Using weights derived from a linearization of the decomposition equation, Yun (2004) develops an alternative methodology for the detailed decomposition, which is free from path dependence and can be expressed as:

$$\overline{Y}_A - \overline{Y}_B = \sum_{i=1}^M W_{\Delta X}^i [\overline{F(X_A \beta_A)} - \overline{F(X_B \beta_A)}] + W_{\Delta \beta}^i \sum_{i=1}^M [\overline{F(X_B \beta_A)} - \overline{F(X_B \beta_B)}] \quad (8)$$

$$\text{where } W_{\Delta X}^i = \frac{(\overline{X}_A^i - \overline{X}_B^i) \widehat{\beta}_A^i}{(\overline{X}_A - \overline{X}_B) \widehat{\beta}_A} \text{ and } W_{\Delta \beta}^i = \frac{\overline{X}_B^i (\widehat{\beta}_A^i - \widehat{\beta}_B^i)}{\overline{X}_B (\widehat{\beta}_A - \widehat{\beta}_B)} \quad (9)$$

The next section discusses results from both methodologies as well as from the standard linear Blinder-Oaxaca method.

RESULTS

Table 7 reports results from a linear probability model of the likelihood of working, which we will use in the decomposition methods applied later. The first five columns show results from the pooled model, while the last two columns show the estimated coefficients when the model is estimated separately on those with no more than a high school diploma and those with a bachelor's degree or more. As column (1) shows, the mean raw difference in employment rates between the two groups is 6.5 percentage points. Once other factors are included in the model, however, this difference quickly disappears or becomes statistically insignificant, as additional regressors “explain” the education differential. The propensity to work declines with age and with the number of health conditions, and it is lower among married women than single women, single men, or married men. In contrast, a working spouse and robust health (good, very good, or excellent) are associated with relatively high employment rates.

TABLE 7
ESTIMATES FROM A LINEAR PROBABILITY MODEL OF EMPLOYMENT,
ADULTS AGES 55 TO 70

	Pooled		Pooled		No More than a High School Diploma		Bachelors Degree or More	
Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(7)
	coeff.	coeff.	coeff.	coeff.	coeff.	coeff.	coeff.	coeff.
Bachelor's degree or more	0.065 ***	0.019	-0.003	0.009	-0.006			
Age		-0.036***	-0.036***	-0.036***	-0.036***	-0.038***	-0.031***	
White		0.002	-0.003	-0.003	-0.005	0.001	-0.036	
African American		0.009	0.009	0.006	0.007	0.023	-0.075	
Female		0.029	0.016	0.031	0.020	0.011	0.049	
Married or partnered		0.007	0.006	0.007	0.007	0.007	0.001	
Female*(married or partnered)		-0.120***	-0.119***	-0.121***	-0.121***	-0.103***	-0.171***	
Spouse is working		0.104***	0.104***	0.104***	0.103***	0.102***	0.110***	
Good, very good, or excellent health		0.140***	0.139***	0.136***	0.136***	0.139***	0.119***	
Number of health conditions		-0.038***	-0.038***	-0.037***	-0.037***	-0.038***	-0.034***	
O*NET indexes								
<i>Physical</i>			-0.002		-0.001	-0.004	0.020	
<i>Cognitive</i>			0.004		0.004	-0.003	0.011***	
<i>Working conditions</i>			-0.010**		-0.009**	-0.009**	-0.010	
<i>Social and stress related</i>			-0.003		-0.003	0.007	-0.012	
Self-reported job characteristics								
<i>Intense physical effort, or stooping/lifting</i>				-0.044***	-0.034***	-0.035***	-0.039	
<i>Computer usage or intense concentration</i>				0.007	0.006	0.016	-0.034	
<i>Lots of stress</i>				-0.034***	-0.036***	-0.029**	-0.051**	
Nonemployment income (in \$100,000)		0.0001	0.0000	0.0000	-0.0001	-0.0005***	0.0054**	
Net worth (in \$100,000)		0.0003	0.0002	0.0003	0.0002	-0.0009	0.0001	
<i>Adjusted R squared</i>	0.004	0.208	0.209	0.211	0.212	0.225	0.174	
<i>Number of observations</i>	31,224	31,224	31,224	31,224	31,224	22,628	8,596	

Source: Authors' calculations using the 1992-2010 HRS matched with ONET.

Notes: Significance * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors, clustered on individuals.

Self-reported job characteristics are also significantly correlated with the likelihood of being employed. People whose most recent job required exerting a lot of physical effort, lifting, or stooping, or involved a lot of stress are less likely to be employed than other people. The effects of these self-reported job demands on work differ by education groups. Stress is more strongly negatively associated with work propensities for older people with a bachelor's degree than for those with no more than a high school diploma, and physical effort does not have a significant impact on employment for college-educated workers.

The effects of O*NET job demands on the propensity to work also differ by education. We combined the detailed O*NET categories into four indexes, computed as the number of physical demands, cognitive demands, difficult working conditions, and social- and stress-related demands at the most recent occupation. Difficult working conditions are associated with lower employment rates for those with no more than a high school education, but their estimated effect does not significantly differ from zero for college graduates, perhaps because the sample size for college graduates in occupations with difficult working conditions is much smaller. On the other hand, cognitive demands are positively associated with employment for college graduates but the relationship is not significant among their less-educated counterparts. Not surprisingly, the pooled model shows estimated coefficients on these variables that lie in between. However, only difficult working conditions remain significant at the 95 percent confidence level.

Because the estimated effects differ for the two comparison groups, as a baseline we present results from the decomposition model that uses the less-educated group as the comparison group, and the

more educated group as the reference group. By fixing the coefficients to the low-educated group levels, we assess the contribution to the education gap that would have occurred if the returns to the factors in the model were fixed to the values in the low-educated sample. We also perform sensitivity analysis showing results from a pooled model and from a model in which the more educated group is used as a comparison category.

Tables 8 and 9 report results from the nonlinear Yun decomposition of the differences in employment rates between older adults with no more than a high school diploma and those with a four-year college degree. Table 8 shows results in percentage terms, and Table 9 shows them in levels. Our discussion focuses on the percentage results. The top rows of each table show the total mean difference in employment rates between the two groups, the share that is explained by differences in characteristics, and the share that remains unexplained (or attributed to differences in the returns to the coefficients and unobservable factors.) Column (1) of Table 8 shows that even without considering job characteristics, differences in demographics, health, income, and wealth can account for 59.7 percent of the observable employment gap. Adding the O*NET job demands indexes raises the explained portion of the gap to 79.9 percent, whereas adding self-reported job characteristics raises it to 74.3 percent.

Column (4) of Table 8 shows the full model, which includes both the O*NET and self-reported job demands and is our preferred specification. Overall, about one-half (49.7 percent) of the total education difference in the employment rate at older ages can be attributed to differences in self-reported health and the prevalence of various health conditions. Both measures are statistically significant at the 99 percent confidence level. Differences in self-reported job characteristics also have a significant explanatory power—19.1 percent of the gap arises from the higher prevalence of jobs that require exerting physical effort, lifting, and stooping among less-educated adults, and another 1.8 percent arises from the lower prevalence of jobs that require intense concentration or computer use among them. Holding the prevalence of stressful jobs constant reduces the explained gap by 5.2 percent, because having a recent stressful job is negatively related with being employed, and those with no more than a high school degree are less likely to find themselves in such jobs. In other words, if less-educated older adults had jobs with the stress intensity of their more educated counterparts, they would have been another 0.3 percentage points less likely to work. Overall, differences in self-reported job characteristics account for 15.6 percent of the gap. Another 15.2 percent of the gap is due to differences in demographics, and differences in income and wealth account for a negative 10 percent.

TABLE 8
NONLINEAR DECOMPOSITION OF DIFFERENCES IN EMPLOYMENT RATES BETWEEN
THOSE WITH NO MORE THAN A HIGH SCHOOL DIPLOMA AND THOSE WITH A
BACHELOR'S DEGREE OR MORE, ADULTS AGES 55 TO 70 (PERCENT)

	(1)	(2)	(3)	(4)
	Percentage distribution			
Total mean difference	100.0%	100.0%	100.0%	100.0%
Explained	59.7%	79.9%	74.4%	83.5%
Unexplained	40.3%	20.1%	25.6%	16.5%
Mean difference attributable to:				
Demographics	14.7%	15.8%	13.7%	15.2%
Self-reported health status	34.9%	34.0%	33.1%	33.0%
Number of health conditions	18.0%	17.3%	17.0%	16.7%
Wealth	-7.8%	-9.2%	-9.5%	-10.1%
O*NET indexes (combined)		22.0%		13.0%
<i>Physical</i>		9.3%		7.6%
<i>Cognitive</i>		-7.1%		-13.0%
<i>Social and stress related</i>		7.6%		7.8%
<i>Working conditions</i>		12.1%		10.6%
Self-reported job chars (combined)			20.0%	15.6%
<i>Intense effort, stooping, or lifting</i>			23.2%	19.1%
<i>Computer usage or intense concentration</i>			1.8%	1.8%
<i>Lots of stress</i>			-5.0%	-5.2%
<i>Number of observations</i>	31,224	31,224	31,224	31,224

Source: Authors' calculations using the 1992-2010 HRS matched with O*NET.

Notes: Yun (2004) nonlinear probit decomposition which is free from path-dependency. The bold face numbers sum the corresponding differences in characteristics. The decompositions are compatible with the regressions in table 7. The coefficients from the model estimated on the first group—those with a high school diploma or less—are used as the reference group in the decomposition; Significance * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors, clustered on individuals.

O*NET job demands account for 13 percent of the education gap in employment at older ages. This share is similar to the portion attributable to self-reported job characteristics, but it is measured less precisely. The physical- and social/stress-related O*NET job demands explain a positive share of the gap but are not statistically significant. Cognitive demands explain a negative 13.0 percent of the gap but are also insignificant. Difficult working conditions are the only O*NET category that consistently have a statistically significant impact at the 95 percent level throughout all specifications, and they account for 10.6 percent of the gap.

Figure 1 presents these results visually, starting with the baseline employment probability for those with no more than a high school diploma and progressively adding other explanatory factors. The figure shows the percentage of less-educated older adults who would have been employed if they possessed the characteristics of their college-educated counterparts instead of their own characteristics. With the exception of wealth and income, self-reported job stress, and O*NET cognitive demands, accounting for differences in each of the various factors shrinks the education gap in old-age employment.

As a sensitivity test we decompose the education difference in employment rates using two other estimators, as described earlier. In Table 10, column (1) shows the linear Oaxaca-Blinder decomposition, column (2) shows the results from the non-linear Yun estimator, and column (3) presents the non-linear

TABLE 9
NONLINEAR DECOMPOSITION OF DIFFERENCES IN EMPLOYMENT RATES BETWEEN
THOSE WITH NO MORE THAN A HIGH SCHOOL DIPLOMA AND THOSE WITH A
BACHELOR'S DEGREE OR MORE, ADULTS AGES 55 TO 70 (LEVELS)

	(1)	(2)	(3)	(4)
	Percentage Points			
Total mean difference	-6.5	-6.5	-6.5	-6.5
Explained	-3.9	-5.2	-4.9	-5.5
Unexplained	-2.6	-1.3	-1.7	-1.1

Mean difference attributable to:	Coeff.	Coeff.	Coeff.	Coeff.
Demographics	-1.0**	-1.0**	-0.9**	-1.0**
Self-reported health status	-2.3***	-2.2***	-2.2***	-2.2***
Number of health conditions	-1.2***	-1.1***	-1.1***	-1.1***
Wealth	0.5	0.6	0.6	0.7
O*NET job demand indexes (combined)		-1.4		-0.9
<i>Physical</i>		-0.6		-0.5
<i>Cognitive</i>		0.5		0.8
<i>Social and stress related</i>		-0.5		-0.5
<i>Working conditions</i>		-0.8**		-0.7**
Self-reported job chars (combined)			-1.3***	-1.0**
<i>Intense effort, stooping, or lifting</i>			-1.5***	-1.3***
<i>Computer usage or intense concentration</i>			-0.1	-0.1
<i>Lots of stress</i>			0.3*	0.3**
<i>Number of observations</i>	31,224	31,224	31,224	31,224

Source: Authors' calculations using the 1992-2010 HRS.

Notes: Yun (2004) nonlinear probit decomposition which is free from path-dependency. The bold face numbers sum the corresponding differences in characteristics. The decompositions are compatible with the regressions in Table 7. The coefficients from the model estimated on the first group—those with no more than a high school diploma—are used as the reference group in the decomposition; Significance * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors, clustered on individuals.

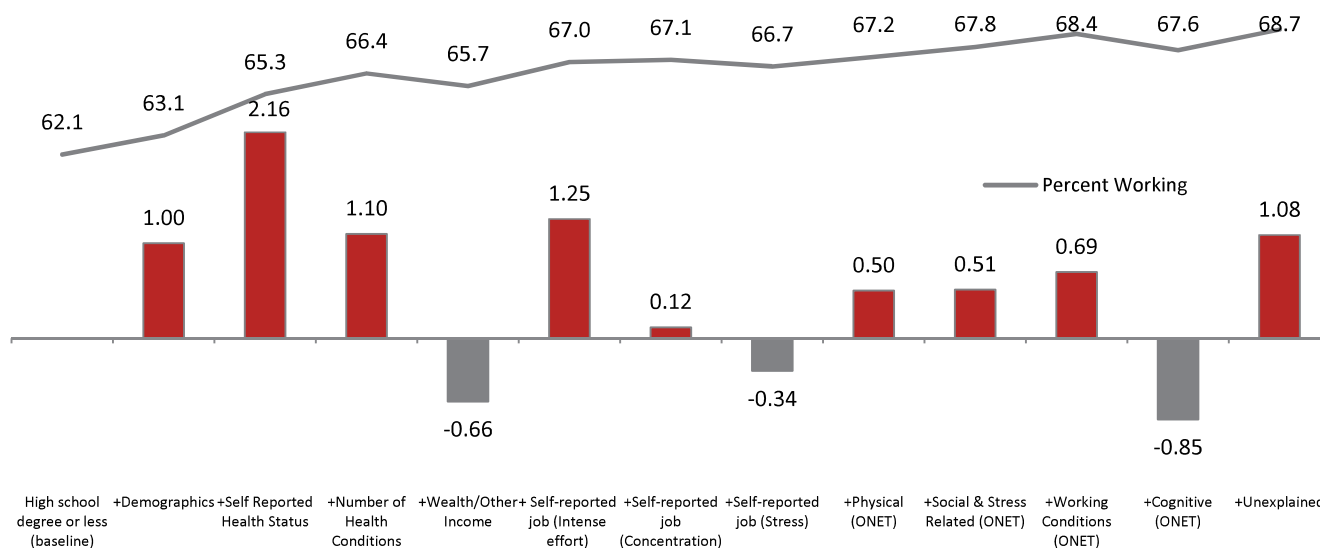
Fairlie estimator. The explained portion of the gap ranges from 83.5 to 90.8 percent of the total difference. Overall, the three estimators perform similarly, with small differences in the decomposed effects, suggesting that addressing non-linearity is not crucial in our particular specification.

Another sensitivity test relates to the importance of choosing a reference group. Table 11 reports nonlinear decomposition results derived from our baseline model that uses coefficients from the less-educated group, and compares it with those derived by using coefficients from the pooled model and coefficients from the model estimated on the well-educated group. The main differences are that the pooled and college-comparison models overpredict the gap, and the signs of the detailed composition estimates of the O*NET factors change across specifications.

For factors that affect employment rates in the same direction for both education groups, the detailed decomposition estimates from the pooled model lie in between those derived from the low-education reference group and the high-education reference group. The ability of most factors to explain the employment gap is similar across specifications, with the exception of O*NET job demands. This is not surprising, given the significantly different effects that those factors have on employment rates for the two education groups. The combined contribution of differences in O*NET factors varies from 13 to 27.8 percent, while the contribution of self-reported job characteristics ranges from 6.9 to 15.6 percent. When the highly educated group is used as the comparison, the separate decomposition effect of differences in

the self-reported physical intensity of the job and difficult working conditions are no longer significant, whereas differences in cognitive demands account for nearly 60 percent of the employment gap. This difference arises because the physical intensity of the job is not a significant predictor of employment for well-educated older adults, whereas cognitive demands are strong positive predictors of their continued employment.

FIGURE 1
ASSIGNING THE CHARACTERISTICS OF THOSE WITH A BACHELOR'S DEGREE OR MORE TO THOSE WITH NO MORE THAN A HIGH SCHOOL DIPLOMA: ESTIMATES FROM A NON-LINEAR DECOMPOSITION



Source: Authors' calculations using the 1992-2010 HRS matched with O*NET.

Notes: Yun (2004) nonlinear probit decomposition which is free from path-dependency; The coefficients from the model estimated on the first group—those with high school diploma or less—are used as the reference group in the decomposition.

CONCLUSIONS

Despite recent employment increases for older adults in the US, significant employment differences persist between groups, particularly with respect to education. Less-educated older individuals are less likely to work at any given age than their more educated counterparts. Using HRS data from 1992 to 2010, this study identified those factors that account for the observable educational gap in old-age employment. An important contribution of the paper was the inclusion of detailed occupational demands derived from the O*NET dataset matched with our HRS sample, which provided us with a more “objective” measure of workers’ job demands and which we used in conjunction with workers’ self-reported job characteristics. Our results show that nearly half (49.7 percent) of the employment gap between less-educated and better educated older adults can be explained by differences in self-reported health and work-restricting health conditions. Differences in self-reported job characteristics and O*NET job demands account for another 28 percent of the gap. Of the job characteristics, self-reported physical demands and difficult working conditions as defined by O*NET have the strongest explanatory power across various specifications.

TABLE 10
DECOMPOSITION OF DIFFERENCES IN EMPLOYMENT RATES BETWEEN THOSE WITH NO MORE THAN A HIGH SCHOOL DIPLOMA AND THOSE WITH A BACHELOR'S DEGREE OR MORE, ADULTS AGES 55 TO 70. COMPARISON OF THREE ESTIMATORS

	GLS (Oaxaca)	Probit (Yun)	Probit (Fairlie)
	Percentage Distribution		
Total mean difference	100.0%	100.0%	100.0%
Explained	90.8%	83.5%	84.0%
Unexplained	9.2%	16.5%	16.0%
Mean difference attributable to:			
Demographics	14.6%	15.2%	13.3%
Self-reported health status	34.7%	33.0%	35.7%
Number of health conditions	17.9%	16.7%	17.3%
Wealth	-5.9%	-10.1%	-10.0%
O*NET job demand indexes (combined)	14.5%	13.0%	12.5%
<i>Physical</i>	7.3%	7.6%	7.3%
<i>Cognitive</i>	-12.7%	-13.0%	-12.3%
<i>Social and stress related</i>	8.9%	7.8%	7.3%
<i>Working Conditions</i>	10.9%	10.6%	10.1%
Self-reported job chars (combined)	15.0%	15.6%	15.2%
<i>Intense effort, stooping, or lifting</i>	18.9%	19.1%	18.1%
<i>Computer usage or intense concentration</i>	1.7%	1.8%	1.7%
<i>Lots of stress</i>	-5.5%	-5.2%	-4.8%
<i>Number of observations</i>	31,224	31,224	31,224

Source: Authors' calculations using the 1992-2010 HRS matched with O*NET.

Notes: The bold face numbers sum the corresponding differences in characteristics. The coefficients from the model estimated on the first group—those with no more than a high school diploma—are used as the reference group in the decomposition; Significance * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors, clustered on individuals.

Working longer and delaying retirement promotes financial security at older ages, enabling people to earn more and thus save more for retirement and avoid penalties for taking early Social Security benefits. Early labor force withdrawals could create financial problems for many less-educated older adults. In fact, older adults with low education are already more likely to be in poverty than their more educated counterparts (O'Brien et al., 2010). Increased employment by better-educated older adults could exacerbate late-life income inequality, which is already rising (Crystal, Shea, & Reyes, 2016).

Various policy reforms can improve the retirement security of older people with limited education. The findings of our study can contribute to the policy debate surrounding changes in Social Security, disability, and employment policy.

As our analysis shows, health problems account for much of the employment shortfall for less-educated older adults. Working to a later age might not be a viable option for those in particularly bad health. In fact, previous literature has shown that the Social Security Disability Insurance program (SSDI) program, which provides financial support to workers with disabilities and their families, is an especially important safety net for less-educated older adults. Older adults with low education are significantly more likely to receive benefits from SSDI than their more-educated counterparts. Among adults ages 60 to 64, 23 percent of those who did not complete high school and 14 percent of those with a high school diploma but without a bachelor's degree received SSDI benefits in 2010, compared with only 6 percent of those

with a bachelor's degree (Favreault, Johnson, & Smith, 2013). However, only about half of adults in their 50s and early 60s with serious disabilities receive benefits (Johnson, Favreault, & Mommaerts, 2010), and those who do collect receive relatively small benefits. For example, 18 percent of people ages 60 to 64 collecting SSDI benefits in 2010 had family incomes below the federal poverty level (Favreault, Johnson, & Smith, 2013). Raising benefits and easing disability standards could provide additional financial protections, but it would exacerbate the programs' existing long-run financial deficit.

TABLE 11
NONLINEAR DIFFERENCES IN EMPLOYMENT RATES BETWEEN THOSE WITH NO MORE THAN A HIGH SCHOOL DIPLOMA AND THOSE WITH A BACHELOR'S DEGREE OR MORE, ADULTS AGES 55 TO 70. COMPARISON OF REFERENCE GROUPS

Comparison group	Pooled	No More than a High School Diploma	Bachelor's Degree or More
Total mean difference	100.0%	100.0%	100.0%
Explained	106.2%	83.5%	101.0%
Unexplained	-6.2%	16.5%	-1.0%
<i>Mean difference attributable to:</i>			
Demographics	17.2%	15.2%	24.1%
Self-reported health status	31.8%	33.0%	28.1%
Number of health conditions	16.1%	16.7%	15.3%
Other income/wealth	1.0%	-10.1%	8.6%
O*NET job demand indexes (combined)	27.8%	13.0%	18.0%
<i>Physical</i>	2.6%	7.6%	-35.3%
<i>Cognitive</i>	20.0%	-13.0%	58.8%
<i>Social and stress related</i>	-4.4%	7.8%	-16.4%
<i>Working conditions</i>	9.7%	10.6%	10.8%
Self-reported job chars (combined)	12.2%	15.6%	6.9%
<i>Intense effort, stooping, or lifting</i>	18.3%	19.1%	21.0%
<i>Computer usage or intense concentration</i>	0.7%	1.8%	-3.8%
<i>Lots of stress</i>	-6.7%	-5.2%	-10.3%
<i>Number of observations</i>	31224	31224	31224

Source: Authors' calculations using the 1992-2010 HRS matched with O*NET.

Notes: Yun (2004) nonlinear probit decomposition which is free from path-dependency. The bold face numbers sum up the corresponding differences in characteristics. The decompositions are compatible with the probit regressions in Table 7; Significance * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors, clustered on individuals.

Select workforce development initiatives targeted to older adults could also boost financial security for people with less education who might otherwise retire early. Our results indicate that many less-educated older adults stop working because their jobs are physically demanding. Workforce development programs could provide training for older workers to move into new occupations.⁶

Finally, the financial shortfall faced by the largest single program in the federal government's budget—the Old-Age and Survivor Insurance (OASI)—has spurred an active policy debate on the ways to reform the program and potentially revise benefit rules. As this study has found, there is significant variation in the health and occupational demands of older workers, which creates substantial variation in the timing of their retirement. Policymakers might find our findings informative when debating the

adequacy and progressivity of the system and when discussing optimal changes to specific rules such as the early and full retirement ages (Haverstick et al., 2007).

ACKNOWLEDGMENTS

The authors gratefully acknowledge financial support from the Alfred P. Sloan Foundation. The opinions and conclusions expressed are solely those of the authors and do not represent the opinions or policy of the Alfred P. Sloan Foundation, the Urban Institute, the Congressional Budget Office, or any agency of the federal government.

ENDNOTES

Before 2000, the retirement earnings test reduced benefits by \$1 for every \$3 earned above a certain amount after the full retirement age and before age 70. Although beneficiaries recouped those lost benefits through higher payments once they stopped working, most beneficiaries appear to have interpreted the earnings test as a simple tax on earnings (Engelhardt & Kumar 2009, 2014).

1. Maestas and Zissimopoulos (2010) provide an interesting and detailed discussion of both the demand and supply factors that shape employment outcomes at older ages.
2. We compared 1998 and 2008 because in both years the HRS is a nationally representative sample of adults ages 55 to 70.
3. An alternative two-fold decomposition uses a third vector β^* of coefficients to determine the contribution of the differences in the predictors. The difference in mean outcomes then can be written as $\hat{R} = [\bar{X}_A - \bar{X}_B]' \hat{\beta}^* + [\bar{X}_B'(\hat{\beta}_A - \hat{\beta}^*) + \bar{X}_A'(\hat{\beta}^* - \hat{\beta}_B)]$, and the decomposition described earlier is a special case where $\hat{\beta}^* = \hat{\beta}_A$. Neumark (1988) advocates using coefficients from the pooled regression over both groups as an estimate of β^* . An issue with that approach, however, is that it may inappropriately transfer some of the unexplained part of the differential into the explained component (Fortin, 2008). For completeness, the results section compares results using estimated coefficients from the regression on the first group, the second group, and the pooled model.
4. If the sample sizes of the two groups differ, Fairlie (2005) suggests drawing many random subsamples of the larger group equal in size to the smaller group, calculating separate decomposition estimates using each of these random subsamples, and then using the mean value of these estimates to approximate results for the entire larger group.
5. For example, the Senior Community Service Employment Program is one such program that helps low-income older unemployed individuals find work. See Aday and Kehoe (2008) for an analysis of some of the benefits of that program.

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