The Interaction of Health, Genetics, and Occupational Demands in SSDI Determinations

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Introduction

Evaluations of Social Security Disability Insurance (SSDI) applications are based not only on poor health, but in many cases, consider the vocational factors of age, education and work experience to determine whether individuals can work. SSDI determinations based on these factors have grown threefold since 1985 (Michaud, Nelson, and Wiczer 2016). Yet little is known about the relationship between SSDI activity and the ability to meet occupational requirements (Rutledge, Zulkarnain, and King 2019). Moreover, there is strong evidence that morbidity and mortality are distributed unequally across occupations (Marmot et al. 1991), perhaps because differential work environments may exacerbate disability but also because individual-level underlying health is unlikely to be randomly distributed across occupations (Mackenbach et al. 2017).

Together, these phenomena result in complex relationships of SSDI determinants with both the independent and joint effects of health and occupational demands. Disentangling the contributions of these forces is challenging, because selection into occupations by health is often unobserved and because data on occupational demands for employment histories is limited. We propose to triangulate between these factors by using a rich set of data linkages from the Health and Retirement Study, including linkage to the Social Security Administration (SSA) disability application file (831 file), and the Department of Labor's O*Net job classification system.

Our study aims are as follows: First, we ask whether there exist differences in SSDI application, receipt, and denial as a function of the occupation and occupational demands of applicants' employment histories. Secondly, we examine whether these differences can be explained by selection into occupational class through a number of life course factors. Finally, we explore the role of health in this selection process by using genetic data to capture unobserved health. We find the following:

1. Structural and social inequities that influence access to opportunity, including race and childhood SES, are more strongly associated with the probability of SSDI application than workplace demands. The exception is a positive psychosocial work environment that gives individuals greater control over how to best meet the demands of their jobs, which is negatively associated with SSDI application.
2. Conditional on SSDI application, physical, mental, and sensory job demands display

stronger associations with SSDI approvals and denials than structural or social factors.

3. Higher genetic risk for depression, cardiovascular disease, BMI, dementia, and rheumatoid arthritis are independently associated with SSDI application and approval.

The remainder of the paper proceeds as follows. We begin with some background and a discussion of relevant literature. We then discuss our data and empirical strategy. After presenting our results, we conclude with a discussion of the policy implications of our findings and suggestions for future research.

Background

The occupational health gradient, job demands, and life course selection

A great deal of attention has been paid to the relationship between occupation and health, and highlighted a near universal occupational health gradient, wherein individuals in lower status jobs have worse health (Clougherty, Souza, and Cullen 2010). Work accounts for a significant portion of Americans' daily lives and is increasingly recognized as a determinant of health status. Research dating to the Whitehall study results of the 1970s has shown a relationship between occupation and long-term health outcomes including mortality, diabetes and cardiovascular disease that cannot be explained by differences in income, education, health behaviors or access to health insurance .

This work has pointed to the role of occupational demands as a primary driver of occupational determinants of health. Extant literature suggests that jobs with high demands and/or low control has been strongly associated with anxiety and depression (Sanne et al. 2005), self-reported musculoskeletal problems (Roelen et al. 2008), high blood pressure (Fauvel Jean Pierre et al. 2001; Steptoe, Cropley, and Joekes 1999) and other cardiovascular problems (Kannel et al. 1986). Differences in associations between job demands and health conditions also differ by occupational class (Schreuder et al. 2008). Psychosocial aspects of jobs may also be associated with poor health behaviors that lead to declines in health, including smoking behavior (Radi, Ostry, and LaMontagne 2007), sleep disturbance (Lange et al. 2009), and alcohol abuse (Azagba and Sharaf 2011; Head, Stansfeld, and Siegrist 2004). While many of these studies are limited to cross-sectional analysis, an important insight gained from research using longitudinal data is that the cumulative or durable impact of working conditions is potentially more relevant for health than any contemporaneous job demands in the years leading up to retirement (Schmitz

2016; Fletcher, Sindelar, and Yamaguchi 2009).

Aside from the direct effect of job demands on health, the link between job demands and disability or early retirement may be confounded by pre-existing poor health (Nicholas, Done, and Baum 2018). Several cohort studies found that self-reported health was a predictor of early retirement, including among Finnish men (Karpansalo et al. 2004) and British civil servants (Mein et al. 2000). Moreover, growing evidence has confirmed the role of early-life environments on later-life outcomes, including health and wealth (Currie and Almond 2011; Smith 2009), suggesting that early-life factors may play important roles in selection into occupation. There is longitudinal evidence that poor childhood health leads to lower professional achievement in adulthood (Mensah and Hobcraft 2008), and some evidence of pre-existing health gradients by profession among young adults (Rabinowitz et al. 2006). Due to persistent confounding by social class and its associated risk factors, causal and selective components of occupational status are difficult to disentangle (Lynch and von Hippel 2016).

Despite this evidence, few papers have looked at the intersection between job demands and health on the likelihood of SSDI receipt. Indeed, being unable to perform job requirements due to physical limitations is associated with earlier retirement (Hudomiet et al. 2018; Sonnega et al. 2018), lower earnings (Kaye 2009; M. K. Jones and Sloane 2010; Choe and Baldwin 2017), and lower job satisfaction (M. Jones et al. 2014). Moreover, compared to non-recipients, SSDI recipients more often work non-managerial, physically demanding jobs such as those in agriculture or construction (Bound 1989) and are more likely to be smokers and to have health conditions including diabetes, arthritis, and lung disease (Coe et al. 2014; Benítez-Silva et al. 1999). They are also older, less likely to be married or college-educated, and have lower incomes (Duggan, Singleton, and Song 2007; Benítez-Silva et al. 1999; Bailey, Michelle n.d.).

There are a few notable exceptions. Rutledge, Zulkarnain and King (2019), found that jobs with higher rates of workers who experience at least one difficulty with a job requirement have a higher share of workers receiving SSDI benefits within a 16-month period. This study, however, used the SIPP and the unit of analysis was a job, and therefore could not control for individual-level factors, including demographic information and early-life characteristics. Nicholas, Done and Baum's (2020) recent work is most relevant to our work. They use self-reports of lifetime jobs in the HRS linked with O*Net to examine the cumulative role of physical and cognitive demands on self-reported SSDI receipt while also accounting for selection into occupation by controlling for childhood health and family SES. They find that greater exposure to a physically demanding job is associated with a higher likelihood of SSDI, while the reverse is true for non-routine cognitive job demands. Moreover, characteristics of jobs at both younger and older ages were predictive of receipt.

The disability determination process and occupational demands

Because we simultaneously consider the role of both health and occupation in SSDI, in our analysis, make distinctions between these two factors in our outcome measures. Specifically, we distinguish whether an application is approved or denied for medical reasons or vocational reasons. We follow the categorization laid out in Schimmel Hyde, Wu and Gil (2020). As such, we describe below the SSA evaluation process that inform our outcome measures.

SSA uses a five-step sequential evaluation process to determine whether an applicant meets the criteria for benefit award. In the first three steps, evaluators assess the applicant's insured status and the medical factors that affect the ability to continue or resume work, often referred to as determinations based on "medical capacity" (Wixon and Strand 2013). For Steps 4 and 5, where we focus most of our attention in this study, evaluators assess the applicant's work capacity relative to vocational requirements of past and potential future jobs. In most cases, the Disability Determination Services assesses whether, in light of their medical impairments, their residual functional capacity (RFC), allows them to perform either past relevant work (PRW), at step 4, or other work, at step 5 (an excellent description of the five-step evaluation process can be found in Wixon and Strand 2013 or Hyde, Wu, and Gill 2020).

In considering RFC at step 5, disability examiners use guidelines known as the "medical-vocational grids." As the name implies, these guidelines consider the current medical impairment of the applicant, in conjunction with job demands required of potential jobs, drawn largely from the Dictionary of Occupational Titles (DOT). The determination of the type of work include exertional demands (e.g. walking, standing, sitting, lifting, etc.) that are grouped as sedentary, light, medium, heavy or very heavy. The guidelines also include non-exertional demands, which include mental demands, postural (balancing), manipulative (e.g. reaching, fingering) visual, communicative, and environmental (e.g. extreme temperature, noise, atmospheric).[1]

[1] Partially in response to research pointing to the DOT as outdated (Warshawsky and Marchand 2015) SSA has recently sponsored a new data set, the Occupational Information System (OIS), which is intended to create a set

These guidelines also consider age, education, and prior work experience in conjunction with the availability of jobs in the national economy. Considerations of prior work experience include the skills acquired through past relevant work (i.e. unskilled, semiskilled, and skilled) and the extent to which these skills are transferable to other work that falls within the individual's residual functional capacity (SSA POMS 25015.015). The criteria for these considerations changes with age (there are separate factors for ages 50-54, 55-59, and 60-69), whereby applicants of "advanced age" (ie. 55 or older) have more lenient criteria for award based on job demand holding disability, education, and work experience constant.

Wixon and Strand (2013) present statistics on the percentage of 2010 DDS disability determinations made at each step of the sequential evaluation process, by program title. All applications sent to a DDS for review have passed Step 1 of the sequential process. For DI, 15.8 percent of DDS determinations resulted in a denial at Step 2 because their impairment was not severe. At Step 3, another 13.6 of applicants were found to be medically eligible because their condition met or equaled the Listings. The rest (nearly 64 percent of these cases) reached Step 4, resulting in the denial of 20.5 percent at this step. The remaining 42.8 percent reached Step 5: at that step, 16.8 were determined to be medically eligible, and 26.0 percent were determined to be ineligible.

<u>The benefits of using genetic data to proxy underlying health</u>

A significant challenge in studying the role of health in employment and labor market attachment is that health is endogenous to employment, making even non-causal directional studies difficult to interpret to interpret (Ravesteijn, Kippersluis, and Doorslaer 2013). Individuals adjust their work schedule and the nature of their work environments based on their overall health and physical capacity. At the same time, work environments themselves can create or exacerbate health problems. The potential selection and behavioral effects, along with the scarcity of truly exogenous variation in occupation, make it extremely difficult to isolate the independent effect of occupation on health.

In this study, we propose the use of genetic data, and specifically polygenic scores (PGS),

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of job demands that are more reflective of the modern workforce and their related job demands. Since some aspects of these data are not yet readily available, namely the mental and cognitive demands, this paper uses the existing medical-vocational to guide analysis about job demand.

as a measure of underlying health to circumvent problems of reverse causality. The use of genetic data provides a number of important advantages. First, conditional on parental genetics, genetic markers are randomly assigned at birth and are static across the life course, allowing us to usurp many of the abovementioned endogeneity issues. Secondly, because individuals do not often know their genetic risk for a disease, they are not subject to behavioral changes over one's life that might influence health.

Genetic data have become increasingly available in large, population-based surveys, including the HRS. The data available capture common genetic variation at millions of genetic markers across the entire genome at sites called single nucleotide polymorphisms (SNPs). SNPs are locations within the human genome where the type of nucleotide present (A, T, G, or C) can differ between individuals. Over the last three decades, large genome-wide association studies (GWAS) have been performed to establish relationships between these genetic markers and a number of health conditions including cardiovascular disease (Nikpay et al. 2015), cancers (Easton et al. 2007; Thomas et al. 2008), arthritis (Okada et al. 2014), hypertension (Levy et al. 2009), obesity (Thorleifsson et al. 2009; Scuteri et al. 2007), Alzheimer's Disease (Beecham et al. 2014; Deming et al. 2017; Lambert et al. 2013; Davies et al. 2015), and a number of other health conditions and health behaviors. These studies credibly demonstrate that there is individual genetic variation towards disease; individuals with more disease-associated SNPs are at a higher risk for that disease. Results from GWAS have also been used to construct weighted PGSs that summarize the individual small effects of SNPs across the genome to yield a single scalar of genetic propensity for a given disease or behavioral trait.

That said, genetic propensities should not be confused with genetic determinism. Even the strongest heritability estimates for the aforementioned diseases are typically between 40 – 50%. As a result, for the majority of complex traits, genetic influence can only be understood in a context of extensive causal interdependence with the social environment (Pescosolido et al. 2008; Rutter, Moffitt, and Caspi 2006; Freese and Shostak 2009). Genetic predisposition is only meaningful insofar that it is correlated with and/or interact with specific environments, including occupation (Harden and Koellinger 2020). As such, we conceptualize the PGSs used in this study as baseline measures of unobserved health that confer vulnerability towards a specific health condition but can—and often are—highly influenced by the social environment.

Contributions of this paper:

Our work complements and extends prior studies in a few important dimensions. Most importantly, with the exception of a few recent papers (Rutledge, Zulkarnain, and King 2019; Nicholas, Done, and Baum 2018), we are one of the only papers to our knowledge to explore the role of individual occupational demands on SSDI application and receipt for individual SSDI applicants. The Rutledge et al. study uses job categories as a unit of analysis and has a 16-month time horizon. Our paper examines individual SSDI applicants as the unit of analysis, allowing us to control for individual-level characteristics and use the respondent's entire working history as a time horizon. We extend the Nicholas et al. work by including a richer set of physical and psychosocial occupational demands that are more carefully matched to the SSA medical-vocational grid. We also distinguish whether approvals and denials are medical or occupational. Moreover, we are the only paper that simultaneously considers the contribution of individual-level occupational demands, childhood SES, and underlying genetic risk to the occupational gradient in SSDI application and receipt. Given the importance of occupation in Step 4 and Step 5 of the determination process, as well as the well-established relationship between occupation and health, our paper represents an important contribution to the existing literature. Our novel use of genetic data also allows for a measure of health that does not suffer from the same endogeneity issues that are present in past work.

Data

We use data from the Health and Retirement Study (HRS), a nationally representative dataset on Americans over age 50 with rich information on health and employment from 1992-2016. We utilize three of important linkages from restricted or sensitive data. First, we utilize the linkage to Social Security data. These include data on applications to SSDI and SSI using the Form 831 SSA data, which includes dates of application, type of claim (Type II or Title XVI), and reasons for approvals and denials. We remove applications for SSI and include all applications for SSDI.

Second, we link expert ratings of job demands taken from the Occupational Information Network (O*NET) to respondent job histories. O*NET is a comprehensive database of over 200 job characteristics produced by the U.S. Department of Labor's Employment and Training Administration and is the leading data source on job ratings (Peterson et al. 2001). O*NET ratings of workplace characteristics are assigned by occupational analysts and are based on information obtained from randomly surveying a broad range of workers within each occupational category. Restricted three-digit occupation codes were used to link the O*NET data with self-reports of respondents longest-held job (Schmitz, 2016). Since the O*NET job characteristics are categorized by the 2000, 2006, or 2009 Standard Occupational Classification (SOC) system, SOC codes were converted to three-digit 2000 Census Occupational Categories to construct a panel that can be merged with the HRS. Importantly, these classifications closely match the SSA-developed Occupational Information System (OIS), which is planned to replace the DOT to be used in vocational determinations in the near future.

Third, we link polygenic scores (PGSs) constructed from genome-wide genotype data for HRS respondents to the SSA and O*NET data. We focus on measures of genetic risk that are common to SSDI-related physical and mental health conditions including rheumatoid arthritis, depression, cardiovascular disease, dementia, and diabetes.

Sample

Our total sample includes 22,752 individuals. Of these, 1,665 respondents have a record in the linked Form 831 file and 21,087 do not. Individuals in the Form 831 file were excluded if they were missing three-digit information on occupation (359), spouses who were born after 1959 (85), respondents who received SSI only (183), respondents who were denied SSI and never applied for SSDI (111), and 3 respondents who were missing a weight for the SSA sample. We excluded individuals who were not in the Form 831 sample but in our final analytic sample for the same reason (i.e., they either did not have occupational information that could be linked with O*NET or they were born outside of the representative HRS sample, or before 1924 or after 1959).

Of the 1,665 respondents with linked Form 831 data in our sample, 699 were denied SSDI and 966 were approved. For approvals, we do not have information on why benefits were received for 83 individuals. Thus, in the reason for approval regressions, we have data on 833 individuals. Of those, 365 were approved for medical reasons and 518 were approved for work capacity reasons. Among the denials, 233 were denied for medical reasons and 466 were denied for work capacity reasons. Our genetic subsample contains data on 8,638 European ancestry individuals[2]. Of these, 703 are in the linked Form 831 SSDI subsample. Table A1 (attached) details the summary statistics for the full HRS analytical sample.

Measures

SSDI outcomes. We examine three SSDI-related outcomes: 1) Whether a respondent applied to SSDI (1 if in the Form 831 file, 0 otherwise); 2) Whether respondents in the Form 831 file were approved (1 if applicants have at least one approved claim, 0 if all claims were denied); and 3) Whether respondents were approved or denied for medical or work capacity reasons (1 if approved/denied for medical reasons, 0 if approved/denied for work capacity reasons). Here, we follow Because of concerns of bias due to who consents to having their SSA data linked, we use weights provided by HRS to address this issue in all our analysis. In our discussion of the results, we conceptualize the first outcome, whether a respondent applied to SSDI, as the "extensive margin" in SSDI, and the outcomes conditional on application (approvals/denials and their reasons) as the "intensive margin."

Occupation: Three-digit Census occupation codes were used to classify workers into two-digit categories for their self-reported longest held job. These include white collar (managerial, professional, administrative, sales), blue collar (mechanical/construction, operators/fabricators, farmers), and service occupations.

Occupational demands: Table 1 shows the job demand indicators we derived from the O*NET data using confirmatory factor analysis. Four composite indicators are aimed at mirroring the demands detailed in the SSA vocational grid: physical, mental, sensory, and environmental demands. We also incorporate a measure of the psychosocial environment (degree of control and influence) that is consistently found to discourage

[2] PGSs from the genotype data were constructed using findings from recent genome-wide association study (GWAS) of arthritis, cardiovascular disease, BMI, diabetes, depression, and hypertension. GWAS are performed within ancestry groups because differences in allele frequency and linkage disequilibrium structure across populations distort estimated relationships in pooled samples, and estimates for one ancestral group are not necessarily accurate or valid for another. Genotyped sample sizes for populations of non-European descent have not yet reached sufficient power to produce separate GWAS for these health outcomes. Thus, we will restrict our analyses to individuals of European ancestry because the PGSs will not have the same predictive power for individuals from other ancestral backgrounds, and genetic comparisons across ancestral groups may be reflecting environmental differences between groups (Martin et al. 2017).

disability claims and premature retirement in the occupational health literature (Ilmarinen and Rantanen 1999; Theorell and Karasek 1996).

Table 1: Job demand indicators derived from the O*NET

	SSA work capacity requirements	Corresponding O*NET variables
Physical demands	Job requires climbing, balancing, fingering and feeling (manual dexterity), kneeling and crawling, stooping, crouching, need to sit and stand, reaching and handling.	Job requires climbing ladders, scaffolds, or poles, using hands to handle, control, or feel objects, tools, or controls, kneeling, crouching, stooping, or crawling, standing, or moving objects.
Sensory demands	Job requires the ability to hear and retain sufficient visual acuity to handle work and avoid ordinary hazards.	Job requires auditory and speech abilities or visual abilities.
Mental demands	Job requires the ability to understand, carry out, and remember simple instructions, use judgement, respond appropriately to supervision, coworkers, and usual work situations.	Job requires oral comprehension, organizational and communication skills, developing constructive working relationships, and being able to concentrate over a period of time without being distracted.
Environmental demands	Job requires being near dangerous moving machinery, working with chemicals, or exposure to excessive dust, noise, extreme heat or cold.	Job requires exposure to weather, extreme temperatures, light, noise, contaminants, or cramped spaces.
Psychosocial environment	N/A, based on evidence from occupational health models	Job allows worker to use their abilities, gives them a sense of achievement, independence, variety, authority, creativity, and status.

Notes: SSA work capacity requirements were obtained from the public version of the Program Operations Manual System (POMS) on the SSA website, https://secure.ssa.gov/apps10/.

Genetic risk: DNA samples were collected from over 15,000 consenting HRS participants in enhanced face-to-face interviews in 2006, 2008, 2010, and 2012, and genotyping was performed.[3] PGSs from the genotype data were constructed using findings from the most recent genome-wide association studies (GWAS). GWAS are performed within ancestry groups because differences in allele frequencies and the correlational structure of the genome across populations distort estimated relationships in pooled samples and estimates for one group are not necessarily accurate or valid for another. Genotyped sample sizes for populations of non-European descent have not yet reached sufficient power to produce separate GWAS of educational attainment. Thus, we restricted

[3] Genotyping was conducted by the Center for Inherited Disease Research (CIDR) using the llumina HumanOmni2.5 BeadChips (HumanOmni2.5-4v1, HumanOmni2.5-8v1), which measures ~2.4 million single nucleotide polymorphisms (SNPs). Individuals with missing call rates >2%, SNPs with call rates <98%, Hardy-Weinberg equilibrium (HWE) p-value < 0.0001, chromosomal anomalies, and first degree relatives in the HRS were removed. The median call-rate—i.e. the fraction of measured or "called" SNPs per sample divided by the total number of SNPs in the dataset—for the 2006-2012 samples is 99.7%. A standard quality control threshold for excluding DNA samples with a low call rate is 95%.

our analyses to individuals of European ancestry (N=12,090) because the PGS will not have the same predictive power for individuals from other ancestral backgrounds and genetic comparisons across ancestral groups may be reflecting environmental differences between groups (Carlson et al. 2013, Martin et al. 2017).[4]

We include five PGSs that overlap with prevalent medical impairments in SSDI applications: depressive symptoms (mental disorders), rheumatoid arthritis (musculoskeletal), BMI (endocrine and metabolic disorders), myocardial infarction (cardiovascular problems), and general cognition (Okada et al. 2014, Nikpay et al. 2015, Davies et al. 2015, Okbay et al. 2016, Yengo et al. 2018). PGSs are continuous measures of genetic propensity that aggregate the contribution of millions of genetic markers across the genome to create a single scalar of genetic risk for a specific trait or disease.

Life course selection factors: We include self-reported childhood health (in models without PGSs), composite measures of childhood SES that capture social capital (maternal investment and family structure), human capital (parental education), and financial capital (financial resources and instability) (Vable et al. 2017), childhood census region, and completion of a GED/HS degree.

Covariates: We control for age at baseline, year of HRS reporting, HRS cohort, two-digit industry related to longest held job, and residential Census division at baseline. When applicable, we define baseline as the first year in the HRS for those not in the 831 file, and the year of first application for those with an SSDI application. In models that utilize genetic data, we also control for the first ten principal components (PCs) of the genetic data matrix to minimize issues from population stratification.

Empirical Model

Our primary model is a stepwise, linear probability model that examines the probability of our three SSDI outcomes as a function of longest held occupation and, sequentially, job demands, education, childhood SES, and childhood health or genetic risk:

[4] The European ancestry sample included all respondents that had 1) genetic principal component (PC) loadings within ± one standard deviations for eigenvectors one and two in the PC analysis, and 2) who self-identified as White, non-Hispanic in survey data.

$$Y_{itc} = \beta_0 + \beta_1 Occ_i + JD_i'\beta_2 + X_i'\beta_3 + \theta_t + \gamma_c + \varepsilon_{itc} \quad (1)$$

$$Y_{itc} = \alpha_0 + \alpha_1 Occ_i + JD_i'\alpha_2 + \alpha_3 Ed_i + X_i'\alpha_4 + \theta_t + \gamma_c + \varepsilon_{itc} \quad (2)$$

$$Y_{itc} = \delta_0 + \delta_1 Occ_i + JD_i'\delta_2 + \delta_3 Ed_i + Child\_SES_i'\delta_4 + X_i'\delta_5 + \theta_t + \gamma_c + \varepsilon_{itc} \quad (3)$$

$$Y_{itc} = \tau_0 + \tau_1 Occ_i + JD_i'\tau_2 + \tau_3 Ed_i + Child\_SES_i'\tau_4 + \tau_5 Child\_Health_i + X_i'\tau_6 + \theta_t + \gamma_c + \varepsilon_{itc} \quad (4)$$

Where *Y* is the SSDI outcome of interest for individual *i* interviewed in time *t* and born in cohort *c*, *Occ* is *i*'s two-digit longest held occupation (with professional occupations omitted as the reference category), *JD* is the corresponding vector of job demand indicators summarized in Table 1, *Ed* is a dichotomous variable for whether or not *i* graduated high school, *Child_SES* is a vector of continuous childhood socioeconomic variables that summarize the financial, social, and human capital resources provided by *i*'s parents, and *Child_Health* is either self-reported health or, in alternative models, *i*'s PGSs for SSDI-related morbidities. Additional covariates in *X* include controls for gender, race, age, age^2, two-digit industry fixed effects, and census division fixed effects. We also include fixed effects for HRS survey year (θ_t) and six-year birth cohort (γ_c). Models with PGSs are estimated in individuals of European ancestry only and also include controls for the first ten PCs of the genetic data. In all analyses, we use weights provided by the HRS that adjust for bias from non-consent to SSA data linkage.

Results:

DI outcomes, occupation, and job demands: Figure 1 displays the results of our stepwise model for the probability of SSDI claiming (excluded category is "professional"), and Tables 4a – 4d provide the full tables of results for the stepwise model. In the figure, the first set of bars display the occupational gradient in SSDI application, wherein white collar workers have a much lower likelihood of SSDI application relative to their counterparts in blue collar and service occupations. We observe this same gradient for approvals. The inclusion of job demands does very little to change the relationship between occupation and the probability of SSDI application or approvals. The exception is the degree of control and influence a worker has over their day-to-day workload, which is significantly associated with SSDI application and attenuates the occupational gradient for white collar occupations. However, conditional on application of DI, physical, mental, and sensory demands, but not psychosocial demands, are associated with the probability of SSDI approval are associated with the probability of approvals/denials, as well as with reasons for approvals and denials. In other words, at the intensive margin, occupational demands specified in the SSA medical vocational grid are more strongly associated with DI outcomes.

Life course selection factors: To examine the role of selection in occupational choice and DI outcomes, we included five important life course factors that may influence occupational choice: completed education, self-reported childhood health, and three measures of childhood SES (financial capital, social capital, and human capital). We utilize childhood SES measures constructed by Vable et al. (2017) that exploit exploratory factor analysis to create composite SES scores, and full-information confirmatory factor analysis to impute missing scale scores to minimize sample attrition due to missing observations. The scores summarize information on respondents' financial resources/instability in childhood (financial score), details on family structure and maternal investment (social score), and mother's and father's years of education (human capital score). All scores are coded so higher numbers reflect higher capital.

All selection factors are strongly associated with the probability of SSDI application. These associations disappear at the intensive margin when we examine approvals and reasons for approvals/denials. The inclusion of life course selection factors in our model also attenuates the remaining occupational gradient in DI application slightly, but strong relationships between blue collar and service occupations and the probability of DI application remain (Fig. 1).

We interpret these findings to reflect the idea that structural and social inequities that influence access to opportunity and educational attainment (including race, childhood SES, and education) are important mechanisms in getting an individual "to the door," of the DI system; however, conditional on DI application, approvals and denials appear to be a function of the determination process itself and not of larger, life course selection mechanisms.

The Role of Health and Genetics: Finally, we consider the role of health selection into DI more carefully with PGSs, which we conceptualize as a measure of unobserved health. Table 3 confirms that PGSs capture statistically significant differences in underlying health between SSDI applicants and non-applicants. DI applicants have higher average genetic risk for depression, BMI, myocardial infarction (MI), rheumatoid arthritis, and lower cognitive function. We also find that genetic risks correspond to the health conditions cited in DI applications; PGSs for depressive symptoms and MI are significantly associated with body system codes related to mental health and cardiovascular function. We do not see any difference in genetic risk for approvals vs. denials or across reasons for approval or denial.

When we include PGSs in the stepwise model, we see strong associations between genetic propensity for depression and BMI on the probability of application, and a remaining association with depression for approvals/denials. The inclusion of the PGSs explains ~1% of the model R^2 for DI application, which is similar to the explanatory power of self-reported childhood health. PGSs also attenuate the DI-occupational gradient to the same extent as childhood health. This suggests PGSs can act as exogenous proxies for underlying health, which our findings suggest is an independent contributor to SSDI application and receipt.

Finally, we explore interactions between underlying health and occupational demands. Here, we run a series of ordinary least squares models in which we interact one PGS at a time with all five occupational demands (Tables 5 and 6). Results confirm the independent effect of the PGSs and the effects of psychosocial work environments on the probability of application, but we do not observe any additional interaction between underlying health and occupational demand for DI application.

Discussion

In summary, three major findings emerge from this work. First, structural and social inequities that influence access to opportunity, including race and childhood SES, are more strongly associated with the probability of SSDI application than workplace demands. The exception is a positive psychosocial work environment that gives individuals greater control over how to best meet the demands of their jobs, which is negatively associated with SSDI application. Secondly, conditional on SSDI application, physical, mental, and sensory job demands display stronger associations with SSDI approvals and denials than structural or social factors. Finally, our results indicate that higher genetic risk for depression, cardiovascular disease, BMI, dementia, and rheumatoid arthritis are independently associated with SSDI application and approval.

These findings have a number of potential implications for DI policy. First, policies that are not specific to DI but are intended to lessen social and economic inequalities will have positive implications on DI policy. Structural forces including disparities in childhood environments, educational attainment and occupational choice have independent and strong influences on whether an individual ends up "at DI's door," and as such, policies that address these inequities may also indirectly affect SSDI caseload.

Indeed, there is a robust literature on the long-ranging positive effects of policies aimed at improving conditions for individuals in early-life. Policy efforts to bolster early childhood education have been shown to have positive impacts on a number of educational outcomes in primary and high school and childhood cognition (W. Steven Barnett 1995), as well as lasting positive effects on such outcomes as greater educational attainment (McCoy et al. 2017), and higher adult earnings (Duncan and Magnuson 2013; Currie and Almond 2011; Duncan, Ziol-Guest, and Kalil 2010). In addition, a number of studies highlighted the returns to society of such early investments (Reynolds et al. 2002; W. S. Barnett and Masse 2007; Currie and Rossin-Slater 2015; García et al. 2016). Policies aimed at reducing childhood poverty also demonstrate large, positive effects on adult earnings, stability of employment, and greater work hours (Duncan, Ziol-Guest, and Kalil 2010). An equally robust literature demonstrates the positive impacts of early-life policies on adult health (Moore et al. 2015; Lillard et al. 2015; Kawachi and Subramanian 2018; Conti, Heckman, and Pinto 2015).

Secondly, our findings corroborate the match between the SSA medical-vocational grid used in determinations with the realized occupational experience of applicants. Indeed, the requirements of physical, mental and sensory capacities in an applicant's employment history are all important determinants in whether an individual's application is approved. Policies targeted at improving workplace conditions—including allowing workers in declining health additional accommodations or transfers to other positions—could help mitigate DI caseload.

SSA's use of vocational factors and its assessment of ability to perform PRW have been a source of some debate in recent years. In reviewing the relationship between vocational factors and employment, Mann, Stapleton and de Richemond (2014) did not find evidence in the literature that vocational factors of age, education and work experience alone could not predict ability to perform work that one has not performed before, but they did find extensive documentation of relationships between the vocational factors and the extent to which people actually work or perform work-related activities. Moreover, a previous review issued by SSA on the same topic (Curtis et al. 1998) confirmed that "individuals with a higher likelihood of physically demanding unskilled and semi-skilled employment…were most likely to become disabled and apply for benefits" (pg. ii).

While most of our results on occupational demands support the existing literature, we do observe a negative relationship between physical demand and application approval. While we are not entirely sure why this is the case, we posit that this relationship may be a function of healthy worker selection, whereby older workers who are less physically capable of meeting job demands leave physically demanding and hazardous jobs prior to the point of application (Curtis et al. 1998). For example, this phenomenon has been used to explain a similar and oft-observed negative association between age and work-related accidents (Root 1981; Breslin and Smith 2005).

Finally, given the evidence that individuals with poorer underlying health (or higher genetic risk) are more likely to end up on DI, earlier health interventions, both at the workplace and in other settings, may help individuals with propensities towards poor health stay employed healthier for longer. Research on strategies to support the employment of people with disabilities indicates that intervening early at the onset of a new serious illness or injury, is critical for allowing a person to maintain their connection to work (Autor and Duggan 2013; Burkhauser et al. 2014; Gimm, Hoffman, and Ireys 2014; Smalligan and Boyens, 2018.; Stapleton, Ben-Shalom, and Mann, 2016). Moreover, early intervention efforts aimed at people who are still employed allows for workplace accommodations that allow them to stay in their current jobs (Smalligan and Boyens, 2018).

Taken together, these findings and their implications underscore the importance of early interventions in SSDI policy. Prior policy efforts and demonstration projects, such as the Ticket to Work and Work Incentives Improvement Act of 1999 and Benefit Offset National Demonstration, sought to support the employment of DI beneficiaries. These initiatives targeted individuals already determined to have a severe, medically determined impairment that limited the ability to work and were thus not strong candidates for employment interventions (Livermore et al. 2013; Weathers and Hemmeter 2011). The early intervention demonstration projects, on the other hand, intervene prior to disability benefit receipt: when an attachment to the workforce remains strongest and when health interventions and various accommodations can be most effective. These interventions have greater potential to improve the employment and well-being of adults with disabilities and to reduce reliance on DI benefits.

Certainly, recent efforts by SSA have pointed towards positive movement towards early intervention. The Bipartisan Budget Act of 2015, for example, extended the SSA's authority to conduct demonstration projects to identify innovative policy approaches. These projects, which have a particular emphasis on providing early intervention employment support to adults with work-disabilities, have the potential to transform disability employment policy in this country. The SSA has announced major demonstrations projects seeking to retain and retrains workers with health impairments including the Retaining Employment After Illness/Injury Network (RETAIN) project and the Promoting Work through Early Interventions Project (PWEIP). This represents a major change from prior ideas of employment support which occurred with DI/SSI beneficiaries and thus after the onset of a work limiting disability and the determination of benefit eligibility. Still, expanding early intervention efforts face significant programmatic and funding constraints, as well as significant political and institutional barriers that limit the ability to fully serve target populations and evaluate and expand promising models (Smalligan and Boyens, 2018).

This project does have a few limitations worth noting. First, the HRS sampling that starts at age 51 limits generalizability for younger workers and applicants. The SSDI linked data does include claims going back to 1988, so it does provide greater age coverage than the HRS sampling itself, but it still does not allow us to make inferences about applicants at younger ages. Related, the HRS Form 831 file does not include data on technical denials, or individuals who are denied at Step 1, which means we are not measuring the full extent of the extensive margin of applications. Secondly, using genetic data limits our analysis with PGSs to European-ancestry populations. While efforts are underway to increase the availability and study of genetic data for non-White samples, those efforts are still relatively nascent and high-fidelity data that would allow these analyses does not yet exist. Finally, a third limitation is the relatively small sample sizes, particularly in the analysis using genetic data, which may be hindering the statistical power necessary to detect some associations.

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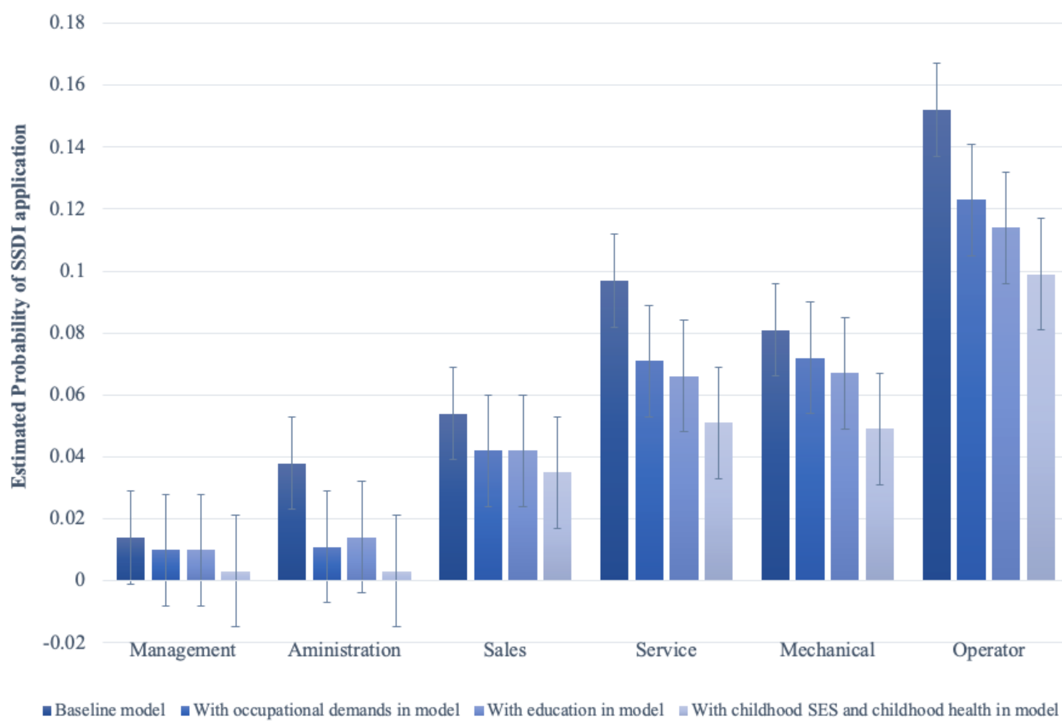
Figures and Tables:

Figure 1. **Estimated Probability of SSDI Application across Occupations.**
(omitted category: professional)



Notes: N=22,752. Bars reflect coefficients from separate linear probability models that regress DI application on fixed effects for occupation, race, sex, survey year, HRS cohort, industry, and residential Census division. We also control for age and age^2 at first claim for applicants or at baseline for non-applicants. Model 2 adds the job demands listed in Table 1. Model 3 adds completion of a GED/HS degree. Model 4 adds childhood SES and health.

Table 1: In text

Table 2. Summary Statistics for Full HRS sample

	Weighted Mean or %	Std. Error
Demographic characteristics		
Female	0.520	(0.006)
White	0.878	(0.009)
Black	0.067	(0.006)
Other race	0.055	(0.006)
Age[1]	55.270	(0.208)
Education and earnings		
Years of education	13.554	(0.081)
No degree	0.097	(0.008)
GED/HS degree	0.505	(0.014)
College degree +	0.399	(0.014)
Household income ($2010)	109,987	(3,551)
Lifetime earnings at age 55 ($2010)	1,259,170	(28,643)
Occupation: longest held job		
Professional	0.219	(0.010)
Managerial	0.151	(0.007)
Administrative	0.156	(0.008)
Sales	0.106	(0.006)
Service	0.118	(0.007)
Mechanical	0.125	(0.007)
Operators	0.115	(0.007)
Farmers	0.011	(0.002)
*O*NET job demands: longest held job (std)*		
Physical demands	-0.039	(0.022)
Environmental demands	-0.334	(0.020)
Mental demands	-0.09	(0.023)
Sensory demands	-0.166	(0.016)
Positive psychosocial environment	0.222	(0.022)
Childhood SES and health		
Financial capital	0.085	(0.023)
Social capital	-0.070	(0.019)
Human capital	0.566	(0.025)
Childhood health excellent/very good	0.765	(0.009)
Birth cohort		
1924-1929	0.118	(0.010)
1930-1935	0.028	(0.002)
1936-1941	0.015	(0.002)
1942-1947	0.309	(0.009)
1948-1953	0.420	(0.013)
1954-1959	0.109	(0.007)

[1]We use age at baseline for respondents not in the Form 831 file and age at first SSDI claim for respondents in the Form 831 file. Estimates weighted to account for complex survey design and linkage consent.

Table 3: Mean differences in characteristics across Full HRS Sample, those applied vs. denied, and reasons for approvals and denials

	Not in Form 831 Files	In Form 831 File	Diff.	SSDI Claims Denied	SSDI Claim Approved	Diff.	Approved for Work Capacity Reasons	Approved for Medical Reasons	Diff.	Denied for Work Capacity Reasons	Denied for Medical Reasons	Diff.
Demographics												
Female	0.510	0.530	-0.020	0.552	0.515	0.037	0.482	0.553	-0.071	0.536	0.587	-0.051
	(0.005)	(0.013)		(0.026)	(0.018)		(0.020)	(0.041)		(0.034)	(0.038)	
White	0.859	0.747	0.112***	0.716	0.770	-0.0537**	0.768	0.788	-0.0195	0.732	0.681	0.051
	(0.007)	(0.018)		(0.023)	(0.020)		(0.024)	(0.026)		(0.023)	(0.050)	
Black	0.085	0.167	-0.082***	0.188	0.151	0.037*	0.147	0.146	0.00177	0.159	0.254	-0.095*
	(0.006)	(0.014)		(0.022)	(0.014)		(0.020)	(0.018)		(0.021)	(0.047)	
Other race	0.055	0.086	-0.030***	0.096	0.079	0.017	0.085	0.067	0.018	0.109	0.065	0.044
	(0.005)	(0.009)		(0.011)	(0.014)		(0.019)	(0.017)		(0.014)	(0.020)	
Age[1]	55.048	53.415	1.633***	51.753	54.604	-2.851***	56.480	53.067	3.414***	51.865	51.505	0.360
	(0.129)	(0.299)		(0.450)	(0.279)		(0.312)	(0.463)		(0.429)	(0.828)	
GED/HS degree only	0.514	0.594	-0.080***	0.604	0.586	0.018	0.609	0.547	0.062	0.626	0.555	0.072
	(0.010)	(0.017)		(0.024)	(0.019)		(0.024)	(0.034)		(0.031)	(0.038)	
Lifetime earnings at age 55	1,257,183	835,322	421,861***	757446	891,750	-134,304***	953329	861012	92317	778299	711118	67181
	(23,968)	(21,141)		(22,826)	(31,002)		(42,412)	(45,553)		(28,371)	(38,593)	
Childhood characteristics												
Financial capital	0.093	-0.166	0.259***	-0.261	-0.107	-0.154**	-0.139	-0.044	-0.095	-0.198	-0.403	0.205*
	(0.019)	(0.038)		(0.064)	(0.044)		(0.054)	(0.085)		(0.072)	(0.103)	
Social capital	-0.011	-0.300	0.289***	-0.342	-0.274	-0.069	-0.304	-0.273	-0.031	-0.356	-0.311	-0.045
	(0.015)	(0.047)		(0.087)	(0.059)		(0.078)	(0.094)		(0.106)	(0.153)	
Human capital	0.466	0.166	0.301***	0.080	0.219	-0.139**	0.177	0.307	-0.129	0.110	0.012	0.098
	(0.020)	(0.044)		(0.057)	(0.049)		(0.060)	(0.066)		(0.075)	(0.091)	
Health excellent/very good	0.788	0.619	0.169***	0.606	0.628	-0.022	0.620	0.646	-0.027	0.600	0.620	-0.019
	(0.007)	(0.013)		(0.022)	(0.017)		(0.025)	(0.036)		(0.028)	(0.039)	

continued…

	Not in Form 831 Files	In Form 831 File	Diff.	SSDI Claims Denied	SSDI Claim Approved	Diff.	Approved for Work Capacity Reasons	Approved for Medical Reasons	Diff.	Denied for Work Capacity Reasons	Denied for Medical Reasons	Diff.
Longest held occupation & job demands												
Professional	0.208	0.103	0.105	0.104	0.103	0.001	0.100	0.117	-0.017	0.106	0.100	0.006
	(0.007)	(0.008)		(0.014)	(0.012)		(0.015)	(0.021)		(0.017)	(0.025)	
Managerial	0.155	0.092	0.063***	0.086	0.097	-0.011	0.089	0.105	-0.016	0.087	0.084	0.003
	(0.006)	(0.008)		(0.013)	(0.012)		(0.015)	(0.019)		(0.016)	(0.023)	
Administrative	0.160	0.145	0.015	0.130	0.156	-0.026	0.140	0.175	-0.035	0.127	0.137	-0.010
	(0.004)	(0.010)		(0.013)	(0.013)		(0.018)	(0.026)		(0.012)	(0.036)	
Sales	0.102	0.091	0.011	0.090	0.092	-0.002	0.079	0.120	-0.041*	0.106	0.056	0.050*
	(0.004)	(0.010)		(0.012)	(0.012)		(0.013)	(0.020)		(0.017)	(0.019)	
Service	0.123	0.173	-0.050***	0.186	0.163	0.023	0.161	0.166	-0.005	0.186	0.187	-0.002
	(0.005)	(0.013)		(0.021)	(0.015)		(0.022)	(0.022)		(0.026)	(0.033)	
Mechanical	0.121	0.140	-0.019	0.129	0.148	-0.019	0.167	0.116	0.052**	0.124	0.140	-0.016
	(0.005)	(0.011)		(0.014)	(0.015)		(0.020)	(0.020)		(0.018)	(0.026)	
Operators	0.119	0.236	-0.117***	0.258	0.220	0.038	0.236	0.189	0.047	0.248	0.283	-0.035
	(0.005)	(0.014)		(0.022)	(0.014)		(0.021)	(0.023)		(0.026)	(0.035)	
Farmers	0.011	0.019	-0.009**	0.017	0.021	-0.004	0.027	0.013	0.014	0.018	0.014	0.004
	(0.002)	(0.004)		(0.007)	(0.005)		(0.007)	(0.007)		(0.008)	(0.007)	
Physical demands	0.008	0.201	-0.193***	0.248	0.167	0.081	0.306	-0.048	0.353***	0.252	0.238	0.014
	(0.020)	(0.023)		(0.038)	(0.036)		(0.062)	(0.068)		(0.038)	(0.089)	
Environmental demands	-0.246	0.017	-0.264***	0.123	-0.058	0.180***	0.007	-0.159	0.167*	0.100	0.173	-0.073
	(0.017)	(0.030)		(0.056)	(0.033)		(0.051)	(0.062)		(0.061)	(0.093)	
Mental demands	-0.105	-0.288	0.182***	-0.262	-0.306	0.044	-0.368	-0.171	-0.196**	-0.276	-0.231	-0.045
	(0.025)	(0.034)		(0.058)	(0.042)		(0.059)	(0.065)		(0.063)	(0.097)	
Sensory demands	-0.021	-0.086	0.065*	-0.027	-0.128	0.101	-0.159	-0.060	-0.010	-0.049	0.022	-0.071
	(0.013)	(0.030)		(0.058)	(0.034)		(0.049)	(0.054)		(0.066)	(0.084)	
Positive psychosocial env.	0.191	-0.180	0.371***	-0.215	-0.154	-0.061	-0.212	-0.038	-0.173*	-0.194	-0.262	0.068
	(0.015)	(0.024)		(0.037)	(0.036)		(0.045)	(0.071)		(0.052)	(0.069)	
N		22,752			1,665			883			699	

Note: Standard errors in brackets. Estimates are weighted to account for HRS complex survey design and respondent's consent to having their survey responses linked to SSA administrative data. *** p<0.01, ** p<0.05, * p<0.1

Table 4a. Relationship between occupational characteristics, education, and childhood SES on probability of SSDI claiming

	(1)	(2)	(3)	(4)	(5)	(6)
	Outcome: 1 if respondent has an SSDI claim in Form 831 file, 0 otherwise					
Longest held occupation and job demands						
Management	0.014	0.017	0.010	0.010	0.004	0.003
	[0.011]	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]
Administrative	0.038***	0.034***	0.011	0.014	0.007	0.003
	[0.011]	[0.011]	[0.015]	[0.015]	[0.015]	[0.015]
Sales	0.054***	0.053***	0.042**	0.042**	0.037**	0.035**
	[0.017]	[0.018]	[0.018]	[0.018]	[0.017]	[0.017]
Service	0.097***	0.093***	0.071***	0.066***	0.058***	0.051***
	[0.015]	[0.017]	[0.020]	[0.020]	[0.019]	[0.019]
Mechanical/Construction/Prec. Prod.	0.081***	0.078***	0.072***	0.067***	0.056***	0.049***
	[0.015]	[0.017]	[0.017]	[0.017]	[0.016]	[0.016]
Operators/Fabricators	0.152***	0.143***	0.123***	0.114***	0.106***	0.099***
	[0.015]	[0.019]	[0.020]	[0.021]	[0.021]	[0.021]
Farmers	0.145**	0.141**	0.135**	0.122*	0.105*	0.103*
	[0.062]	[0.064]	[0.063]	[0.063]	[0.060]	[0.058]
Physical capacity		-0.001	-0.003	-0.002	-0.003	-0.004
		[0.006]	[0.007]	[0.007]	[0.007]	[0.007]
Enviromental hazards		-0.001	-0.004	-0.005	-0.006	-0.006
		[0.007]	[0.007]	[0.007]	[0.007]	[0.007]
Mental capacity		-0.008	-0.001	-0.001	0.000	0.001
		[0.007]	[0.008]	[0.008]	[0.008]	[0.008]
Sensory (hearing and vision)		-0.001	-0.001	-0.001	-0.000	0.001
		[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
Degree of control and influence			-0.017**	-0.015**	-0.016**	-0.017**
			[0.007]	[0.007]	[0.007]	[0.007]
Education						
High school degree or higher				-0.049***	-0.044***	-0.035***
				[0.014]	[0.013]	[0.012]
Childhood variables (std)						
Childhood financial capital					-0.014***	-0.011***
					[0.004]	[0.004]
Childhood social capital					-0.021***	-0.019***
					[0.004]	[0.004]
Childhood human capital					-0.018***	-0.016***
					[0.006]	[0.006]
Childhood health excellent/very good						-0.092***
						[0.010]
Female	0.024**	0.025**	0.022**	0.021**	0.015	0.015
	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]
Black	0.085***	0.084***	0.083***	0.079***	0.068***	0.068***
	[0.015]	[0.015]	[0.015]	[0.015]	[0.015]	[0.015]

Other race	0.046**	0.046**	0.046**	0.040*	0.050**	0.045**
	[0.020]	[0.020]	[0.020]	[0.020]	[0.020]	[0.019]
Age	-0.149***	-0.149***	-0.149***	-0.149***	-0.148***	-0.147***
	[0.012]	[0.012]	[0.012]	[0.012]	[0.011]	[0.011]
Age2	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	22,752	22,752	22,752	22,752	22,752	22,752
R-squared	0.105	0.105	0.106	0.107	0.122	0.133

Note: Standard errors in brackets. All models control for industry, cohort, survey year, and census division fixed effects. Models with childhood outcomes also control for census division in childhood. Dummies for missing variables are included where needed to avoid dropping participants with missing information on race or childhood SES. Estimates are weighted to account for HRS complex survey design and respondent's consent to having their survey responses linked to SSA administrative data. *** p<0.01, ** p<0.05, * p<0.1

Table 4b. Relationship between occupational characteristics, education, and childhood SES on probability of SSDI approval

	(1)	(2)	(3)	(4)	(5)	(6)
	Outcome: 1 if SSDI claim was approved, 0 if claim was denied					
Longest held occupation and job demands						
Management	-0.008	-0.045	-0.050	-0.049	-0.040	-0.040
	[0.076]	[0.075]	[0.075]	[0.075]	[0.076]	[0.077]
Administrative	0.021	0.016	-0.019	-0.018	-0.013	-0.012
	[0.062]	[0.060]	[0.061]	[0.062]	[0.062]	[0.062]
Sales	-0.046	-0.068	-0.078	-0.078	-0.078	-0.078
	[0.078]	[0.078]	[0.077]	[0.077]	[0.077]	[0.078]
Service	-0.018	0.020	-0.013	-0.014	-0.004	-0.003
	[0.067]	[0.069]	[0.076]	[0.076]	[0.075]	[0.074]
Mechanical/Construction/Prec. Prod.	0.024	0.073	0.070	0.069	0.087	0.087
	[0.065]	[0.063]	[0.063]	[0.063]	[0.065]	[0.065]
Operators/Fabricators	-0.018	0.049	0.024	0.022	0.042	0.043
	[0.068]	[0.071]	[0.074]	[0.073]	[0.077]	[0.076]
Farmers	0.195	0.242	0.234	0.233	0.264	0.268
	[0.175]	[0.175]	[0.176]	[0.175]	[0.178]	[0.176]
Physical capacity		-0.036*	-0.041**	-0.041*	-0.041**	-0.041**
		[0.020]	[0.020]	[0.020]	[0.020]	[0.020]
Enviromental hazards		-0.013	-0.019	-0.019	-0.015	-0.015
		[0.025]	[0.026]	[0.026]	[0.026]	[0.026]
Mental capacity		0.019	0.034	0.033	0.036	0.036
		[0.026]	[0.029]	[0.029]	[0.028]	[0.028]
Sensory (hearing and vision)		-0.009	-0.011	-0.010	-0.013	-0.013
		[0.016]	[0.016]	[0.015]	[0.016]	[0.016]
Degree of control and influence			-0.031	-0.030	-0.030	-0.030
			[0.024]	[0.024]	[0.024]	[0.024]
Education						
High school degree or higher				-0.009	-0.027	-0.028
				[0.034]	[0.035]	[0.035]
Childhood variables (std)						
Childhood financial capital					0.020	0.020
					[0.016]	[0.016]
Childhood social capital					0.005	0.005
					[0.012]	[0.012]
Childhood human capital					0.022	0.022
					[0.018]	[0.018]
Childhood health excellent/very good						0.010
						[0.029]
Female	-0.039	-0.049	-0.053	-0.054	-0.042	-0.041
	[0.037]	[0.037]	[0.037]	[0.037]	[0.036]	[0.037]
Black	-0.020	-0.017	-0.020	-0.020	-0.011	-0.011

	[0.041]	[0.041]	[0.041]	[0.042]	[0.044]	[0.044]
Other race	-0.067	-0.069	-0.071	-0.072	-0.049	-0.047
	[0.057]	[0.056]	[0.055]	[0.056]	[0.060]	[0.061]
Age	0.014	0.014	0.013	0.013	0.012	0.013
	[0.020]	[0.020]	[0.020]	[0.020]	[0.020]	[0.020]
Age2	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	1,665	1,665	1,665	1,665	1,665	1,665
R-squared	0.080	0.086	0.087	0.088	0.099	0.100

Note: Standard errors in brackets. All models control for industry, cohort, survey year, and census division fixed effects. Models with childhood outcomes also control for census division in childhood. Dummies for missing variables are included where needed to avoid dropping participants with missing information on race or childhood SES. Estimates are weighted to account for HRS complex survey design and respondent's consent to having their survey responses linked to SSA administrative data. *** p<0.01, ** p<0.05, * p<0.1

Table 4c. Relationship between occupational characteristics, education, and childhood SES on probability of SSDI approval for a medical claim

	(1)	(2)	(3)	(4)	(5)	(6)
	Outcome: 1 if SSDI claim was approved for medical reasons, 0 if approved for work capacity reasons					
Longest held occupation and job demands						
Management	0.066	0.053	0.064	0.066	0.072	0.073
	[0.074]	[0.068]	[0.068]	[0.068]	[0.067]	[0.067]
Administrative	0.079	0.080	0.135	0.139	0.131	0.134
	[0.078]	[0.075]	[0.084]	[0.083]	[0.081]	[0.081]
Sales	0.211**	0.231**	0.244**	0.247**	0.242**	0.243**
	[0.095]	[0.095]	[0.092]	[0.093]	[0.095]	[0.095]
Service	0.021	0.038	0.096	0.094	0.099	0.102
	[0.070]	[0.073]	[0.085]	[0.085]	[0.083]	[0.084]
Mechanical/Construction/Prec. Prod.	-0.051	-0.002	0.005	-0.003	-0.003	-0.003
	[0.094]	[0.097]	[0.096]	[0.097]	[0.100]	[0.100]
Operators/Fabricators	-0.012	0.031	0.068	0.060	0.053	0.055
	[0.088]	[0.100]	[0.098]	[0.098]	[0.099]	[0.102]
Farmers	0.054	0.113	0.118	0.112	0.124	0.128
	[0.174]	[0.171]	[0.169]	[0.165]	[0.163]	[0.161]
Physical capacity		-0.064**	-0.058*	-0.056*	-0.055*	-0.054*
		[0.028]	[0.029]	[0.029]	[0.030]	[0.029]
Enviromental hazards		-0.016	-0.006	-0.007	-0.005	-0.004
		[0.025]	[0.026]	[0.027]	[0.026]	[0.026]
Mental capacity		-0.049*	-0.076**	-0.077**	-0.076**	-0.075**
		[0.027]	[0.032]	[0.032]	[0.031]	[0.031]
Sensory (hearing and vision)		0.052***	0.056***	0.057***	0.053***	0.052***
		[0.015]	[0.013]	[0.013]	[0.015]	[0.015]
Degree of control and influence			0.052	0.055	0.052	0.053
			[0.036]	[0.035]	[0.034]	[0.035]
Education						
High school degree or higher				-0.031	-0.034	-0.035
				[0.050]	[0.050]	[0.049]
Childhood variables (std)						
Childhood financial capital					0.010	0.010
					[0.025]	[0.025]
Childhood social capital					0.007	0.007
					[0.015]	[0.015]
Childhood human capital					0.006	0.006
					[0.028]	[0.028]
Childhood health excellent/very good						0.013
						[0.048]
Female	-0.035	-0.051	-0.047	-0.050	-0.047	-0.047
	[0.049]	[0.048]	[0.049]	[0.050]	[0.047]	[0.047]
Black	-0.032	-0.035	-0.034	-0.036	-0.038	-0.037
	[0.050]	[0.050]	[0.051]	[0.051]	[0.051]	[0.051]

Other race	-0.015	-0.031	-0.028	-0.032	-0.027	-0.024
	[0.069]	[0.074]	[0.073]	[0.073]	[0.081]	[0.079]
Age	-0.004	-0.002	0.003	0.003	0.003	0.004
	[0.043]	[0.041]	[0.042]	[0.042]	[0.042]	[0.043]
Age2	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	883	883	883	883	883	883
R-squared	0.126	0.140	0.143	0.143	0.155	0.155

Note: Standard errors in brackets. All models control for industry, cohort, survey year, and census division fixed effects. Models with childhood outcomes also control for census division in childhood. Dummies for missing variables are included where needed to avoid dropping participants with missing information on race or childhood SES. Estimates are weighted to account for HRS complex survey design and respondent's consent to having their survey responses linked to SSA administrative data. *** p<0.01, ** p<0.05, * p<0.1

Table 4d. Relationship between occupational characteristics, education, and childhood SES on probability of SSDI denials for a medical claim

	(1)	(2)	(3)	(4)	(5)	(6)
	Outcome: 1 if SSDI claim was denied for medical reasons, 0 if denied for work capacity reasons					
Longest held occupation and job demands						
Management	0.020	0.004	0.001	-0.001	0.004	0.003
	[0.109]	[0.110]	[0.111]	[0.111]	[0.112]	[0.112]
Administrative	-0.034	-0.023	-0.050	-0.044	-0.036	-0.036
	[0.094]	[0.096]	[0.105]	[0.104]	[0.101]	[0.102]
Sales	-0.169	-0.164	-0.173	-0.181	-0.205	-0.204
	[0.122]	[0.123]	[0.124]	[0.125]	[0.124]	[0.124]
Service	-0.019	0.002	-0.021	-0.028	-0.018	-0.018
	[0.083]	[0.096]	[0.104]	[0.104]	[0.108]	[0.107]
Mechanical/Construction/Prec. Prod.	0.077	0.097	0.097	0.089	0.090	0.090
	[0.092]	[0.104]	[0.104]	[0.104]	[0.102]	[0.102]
Operators/Fabricators	0.048	0.085	0.064	0.051	0.064	0.064
	[0.086]	[0.106]	[0.110]	[0.111]	[0.115]	[0.114]
Farmers	0.043	0.054	0.039	0.034	0.045	0.049
	[0.146]	[0.155]	[0.158]	[0.168]	[0.175]	[0.178]
Physical capacity		-0.016	-0.022	-0.023	-0.020	-0.020
		[0.031]	[0.034]	[0.034]	[0.034]	[0.034]
Enviromental hazards		0.002	-0.001	-0.001	-0.004	-0.004
		[0.037]	[0.037]	[0.037]	[0.035]	[0.035]
Mental capacity		0.016	0.025	0.022	0.018	0.018
		[0.036]	[0.039]	[0.038]	[0.039]	[0.039]
Sensory (hearing and vision)		0.003	0.003	0.006	0.011	0.011
		[0.019]	[0.019]	[0.019]	[0.018]	[0.018]
Degree of control and influence			-0.023	-0.016	-0.008	-0.008
			[0.040]	[0.040]	[0.038]	[0.038]
Education						
High school degree or higher				-0.079	-0.075	-0.075
				[0.053]	[0.058]	[0.057]
Childhood variables (std)						
Childhood financial capital					-0.044**	-0.044**
					[0.018]	[0.018]
Childhood social capital					0.020	0.020
					[0.018]	[0.018]
Childhood human capital					-0.009	-0.009
					[0.027]	[0.027]
Childhood health excellent/very good						0.005
						[0.040]
Female	0.073*	0.070*	0.067	0.062	0.058	0.058
	[0.042]	[0.041]	[0.042]	[0.042]	[0.042]	[0.042]
Black	0.135**	0.139**	0.135**	0.126**	0.121*	0.120*
	[0.060]	[0.059]	[0.059]	[0.057]	[0.061]	[0.061]

Other race	-0.108	-0.104	-0.105	-0.120	-0.121	-0.120
	[0.079]	[0.078]	[0.078]	[0.079]	[0.086]	[0.087]
Age	-0.085***	-0.083***	-0.083***	-0.083***	-0.095***	-0.095***
	[0.028]	[0.028]	[0.028]	[0.028]	[0.027]	[0.027]
Age2	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	699	699	699	699	699	699
R-squared	0.106	0.107	0.108	0.111	0.134	0.134

Note: Standard errors in brackets. All models control for industry, cohort, survey year, and census division fixed effects. Models with childhood outcomes also control for census division in childhood. Dummies for missing variables are included where needed to avoid dropping participants with missing information on race or childhood SES. Estimates are weighted to account for HRS complex survey design and respondent's consent to having their survey responses linked to SSA administrative data. *** p<0.01, ** p<0.05, * p<0.1

Table 5. Mean differences in Polygenic Risk Scores by SSDI Application Status

	Did not apply to SSDI		**Did apply to SSDI**		
Polygenic risk score (PGS)	**Mean difference**	**SE**	**Mean difference**	**SE**	**Difference**
Depressive Symptoms PGS	-0.043	0.016	0.089	0.032	-0.132***
BMI PGS	-0.034	0.013	0.166	0.044	-0.201***
MI PGS	-0.024	0.018	0.113	0.044	-0.137***
General Cognition PGS	0.018	0.017	-0.128	0.038	0.157***
Rheumatoid Arthritis PGS	-0.125	0.012	-0.058	0.034	-0.0673*

Notes: SE: standard error. N= 8,638. ***p<0.01; **p<0.05; *p<0.10. BMI: body mass index. MI: myocardial infarction

Table 6: Relationship between Polygenic Risk Score and Job Demand, including interactions, related to application of SSDI

Outcome: Applied to SSDI

	PGS: Depressive symptoms	PGS: Myocardial infarction	PGS: Body Mass Index (BMI)	PGS: General cognition	PGS: Rheumatoid Arthritis
PGS (std)	0.011***	0.006*	0.016***	-0.008**	0.011**
	[0.003]	[0.003]	[0.004]	[0.004]	[0.005]
Physical demands (std)	-0.004	-0.004	-0.004	-0.004	-0.004
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
Mental demands (std)	-0.003	-0.003	-0.004	-0.003	-0.004
	[0.004]	[0.004]	[0.005]	[0.004]	[0.005]
Psychosocial work environment (std)	-0.015***	-0.016***	-0.014**	-0.015***	-0.014**
	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]
PGS x physical demands	-0.003	-0.002	0.001	-0.002	-0.001
	[0.003]	[0.003]	[0.004]	[0.003]	[0.005]
PGS x mental demands	0.003	-0.001	0.005	0.001	-0.003
	[0.003]	[0.003]	[0.004]	[0.003]	[0.005]
PGS x psychosocial work environment	-0.006*	0.003	-0.006	0.002	0.001
	[0.004]	[0.004]	[0.004]	[0.004]	[0.006]
N	9413	9413	9413	9413	9413

Note: PGS estimates are available for the European ancestry subsample only. All models control for longest held occupation, sex, age, age2, industry, cohort, survey year, census division fixed effects, and the first ten European ancestry genetic principal components. *** p<0.01, ** p<0.05, * p<0.1