

Skills, Family, and the Disability Pay Gap

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Abstract

Workers with disabilities earn 23 percent less than comparable peers. We decompose this gap using direct pre-market skill measures and a sibling fixed-effects design. Pre-market skills explain one-fifth of the gap; education and occupational sorting raise the explained share to nearly half, leaving a within-occupation residual of 13 percent. Sibling comparisons attenuate the gap, though power constraints prevent precise within-family estimates. Mental disability penalties persist within families. Workers with disabilities are less likely to enter and remain in high-paying occupations. This gap implies an annual earnings shortfall of approximately \$82 billion and foregone federal tax revenue of \$16 billion.

(99 words)

JEL Codes: J14, J24, J70, H53, I38

Keywords: Disability, Skills, Family Background, Occupational Choice, Disability Insurance

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1. Introduction

A central question in the economics of disability is whether the large and persistent earnings gap between workers with and without disabilities originates in disadvantages that accumulate before workers enter the labor force, or in barriers that operate within the labor market itself. This distinction is fundamental to interpreting four decades of unchanged disparities despite expansions of disability-targeted policy (Meyer and Mok 2019; Mann and Wittenburg 2015). It also has direct implications for whether residual pay gaps reflect unobserved productivity differences or unequal treatment in employment. The two interpretations point to different policy margins, with pre-market origins implicating skill formation and family environment, while labor-market origins call for accommodation, advancement, and program design. Existing decompositions of the gap rely on observable characteristics, including education, occupation, and demographic controls, that conflate pre-market endowments with labor market outcomes and cannot separate the two.

A large literature documents disability-related earnings disparities and examines their proximate causes (Haveman and Wolfe 1990; Baldwin and Johnson 1994, 1995; Charles 2003; Meyer and Mok 2019; Mann and Wittenburg 2015). Charles (2003) shows that work-limiting disabilities produce earnings losses that begin years before disability onset and persist for at least a decade afterward, suggesting that the gap reflects long-run accumulated disadvantage rather than a sudden shock. Meyer and Mok (2019) document that disability is associated with sharp and persistent reductions in consumption as well as earnings, indicating that household-level mechanisms do not fully insure affected workers. Decomposition studies of the earnings gap find that observable factors explain only part of the disparity, leaving a substantial residual attributed variously to discrimination, unobserved productivity differences, or institutional constraints (DeLeire 2001; Longhi, Nicoletti, and Platt 2012; Baldwin and Choe 2014). Workers with disabilities have lower educational attainment than peers (Kruse and Schur 2003; Mann and Wittenburg 2015) and concentrate in lower-paying occupations and in roles outside managerial and professional ranks (Maroto and Pettinicchio 2014; Kruse et al. 2018), yet substantial within-occupation gaps persist after detailed three-digit occupational controls.

The productivity interpretation of the residual gap has direct policy implications. Section 14(c) of the Fair Labor Standards Act permits employers to pay workers with disabilities below the federal minimum wage when their productivity is deemed lower (U.S. Department of Labor 2022);

approximately 40,500 workers were employed under 14(c) certificates in 2024 (U.S. Department of Labor 2024), supporting a median hourly wage of \$3.50 and a substantial share of payments below \$1 per hour (U.S. Government Accountability Office 2023). Whether pre-market skills account for the residual has nevertheless not been tested. Decomposition methods using direct assessments of cognitive, non-cognitive, and social skills measured before labor market entry have been applied to gender and racial disparities in labor market outcomes. Speer (2017a), for example, shows that pre-market skill differences explain a substantial share of gender differences in occupational sorting, while Yamaguchi (2018) finds that non-cognitive skill differences explain a meaningful share of the female-male gap among non-college workers (see also Urzúa 2008; Borghans, ter Weel, and Weinberg 2014; Rauh and Valladares-Esteban 2023). The disability gap has not been examined this way.

Two related mechanisms remain similarly underexplored. The first is family background. Households with fewer economic resources, less stable environments, or greater health burdens may produce children simultaneously more likely to develop limiting conditions and, through channels unrelated to disability, less prepared for the labor market (Currie and Madrian 1999; Grätz and Torche 2016; Frijters, Johnston, Shah, and Shields 2013). Cross-sectional estimates therefore conflate disability with family-level disadvantage, and the conflation has empirical consequences: a residual that disappears within families locates the gap before labor market entry, whereas one that persists implies mechanisms operating in adulthood. The second mechanism concerns career dynamics. Disability may compound over the lifecycle if workers enter and exit occupations at different rates than peers, experience slower wage growth within jobs, or encounter advancement barriers that accumulate with experience. Neither the occupational mobility literature (Kambourov and Manovskii 2009; Moscarini and Thomsson 2007) nor the cumulative disadvantage literature (Autor and Dorn 2013) has examined these dynamics for workers with disabilities.

We use longitudinal data from the National Longitudinal Survey of Youth 1997 (NLSY97) to decompose the disability earnings gap into pre-market cognitive, non-cognitive, and social skills, education, and occupational sorting. We find that pre-market skills account for one-fifth of the gap directly and, together with education and occupational sorting, explain nearly half overall, leaving a within-occupation residual of approximately 13 percent that the decomposition alone cannot

interpret as unmeasured skills or labor market barriers. Sibling fixed effects roughly halve the gap, with the residual small and statistically insignificant. However, the sibling design is underpowered, and we interpret the estimate as evidence that family background explains a meaningful share of cross-sectional disparities rather than as a precise estimate of any residual disability effect. Heterogeneity by disability type reveals that earnings penalties for workers with mental disabilities remain large within families, while those for workers with non-mental disabilities attenuate to near zero.

The disability gap also grows over careers, with workers with disabilities 6.6 percentage points less likely to enter high-paying occupations at labor market entry, even conditional on pre-market skills and education, and exiting those occupations at rates approximately 5 percentage points higher than peers over the next fifteen years. Within initial occupational categories, earnings gaps grow over time conditional on pre-market skills and education, suggesting differential wage growth among workers who began their careers in similar roles. Cohort evidence from the American Community Survey shows modest narrowing across birth cohorts between 1980 and the early 1990s, with the largest improvements among women and Black workers, though substantial disparities persist.

Aggregating to the employed working-age population, the 23 percent average gap, applied to approximately 7.5 million employed working-age Americans who report a disability (BLS 2023; ACS 2022), corresponds to an annual earnings shortfall of approximately \$82 billion and foregone federal tax revenue of approximately \$16 billion. Drawing on existing estimates of SSDI elasticities (Autor and Duggan 2003; French and Song 2014; Maestas, Mullen, and Strand 2013), the implied combined fiscal cost is on the order of \$30 to \$35 billion annually. We do not estimate program elasticities directly, and the calculation is back-of-envelope, but the magnitudes indicate that the welfare consequences of the disability pay gap are substantial.

This paper makes three contributions. First, we provide the first direct evidence on the role of pre-market cognitive, non-cognitive, and social skills in the disability earnings gap, applying decomposition methods previously used to study gender and racial disparities (Borghans, ter Weel, and Weinberg 2014; Speer 2017a, 2017b; Rauh and Valladares-Esteban 2023; Urzúa 2008; Yamaguchi 2018) and quantifying how much of the residual identified in prior work (DeLeire 2001; Charles 2003; Meyer and Mok 2019; Baldwin and Choe 2014) reflects measurable rather

than unobserved differences. Second, we use sibling comparisons and career-trajectory evidence to test whether what remains reflects family-level confounding or labor market mechanisms operating beyond pre-market endowments, and we document that mental disability penalties persist within families in ways non-mental disability penalties do not. Third, we connect these estimates to the fiscal stakes of policy responses, building on the public economics literature on disability programs (Autor and Duggan 2003; Maestas, Mullen, and Strand 2013; Deshpande, Gross, and Su 2021).

The paper proceeds as follows. Section 2 describes the data and the construction of disability and skill measures. Section 3 outlines the empirical approach. Sections 4 and 5 present the main decomposition, the sibling fixed-effects analysis, and the mechanism analysis through education, occupational sorting, and career trajectories. Section 6 presents cohort evidence and Section 7 reports robustness checks. Section 8 quantifies the fiscal magnitudes implied by our estimates, and Section 9 concludes.

2. Data and Measures

We use data from the National Longitudinal Survey of Youth 1997 (NLSY97), a nationally representative panel of 8,984 youths born between 1980 and 1984. The survey was initiated in 1997, when respondents were aged 12 to 17, and has collected detailed information on education, employment, training, income, and health at annual intervals through 2011 and biennial intervals thereafter. By the 2021 release (round 20), approximately 75 percent of the original sample remained active. Our analysis uses data from 1997 through 2021. Several features of the NLSY97 make it particularly well-suited to our questions: adolescent disability information collected before labor market entry, direct skill assessments measured during adolescence, longitudinal earnings histories spanning ages 23 through 40, and household identifiers that permit comparisons among siblings raised in the same family.

2.1 Definition of Disability

We infer disability status from NLSY97 questions about whether the youth had ever experienced physical or mental impairments. These questions appeared in Round 1 (1997), Round 6 (2002), and Rounds 11 through 13 (2007 through 2009); with the specific items for each round

listed in Table 1. Parents reported in Round 1; subsequent rounds asked the respondent directly. Each round identified four impairment categories: physical impairments (bodily deformities); chronic impairments (asthma, diabetes, epilepsy, cancer, and other chronic conditions); sensory impairments (vision, hearing, or speech difficulties); and mental impairments (learning disabilities, emotional or behavioral conditions, intellectual disabilities, and eating disorders). Respondents reported the age at onset for each condition and whether the impairment currently limited the youth's activities.

In 1997, 29 percent of parents reported that their child had at least one impairment, but only 12 percent (10.6 percent in our analytical sample) reported that the condition currently limited daily activities. We use the limiting-condition definition as our disability proxy throughout, since the broader measure may capture relatively minor or fully resolved conditions such as vision corrected with eyeglasses, and the limiting-condition definition aligns with the functional-limitation framework articulated by the World Health Organization (2001).¹ The 10.6 percent prevalence is consistent with external estimates from the National Health Interview Survey, which reported childhood activity limitations of 8 to 13 percent in 1997 (Bloom and Tonthat 2002), and from the Survey of Income and Program Participation, which reported 10.6 percent in the same year (Appendix Table C.1). As a robustness check, we restrict the definition to cases in which both parent (1997) and youth (2002) reported the same impairment type, which ensures greater cross-report consistency in exchange for a smaller sample.

2.2 Pre-Market Skills

Pre-market skill assessments administered before labor market entry allow us to construct indices of cognitive, non-cognitive, and social skills following the prior literature.

For cognitive skills, we use the Armed Services Vocational Aptitude Battery (ASVAB) Math-Language percentile, constructed from the Arithmetic Reasoning, Mathematical Knowledge, Word Knowledge, and Paragraph Comprehension subtests. The composite parallels the Armed Forces Qualification Test (AFQT) used in the NLSY79 and predicts educational attainment,

¹ See Appendix Table C.2 for sample sizes under alternative disability definitions: any impairment, our preferred definition of limiting impairment, and a more restrictive definition requiring the same impairment to be reported in both 1997 and 2002, which we use as a robustness check.

occupational sorting, and earnings (Heckman, Stixrud, and Urzúa 2006; Speer 2017a). Because the test is administered during adolescence prior to labor market entry, it provides a measure of academic skill less affected by labor market experience, though still shaped by educational environments through age 18 (Cawley, Heckman, and Vytlačil 2001).

We measure non-cognitive skills through an index constructed from items in the Big Five Inventory and the Ten-Item Personality Inventory, following Deming (2017), which captures conscientiousness-related traits — organization, reliability, discipline, and persistence — and predicts educational attainment, labor force attachment, and wages (Goldberg 1990; Heckman, Stixrud, and Urzúa 2006; Borghans, ter Weel, and Weinberg 2008). For social skills, we follow Deming (2017) and use two extraversion items from the Big Five framework, "Extraverted/Enthusiastic" and reverse-coded "Reserved/Quiet" (Goldberg 1990), which capture sociability, assertiveness, and interpersonal engagement and predict wages particularly in nonroutine and interaction-intensive occupations (Weidmann and Deming 2021).

We construct each index by residualizing the underlying measures on age and schooling at the time of assessment, standardizing all components to mean zero and unit variance, averaging within domain, and renormalizing. Cross-correlations across the three indices are modest, with values of 0.025, 0.120, and 0.104 between cognitive and non-cognitive, cognitive and social, and non-cognitive and social skills respectively (Appendix Table A.1), consistent with prior work using the NLSY79 (Heckman, Stixrud, and Urzúa 2006; Deming 2017).

ASVAB and personality measures have established predictive validity (Heckman and Kautz 2012) but capture only a subset of pre-market abilities. The ASVAB is dominated by academic skills, and the personality measures are short-form self-reports that proxy broad traits rather than observed workplace behaviors, leaving occupation-specific competencies, task content, health-related work capacity, and worker-job match quality unobserved. Executive function, working memory under stress, and social-emotional regulation are inadequately captured for workers with mental disabilities, while physical capacity and adaptive functioning are absent for workers with non-mental disabilities, despite all of these abilities predicting labor market outcomes (Heckman, Stixrud, and Urzúa 2006; Kautz et al. 2014). Classical measurement error attenuates estimated coefficients on observed skills, biasing the estimated explanatory share downward, so the residual

gap may reflect either unmeasured skills or labor market barriers, a distinction we cannot make directly.

2.3 Outcome Variables and Sample Selection

Our primary outcome is the natural logarithm of real annual income from main employment in 2017 U.S. dollars, observed between ages 23 and 40. We also use years of completed education and occupational category at age 25, hourly wages, weekly hours, and full-time employment status as outcomes in additional analyses. We restrict the sample to individuals at least 23 years old and not currently enrolled, ensuring completed education, and to the 1st through 99th percentiles of the annual income distribution; results are unchanged when we include the top and bottom percentiles.

2.4 Sample Characteristics

Table 2 reports descriptive statistics for the NLSY97 analytical sample by disability status reported by parents in 1997. Approximately 10.6 percent of respondents are identified as having a limiting disability, of whom 51 percent had mental conditions, 33 percent had sensory conditions, 33 percent had chronic conditions, and 4 percent had physical conditions, with 19 percent reporting more than one disability type and 11 percent reporting the impairment since birth.

Workers with disabilities differ systematically from peers along several dimensions. They are more likely to be male and less likely to be members of racial or ethnic minorities, completed 1.2 fewer years of education on average, and faced lower labor market outcomes across the margins we observe. Employment rates in adulthood were 8 percentage points lower, full-time employment (35 or more hours per week) was 5 percentage points lower, annual earnings were approximately \$6,775 lower, hourly wages and total compensation were lower by \$3.03 and \$4.45 respectively, and weekly hours were 0.6 lower on average. Hours and wages contribute roughly comparable shares to the annual earnings gap in our sample, so policies addressing only one margin would close roughly half of the observed disparity.

Pre-market skill measures differ systematically as well, with workers with disabilities scoring about 10 percentile points lower on the ASVAB, 0.13 standard deviations lower on non-cognitive skills, and 0.10 standard deviations lower on social skills. As Table 3 and Figure 1 show, these differences are concentrated among youths with mental or learning disabilities, while differences between youths with non-mental disabilities and peers are small in magnitude and not statistically significant. Mental disabilities and non-mental disabilities operate through different channels, a pattern that recurs throughout our analysis.

3. Empirical Method

We estimate the long-term disability earnings gap and decompose it into components attributable to pre-market skills, education, occupational sorting, and shared family environment. We begin with the full NLSY97 sample using a selection-on-observables approach, then exploit within-household variation through sibling comparisons to distinguish compositional selection from family-level confounding, and finally test whether the gap varies across the skill distribution through nonlinear specifications.

3.1 Main Specification

Our analytical sample includes individuals aged 13 through 17 in 1997, the year disability status was first reported by parents. We relate adult earnings to baseline disability status and a set of predetermined individual characteristics in the baseline specification:

$$y_{iat} = \alpha + \beta \cdot disability_{i,1997} + X'_{iat} \delta + \varepsilon_{iat} \quad (1)$$

where y_{iat} is the natural logarithm of annual earnings (in 2017 U.S. dollars) for individual i of age a in year t , and $disability_{i,1997}$ equals one if a parent reported any limiting condition during the first survey round in 1997. The control vector X_{iat} contains race-by-gender indicators, census region of residence, urbanicity, and an indicator for whether at least one parent had completed at least some college. The coefficient β captures the covariates-adjusted earnings difference between youths with and without disabilities. We include both age and year fixed effects to capture lifecycle and macroeconomic variation in earnings, using earnings observations from ages 23 through 40.

To account for differences in pre-market skill endowments, we decompose the residual term as:

$$\varepsilon_{iat} = skill_i' \gamma + \phi_t + \phi_a + v_{iat} \quad (2)$$

Where $skill_i'$ includes standardized measures of cognitive, non-cognitive, and social skills described in Section 2.2, and ϕ_a and ϕ_t denote age- and year- fixed effects. We progressively introduce additional controls beyond pre-market skills: a full set of education indicators controls nonparametrically for years of completed schooling, and three-digit occupation fixed effects isolate within-occupation differences in earnings. The sequential approach assesses the direct explanatory power of pre-market skills and the indirect explanatory power that operates through education and occupational sorting. All estimations use NLSY97 person-level weights, and standard errors are clustered at the individual level to allow for within-person correlation across earnings observations.

3.2 Sibling Specifications

We supplement the full-sample analysis with two sets of sibling-based estimates that together allow us to decompose the cross-sectional gap into compositional selection and family-level confounding. We first re-estimate Equation (1) on the sibling subsample without household fixed effects. Sibling families may differ systematically from the broader population—they may be larger on average, have different socioeconomic profiles, or face different patterns of disability incidence. Comparing this estimate to the full-sample estimate allows us to test whether the subsample is compositionally representative. If the two sets of estimates are similar, further attenuation when household fixed effects are added can be attributed to shared family environment rather than to differences in sample composition.

We then re-estimate the same models with household fixed effects. The within-family specification compares siblings who lived in the same household in 1997, absorbing all time-invariant family characteristics common to both siblings: parental preferences, household resources, neighborhood environment, and shared genetic endowments (Grätz and Torche 2016; Frijters et al. 2013). This estimate identifies the disability earnings gap from variation between siblings, one of whom was reported to have a limiting condition in 1997 and one of whom was

not. Because the analysis requires families with at least two NLSY97 respondents, the sample is necessarily smaller than the full sample, and statistical power to detect modest within-family effects is limited. The implications of this power constraint for the interpretation of our results are discussed in Section 4.

3.3 Nonlinear Specifications

To assess whether the disability earnings gap varies systematically across the skill distribution, we extend the baseline specification to allow for nonlinear relationships between earnings and skills. The average treatment effect estimated in the linear specification may mask heterogeneity in the disability penalty across different points of the skill distribution. We group individuals into quintiles for each skill dimension, and quintile fixed effects (ϕ_q) and interactions between disability status and skill quintiles enter the specification:

$$y_{iat} = \alpha + \beta_q \cdot (\phi_q \times disability_{iat}) + X'_{iat} \delta + \phi_q + \varepsilon_{iat} \quad (3)$$

This specification allows the disability earnings gap to differ across skill quintiles, relaxing the linearity assumption embedded in the baseline models.

4. Main Results

4.1 Decomposition of the Disability Earnings Gap

Table 4 presents estimates from our main analysis, progressively incorporating pre-market skills, education, and occupational sorting. Panel A reports results for the full sample, Panel B1 for the sibling subsample without household fixed effects, and Panel B2 with household fixed effects added.

In Column (1) of Panel A, workers with disabilities earn 0.256 log points less than peers, or approximately 23 percent lower annual income, conditional on demographics, region of residence, and urbanicity. Adding pre-market cognitive, non-cognitive, and social skills in Column (2) reduces the gap to 0.200 log points, implying that measured skills account for approximately one-fifth of the baseline difference. Coefficients on individual skill measures (Appendix Tables C.8 through C.10) are positive and statistically significant in the expected directions, confirming that

these characteristics predict earnings as in the prior literature (Heckman, Stixrud, and Urzúa 2006; Deming 2017).

Adding educational attainment in Column (3) reduces the gap further to 0.164 log points, with the additional reduction reflecting the indirect pathway through which pre-market skills shape earnings via human capital accumulation. Adding three-digit occupation fixed effects in Column (4) brings the gap to 0.134 log points, or approximately 13 percent. Conditional on measured pre-market skills, educational attainment, and detailed occupational categories, workers with disabilities earn approximately 13 percent less than peers within the same occupations, a residual reflecting wage differences arising within occupations rather than sorting into lower-paying jobs alone. Appendix Table C.4 replicates this decomposition for hours worked and full-time employment status and finds that pre-market skills, education, and occupation account for a substantially smaller share of disability gaps along these labor supply margins than along the wage margin.

The decomposition alone cannot determine whether this residual reflects unmeasured skill dimensions (e.g. occupation-specific competencies, health-related work capacity, and task-specific abilities not captured by ASVAB and personality measures) or labor market barriers (e.g. inadequate accommodation, employer discrimination, and limited advancement opportunities). While the pre-market skill measures may be incomplete and understate the contribution of skills, the residual is also consistent with workplace constraints that operate independently of productivity differences. Two pieces of evidence weigh against the pure unmeasured-skill interpretation. First, the 13 percent within-occupation gap remains large even after conditioning on three-digit occupational categories that should absorb most of the sorting on unobserved task-specific ability. Second, we show in Section 5.3 that the gap grows over careers conditional on initial occupational placement and pre-market skills, a pattern more consistent with cumulative barriers than with a fixed productivity differential that should be approximately constant once selection on initial occupation is controlled for.

4.2 Sibling Comparisons and the Role of Family Background

Panel B1 of Table 4 reports estimates on the sibling subsample without household fixed effects. The baseline gap is 0.225 log points, similar to the full-sample 0.256, and the fully adjusted

estimate in Column (4) is 0.143 log points, comparable to the full-sample 0.134. The modest attenuation moving from Panel A to Panel B1 indicates that families with within-family disability variation are broadly representative of the population, so any further attenuation when household fixed effects are added in Panel B2 reflects shared family environment rather than compositional selection. Panel B2 adds household fixed effects, holding constant all time-invariant family characteristics. The baseline within-family gap in Column (1) is 0.111 log points, roughly half the Panel B1 estimate of 0.225, indicating that shared family environment accounts for a meaningful share of the cross-sectional disability earnings penalty in the sibling sample. Adding pre-market skills in Column (2) reduces the gap to 0.054 log points, no longer statistically distinguishable from zero.

Interpreting the within-family null requires care given the limited statistical power of the design. The standard error of 0.055 in Column (2) implies a minimum detectable effect of 0.153 log points, or approximately 17 percent (Appendix Table C.3), well above our 0.054 point estimate, so the data are consistent with both true within-family gaps near zero and gaps of moderate size we cannot detect. We therefore interpret the null estimate as suggestive evidence that family background contributes meaningfully to cross-sectional disability earnings disparities, not as a precise estimate of the residual within-family disability effect. More robust evidence comes from the substantial attenuation moving from Panel B1 to Panel B2, with the Column (1) estimate falling from 0.225 to 0.111, a magnitude too large to reflect chance variation alone and indicating that families with children with disabilities differ systematically from other families in ways that affect adult earnings outcomes for all children in the household.

4.3 Heterogeneity by Disability Type

Our heterogeneity analysis by disability type provides informative evidence on the role of family background. Differences in attenuation across types when household fixed effects are added reveal which subpopulations have earnings gaps operating primarily through family-level channels and which have gaps that persist beyond shared upbringing. Figure 2 plots the fully adjusted disability earnings gap—after controlling for demographics, pre-market skills, education, and occupation—for each mutually exclusive disability type across the three samples; full results appear in Appendix Table C.5.

Workers with mental-only disabilities face a fully adjusted earnings penalty of approximately 0.12 log points in the full sample. The corresponding Panel B1 estimate is 0.18 log points, somewhat larger than the full-sample estimate but consistent with it given the smaller sample. The Panel B2 estimate is 0.11 log points, though imprecisely estimated given limited within-family variation. Persistence of a sizable point estimate after accounting for shared family background distinguishes mental disabilities from other disability types. About one-third of the unadjusted mental disability gap is explained by pre-market skills, consistent with the larger skill differences observed for this group in Table 3.

Several mechanisms beyond family environment could account for the residual within-family penalty for workers with mental disabilities. Workplace accommodation needs for mental disabilities are often less visible to employers and less codified than those for physical disabilities (Schur et al. 2014), which may translate into lower rates of effective accommodation. Episodic conditions such as depression, anxiety, and bipolar disorders generate variability in productivity that is difficult to schedule around in standard employment relationships (Banerjee, Chatterji, and Lahiri 2017). Stigma and disclosure decisions also differ systematically: workers with mental conditions face stronger incentives to conceal their condition from employers, which constrains their access to formal accommodations even when they would benefit from them (Jones 2008). Mental disability earnings gaps are not driven primarily by family-level factors; mechanisms beyond shared upbringing contribute for workers with mental impairments, though our power constraints prevent precise conclusions about the magnitude of the within-family residual.

For workers with non-mental-only disabilities (physical, chronic, or sensory only), the fully adjusted penalty in the full sample is approximately 0.15 log points. The Panel B1 estimate is 0.12 log points, broadly similar to the full-sample value. In Panel B2, the estimate attenuates to 0.01 log points and becomes statistically insignificant. Much of the observed earnings disadvantage associated with non-mental disabilities reflects shared family background rather than disability-specific factors operating in adulthood, though the same power constraints prevent ruling out effects of moderate size.

Workers with multiple disabilities, who report both mental and non-mental impairments, face fully adjusted gaps of approximately 0.12 log points in Panel A, similar in magnitude to those with mental-only disabilities. In the sibling samples, the multiple-disability gap attenuates in Panel B1

and approaches zero in Panel B2, though estimates are imprecise due to limited within-family variation among those with multiple conditions. Formal F-tests of equality across disability types appear in Appendix Table C.5: the test rejects equality only in Panel B1, Column (1), and fails to reject equality at conventional levels in other specifications. The disability-type differences are therefore suggestive rather than a definitive ranking of disability-specific earnings penalties. Persistence of mental disability gaps within families is the most robust pattern from this heterogeneity analysis and, as Section 8 discusses, has direct implications for understanding the disproportionate representation of workers with mental disabilities among recipients of federal disability transfers.

4.4 Heterogeneity by Gender and Race

Figure 3 plots the fully adjusted disability earnings gap by gender across Panels A, B1, and B2 (full results in Appendix Table C.6). In the full sample, the fully adjusted gap is small and borderline significant for women (approximately 0.06 log points) but larger and statistically significant for men (approximately 0.18 log points). Although the unadjusted gap is similar for women (0.25 log points, approximately 22 percent) and men (0.27 log points, approximately 23 percent), adjustment for pre-market skills, educational attainment, and occupational sorting narrows the gap substantially more for women than for men. Differences in education and occupational sorting account for most of women's earnings disadvantage but only about one-third of men's, consistent with prior findings that men with disabilities face additional barriers not captured by standard human capital measures or occupational sorting (Pettinicchio and Maroto 2017; Kruse et al. 2018).

Sibling estimates are less precise but broadly consistent with the full-sample patterns. Among women, the Panel B1 estimate (approximately 0.11 log points) is larger than Panel A; Panel B2 attenuates toward zero with wide confidence intervals. Among men, Panel B1 remains sizeable and statistically significant; Panel B2 is imprecisely estimated. Similarity of Panel B1 to Panel A for both groups suggests limited compositional bias from the sibling sample restriction. Attenuation in Panel B2 relative to Panel B1 indicates that shared family environment explains a portion of the observed earnings disadvantage, though wide confidence intervals preclude strong conclusions about the within-family residual gap.

Figure 4 plots the fully adjusted disability earnings gap by race and ethnicity (full results in Appendix Table C.7). The fully adjusted full-sample gap is approximately 0.13 log points for non-Hispanic Whites, 0.21 log points for non-Hispanic Blacks, and 0.07 log points for Hispanics. Unadjusted, the earnings penalty is largest for non-Hispanic Blacks (0.37 log points, approximately 31 percent lower earnings); controlling for pre-market skills has limited explanatory power for the Black-White disability gap. Education and occupational sorting explain a greater share of the White disability gap than the Black disability gap.

Sibling patterns diverge across racial groups in informative ways. For non-Hispanic White workers, the disability penalty is stable across Panels A, B1, and B2, suggesting that the White disability gap is not primarily driven by shared family background. For non-Hispanic Black workers, the Panel B1 estimate remains close to the full-sample Panel A estimate, but the Panel B2 estimate is substantially larger (0.35 log points). For Hispanic workers, the gap shrinks across panels and becomes statistically indistinguishable from zero. Persistence and amplification of the Black disability gap in within-family comparisons suggests that Black workers with disabilities face earnings penalties not attributable primarily to skills or family background, consistent with prior evidence on the intersection of race, disability, and labor market disadvantage (Brooks 2021; Goodman, Morris, and Boston 2017; Browne and Misra 2003; Greenman and Xie 2008).

4.5 Robustness of the Main Decomposition

We assess sensitivity to functional form and skill aggregation. Decomposing the cognitive skill index into the four ASVAB subtests yields attenuation patterns nearly identical to the baseline specification using the composite measure (Appendix Tables C.8 through C.10). Among the individual components, math ability is the strongest predictor of adult earnings; verbal components contribute less. The magnitude of the residual disability earnings gap remains similar to the aggregated index, indicating that the explanatory contribution of cognitive skills is not driven by index construction or weighting choices.

Allowing the disability coefficient to differ across quintiles of cognitive, non-cognitive, and social skills using Equation (3) reveals no systematic variation in the disability gap across skill quintiles for any skill dimension, as reported in Figure 5. Joint tests fail to reject equality across

quintiles. Our results are not driven by linear functional form assumptions or by differential disability penalties at the top or bottom of the pre-market skill distribution.

5. Mechanisms

The decomposition in Section 4 shows that pre-market skills explain about one-fifth of the disability earnings gap directly, while adding education and occupational sorting brings the explained share to approximately one-half. This section examines how skills operate through these channels and tests whether disability shapes career trajectories beyond initial labor market entry. The investigation proceeds in three steps: first, whether disparities in skill endowments explain gaps in educational attainment; second, occupational sorting at labor market entry; third, occupational mobility and earnings trajectories over the first fifteen years of careers.

5.1 Education

Table 5 presents fully adjusted estimates of the association between disability status in 1997 and educational attainment by age 25, with the full set of results in Appendix Table C.11. In the full sample (Panel A), workers with disabilities complete substantially fewer years of schooling than peers even after accounting for pre-market skills and demographic characteristics. The estimated gap is largest for mental disabilities (-0.72 years), followed by all disabilities combined (-0.58 years) and non-mental disabilities (-0.43 years).

The sibling sample without household fixed effects (Panel B1) yields estimates similar to Panel A for all disabilities and mental disabilities, suggesting that the full-sample findings are not driven primarily by selection into sibling families. The non-mental disability coefficient becomes small and statistically insignificant in the sibling sample, indicating that sibling families with non-mental disabilities may not be representative of the broader non-mental disability population. With household fixed effects (Panel B2), the estimated education gaps attenuate substantially and become statistically insignificant. The mental disability coefficient remains negative (-0.36 years); the non-mental disability coefficient becomes positive (0.59 years). Wide confidence intervals reflect limited within-family identifying variation. While the within-family results for educational attainment are too imprecise to support strong conclusions, the overall pattern suggests that both

pre-market skills and family background contribute importantly to educational disparities associated with disability status, particularly for workers with mental disabilities.

5.2 Occupational Sorting at Labor Market Entry

Pre-market skills may influence early labor market outcomes through occupational sorting, which reflects not only educational attainment but also broader structural constraints such as employer hiring practices and job-specific skill demands (Autor and Dorn 2013; Maroto and Pettinicchio 2014). To examine this channel, we analyze the likelihood of employment in different occupational groups at age 25, capturing initial occupational placements. Three-digit occupations are classified into three earnings-based categories: low-paying (service, transportation, administrative support, machine operators); medium-paying (sales, farming, construction, technical trades); and high-paying (managerial, professional, repair roles).

Table 6 presents estimates of occupational sorting by disability status. Panel A shows that workers with disabilities are more likely to start in low-paying occupations and less likely to enter high-paying ones. In the fully adjusted specification—controlling for demographics, pre-market skills, and education—workers with disabilities are 6.6 percentage points less likely to enter high-paying occupations ($p < 0.01$) and 2.6 percentage points more likely to be employed in low-paying jobs, though the latter estimate is not statistically significant. The gap in entry into high-paying occupations persists even after conditioning on pre-market skills and educational attainment, suggesting that disability-related barriers to well-paying roles operate beyond skill and credential differences.

Sibling results are directionally consistent with the full-sample patterns, though less precisely estimated due to the smaller sample. The Panel B1 gap in entry into high-paying occupations is 5.7 percentage points; low-paying coefficients are small and imprecise. Panel B2 attenuates the high-paying gap to 2.4 percentage points, with low-paying and medium-paying coefficients remaining small. Persistence of a negative Panel B1 coefficient for high-paying occupations, similar in magnitude to Panel A, reinforces that the sorting disadvantage at labor market entry is not driven solely by family composition. The Panel B2 attenuation may reflect limited statistical power given the small number of sibling pairs with within-family disability variation observed at

age 25. Pre-market skills and education explain part, but not all, of the initial occupational sorting disadvantage faced by young adults with disabilities.

5.3 The Role of Initial Occupation and Career Trajectories

Section 5.2 establishes that workers with disabilities are less likely to enter high-paying occupations and more likely to enter low-paying ones at labor market entry. We next examine how initial occupational placement shapes long-term earnings trajectories. We track career progression based on occupation observed at ages 23 to 24. Using the classification of low-, medium-, and high-paying occupations from Section 5.2, we estimate the conditional probability of remaining in or transitioning out of one's initial occupational group g at age $a > 24$:

$$P_{iga} = P(\text{group}_{ia} = g \mid \text{disability}_{i,1997}, \text{group}_{i,\text{age}=23,24} = g, \text{age} = a) \quad (4)$$

Figure 6 presents occupational retention rates by initial occupational group. The left panel shows that workers with disabilities who start in high-paying occupations at ages 23 to 24 are approximately 5 percentage points less likely to remain in high-paying roles than peers without disabilities by age 39. The right panel shows that workers with disabilities are similarly likely to remain in low-paying occupations as their non-disabled counterparts over their career progression. The asymmetry of these mobility patterns has not been previously documented in the disability earnings literature: high-paying occupations are exited at higher rates by workers with disabilities, but low-paying occupations are not, a pattern that contributes to cumulative earnings disadvantage over careers.

To further examine earnings trajectories conditional on initial occupational placement, we estimate average earnings by disability status, initial occupation, and age, with controls for background characteristics and pre-market skills:

$$\ln(\text{earn}_{it}) = \alpha \cdot \text{Dis}_{1997} + \beta_1 \cdot \text{Mid}_{<25} + \beta_2 \cdot \text{High}_{<25} + \gamma_1 \cdot \text{Mid}_{<25} \times \text{Dis}_{1997} + \gamma_2 \cdot \text{High}_{<25} \times \text{Dis}_{1997} + \text{skills}'_i \gamma + X'_{it} \delta + \varepsilon_{it} \quad (5)$$

Low-paying occupations serve as the reference group; the parameters α , γ_1 , and γ_2 capture the adjusted earnings gaps for workers who started in low-, medium-, and high-paying occupations respectively.

Table 7 presents estimates from Equation (5). Annual earnings are reported in Columns (1) through (3); hourly wages in Columns (4) through (6). Workers with disabilities who began in low-paying occupations earn 0.17 log points less in annual income than peers in the same category. Adjusting for pre-market skills reduces the gap to 0.12 log points; further controlling for education narrows it to 0.11 log points. For workers who started in medium-paying occupations, the gap is smaller (around 0.11 log points) and becomes statistically insignificant once skills and education are included. Among workers who began in high-paying occupations, annual earnings differences are minimal (0.03-0.06 log points and not statistically significant), but hourly wage gaps of 8 to 11 percent are statistically significant until education is accounted for. Workers with disabilities who started in high-paying occupations work similar total hours to peers but earn lower hourly wages, indicating persistent within-occupation wage penalties even among higher earners.

Figure 7 tracks income trajectories by initial occupational group. Even when workers with disabilities start in the same occupational groups as peers, significant wage gaps persist throughout careers. Among workers who started in high-paying occupations, wage gaps are minimal at ages 23 to 25 but widen to 8 to 10 percent by ages 33 to 35. The growing gaps cannot be fully explained by cognitive, non-cognitive, or social skill differences measured before labor market entry. Both initial sorting and differential wage growth within career paths shape the disability earnings gap.

The asymmetric mobility pattern—higher exit from high-paying occupations but equal retention in low-paying ones—has implications for interpreting the residual within-occupation gap documented in Section 4.1. A pure productivity-differential explanation would predict either symmetric attrition (workers with disabilities exit all occupations at higher rates because their match quality is lower across the board) or, if matching frictions are absent, no differential attrition at all. The observed pattern instead resembles the dynamics of cumulative disadvantage documented in other contexts (Autor and Dorn 2013): workers in high-paying occupations face advancement and retention barriers that are absent or weaker in low-paying occupations, where employer expectations, accommodation costs, and promotion criteria differ. Within-occupation wage growth differentials reinforce this interpretation. If workers with disabilities who remain in high-paying occupations were a positively selected subgroup with productivity matching peers, wage growth gaps would close over time as selection works its way through. The opposite pattern

is observed: gaps widen over time, suggesting that even retained workers face advancement constraints that compound across the career.

6. Cohort Evidence

The NLSY97 covers a single birth cohort of Americans born between 1980 and 1984. To examine generational change, we use data from the American Community Survey (ACS), a nationally representative cross-sectional survey of approximately 3.5 million U.S. households administered annually by the U.S. Census Bureau. We use ACS data from 2008 through 2022 in which six disability types are consistently identified: hearing, vision, self-care, independent living, cognitive, and ambulatory. We restrict the sample to early-career workers aged 23 to 33, exclude those in military occupations, and group individuals into three birth cohorts: 1980–1985, 1985–1990, and post-1990. Because the ACS lacks direct measures of pre-market skills, the cohort analysis focuses on how education, occupation, and demographic composition account for cohort-level variation in the gap.

For each cohort, we estimate

$$y_{iact} = \alpha_c + \beta_c \cdot disability_{iact} + X'_{iact} \delta_c + \phi_{a(c)} + \phi_{s(c)} + \varepsilon_{iact} \quad (6)$$

where y_{iact} is the natural logarithm of annual earnings (in 2017 dollars) for individual i of age a born in cohort c in state s and year t , X'_{iact} contains controls for age interacted with race, gender, and disability status along with indicators for educational attainment, marital status, and citizenship, and $\phi_{a(c)}$ and $\phi_{s(c)}$ denote cohort-specific age and state effects. A smaller β_c for more recent cohorts indicates a narrowing gap.

Table 8 reports estimates across cohorts. Workers with disabilities born before 1985 earn 0.55 log points less than comparable workers without disabilities (approximately 42 percent lower earnings). The gap declines to 0.52 log points (40 percent) among those born between 1985 and 1990 and to 0.44 log points (36 percent) among those born after 1990. Adjusting for occupational sorting narrows each cohort's gap further but preserves the declining trend. After accounting for education and occupation, the residual gap for workers born after 1990 is approximately 20 percent smaller than for workers born before 1985.

To assess whether this decline in the disability earnings gap reflects wage compression, hours, or both, we re-estimate the model with hourly wages, weekly hours, and full-time status as outcomes (reported in Appendix Table C.13). Each margin narrows steadily across cohorts, yet substantial disparities remain among workers born after 1990, with an hourly wage gap of 0.085 log points, weekly hours 4.3 lower on average, and a 12 percentage point lower probability of working more than 35 hours per week, indicating that progress to date has been incremental.

The decline is more pronounced for women and Black workers (Appendix Table C.14). Between the pre-1985 and post-1990 cohorts, the gap declined by 27 percent for women and 13 percent for men, and by 22 percent for Black workers and 17 percent for White and Hispanic workers, indicating that improvement has been concentrated among groups historically subject to compounded labor market disadvantage.

As an additional robustness check, we compare the association between health limitations and earnings across the NLSY79 and NLSY97 cohorts (Appendix B). Despite measurement differences that limit direct comparability, earnings penalties associated with health limitations remain large across cohorts and are only partially explained by education, occupation, and cognitive skills.

7. Robustness

This section presents additional analyses to assess whether the main results are robust to variations in sample selection, model specifications, and the definitions of disability status and skill proxies.

7.1 Alternative Construction of Disability Status

The NLSY97 asked whether the youth had any sensory, chronic, learning or emotional, or physical impairments (Table 1). Several of these questions are broad enough to capture conditions that do not constitute disabilities, so our main analysis uses the follow-up question on whether the impairment limited the youth's activities. As an alternative, we define disability status by matching parent (1997) and youth (2002) reports of the same condition type, regardless of whether the condition was classified as limiting. Appendix Table C.15 replicates Table 4 under this alternative definition; the disability coefficient is nearly identical in magnitude and significance.

7.2 Excluding Workers with Congenital Disabilities

Workers with congenital disabilities may differ developmentally and in labor market trajectories from those who acquired disabilities later in life, since genetic and early neurological conditions can shape skill formation differently from impairments emerging in adolescence or adulthood. Consistent with this, youths with congenital disabilities show larger gaps in cognitive and social skills than peers with later-acquired disabilities (Appendix Table C.16). Excluding workers with congenital disabilities (Appendix Table C.17) reduces the magnitude of the earnings gap, but the relative explanatory power of pre-market skills, education, occupational sorting, and family background is unchanged.

7.3 Alternative Constructions of Skill Proxies

We test whether our findings depend on how the skill indices are constructed. Using principal component analysis (PCA) to generate weighted indices in place of averaged standardized components yields nearly identical estimates: the disability earnings gap declines to 0.14 log points after accounting for PCA-based skills and to 0.11 log points after further adjustment for education and occupation (Appendix Table C.18). Controlling separately for each component used to construct the indices yields the same conclusion (Appendix Tables C.8 through C.10). Decomposing the ASVAB into math and verbal subcomponents produces attenuation that closely matches the composite specification, with math the strongest predictor of earnings among the four. Individual non-cognitive and social traits including discipline, organization, and extraversion are predictive of earnings on their own, but entering them separately does not change the magnitude of the residual gap.

7.4 Comparison with Gender and Race Earnings Gaps

We apply the same decomposition to the gender and Black-White earnings gaps to assess whether pre-market skills carry similar explanatory power across other major disparities. Controlling for skills does not significantly reduce the gender gap once education and occupation are accounted for (Appendix Table C.19, Panel A), but the Black-White gap declines from 0.15 to 0.10 log points, a 4.5 percentage point reduction (Panel B). These results align with prior work finding that skills do not explain the gender wage gap (Humphries, Joensen, and Veramendi 2024;

Rotman and Mandel 2023) but partially account for Black-White disparities (Rauh and Valladares-Esteban 2023). The contrast supports the validity of our skill measures, which carry explanatory power for the gaps where the literature predicts they should and not for those where it predicts they should not.

7.5 Recession Timing

We test whether differential exposure to the 2001 to 2002 recession confounds the disability earnings gap. Workers with disabilities may have disproportionately graduated high school during the recession (proxied as birth year plus 18 falling in 2001 or 2002), and a weaker labor market at entry could produce lasting earnings penalties (Kahn 2010; Oreopoulos, von Wachter, and Heisz 2012). Appendix Table C.20 reports estimates from models that include an indicator for recession-era graduation and its interaction with disability status. The disability earnings coefficient is stable across specifications (-0.134 to -0.166 log points), and the graduation-timing interaction is small and statistically insignificant. The disability earnings gap is not driven by differential cohort exposure to cyclical labor market conditions at career entry.

7.6 Birth Order

A final concern is whether birth order confounds the sibling fixed-effects estimates. If children with disabilities are disproportionately later-born and birth order independently affects earnings, within-family disability coefficients could be biased. We add a first-born indicator to the sibling-sample specifications in Appendix Table C.21. The disability coefficient changes little across the three model specifications, and the first-born indicator is small and statistically insignificant. Birth order does not materially confound our sibling-based disability estimates.

8. Fiscal Magnitudes

This section translates the earnings gap estimates from Sections 4–7 into fiscal magnitudes using publicly available data on tax incidence and federal disability program expenditures. See Appendix D for computational details.

8.1 Aggregate Earnings Shortfall and Foregone Tax Revenue

Table 9 reports estimates of the aggregate annual earnings shortfall. Using ACS 2022 data and BLS employment rates, there are approximately 7.5 million employed working-age adults with disabilities. Applied to mean non-disabled earnings of \$48,463 in 2022 dollars, the baseline coefficient of -0.256 log points implies a per-worker gap of approximately \$10,963 and an aggregate annual shortfall of approximately \$82 billion. This estimate is conservative because it covers only employed workers. Extending to all 21.4 million working-age adults with disabilities yields approximately \$235 billion; ACS-based estimates including older workers range from \$92 to \$145 billion. Table 9 also decomposes the aggregate by mechanism: approximately \$16 billion is attributable to pre-market skills, \$11 billion to education beyond skills, \$9 billion to occupational sorting, and \$45 billion to the within-occupation residual.

Table 10 translates the aggregate shortfall into foregone tax revenue. Applying comprehensive federal and state-local effective rates for middle-quintile households (CBO 2026; ITEP 2024), foregone tax revenue is approximately \$20 to \$24 billion annually.

8.2 Federal Disability Program Expenditures

Beyond foregone tax revenue, the disability earnings gap has direct program expenditure implications. SSDI paid \$143.6 billion in benefits in 2022 to 8.96 million beneficiaries (SSA 2023). Federally administered SSI payments totaled \$55.8 billion in 2022, of which approximately \$31 billion went to working-age disabled recipients. Combined, SSDI and the working-age portion of SSI totaled approximately \$175 billion. Disability-related Medicaid expenditures totaled approximately \$225 billion in fiscal year 2022 (CMS 2023).

Workers with mental disabilities, who in our analysis face the most persistent within-family earnings penalties, are also disproportionately represented among recipients of federal disability transfers (Table 11). Approximately 28.8 percent of disabled-worker SSDI beneficiaries in December 2022 had mental disorders as their primary impairment, including depressive, bipolar, intellectual, and other mental disorders (Social Security Administration 2023). By comparison, workers with mental disabilities represent only approximately 5 to 6 percent of the working-age population (BLS 2023; ACS 2022). The implied overrepresentation is the largest of any disability category, exceeding the ratios for musculoskeletal, sensory, or circulatory disorders. Combined with our finding that mental disability earnings gaps persist within families even after accounting

for measured skills, this disproportionate representation suggests that workers with mental disabilities account for some of the largest unexplained fiscal stakes in the disability earnings literature.

8.4 Implied SSDI Savings

French and Song (2014) and Maestas, Mullen, and Strand (2013) report participation elasticities of 0.30 to 0.35 using examiner-assignment designs. Applied to the 23 percent earnings gap, these imply annual SSDI savings of approximately \$10 to \$12 billion. Summing foregone tax revenue and implied SSDI savings, the combined fiscal stakes of the disability earnings gap are on the order of \$30 to \$35 billion annually. The skills-explained portion of the gap (22 percent of the shortfall) corresponds to approximately \$7 billion if eliminated through pre-market interventions; the within-occupation residual portion (52 percent) corresponds to approximately \$16 billion if eliminated through labor-market interventions. Appendix D.7 documents sensitivity to alternative denominators, tax rates, and behavioral responses.

9. Conclusion

This paper provides new evidence on the sources of the disability earnings gap and the extent to which early-life factors shape later labor market outcomes. Cognitive, non-cognitive, and social skills explain a meaningful share of the earnings disparity, largely through their influence on educational attainment and entry into higher-paying occupations, and sibling comparisons indicate that shared family background contributes an additional substantial share. Earnings gaps nevertheless persist within occupations and grow over careers conditional on initial occupational placement and pre-market skills, and the disadvantage is especially pronounced for workers with mental disabilities, who continue to face sizable earnings penalties in within-family comparisons. The compounding of disability and racial disadvantage is also visible in the data: penalties are largest for Black workers with disabilities, and cohort evidence shows modest improvement across birth cohorts but substantial remaining disparities, particularly along the wage and hours margins.

Two patterns place weight on the labor-market-barriers interpretation of the residual relative to the unmeasured-productivity interpretation. Workers with disabilities exit high-paying occupations at higher rates than peers but exit low-paying occupations at the same rate, and within-

occupation earnings gaps widen rather than close once initial sorting is held constant. A fixed productivity differential would not produce either pattern. We do not identify the specific mechanisms operating within firms, but the dynamic evidence is harder to reconcile with a static productivity story than with cumulative disadvantage in advancement, accommodation, or match quality. The disproportionate concentration of workers with mental disabilities among federal disability transfer recipients connects directly to this finding, since the population most affected by the within-family residual is also the population that bears the largest fiscal weight in current programs.

Three constraints on the analysis bear emphasis. Pre-market skill measures are bounded by what the NLSY97 instruments capture, so a portion of what we attribute to labor market barriers may reflect skill dimensions that better assessments would reveal. The sibling design is powered to detect substantial within-family effects but not modest ones, so the within-family null is less informative than the substantial attenuation in the disability earnings gap once family fixed effects are introduced. The cohort analysis cannot directly extend the NLSY97 decomposition because the ACS lacks comparable skill measures, leaving the evolution of the skill component across cohorts unresolved.

The findings indicate that the disability earnings gap reflects both early-life inequality and ongoing labor market barriers, and that the relative weight of these channels varies by disability type and across the career. Closing it requires evidence we cannot generate from household survey data alone. Linked employer-employee data would identify whether the within-occupation widening reflects employer-side or worker-side mechanisms. Audit studies could test directly whether equal-skill workers face differential hiring and accommodation outcomes, and quasi-experimental variation in workplace accommodation requirements would isolate the causal effect of one specific labor-market margin. Within-firm dynamics for workers with mental conditions are where the marginal return to additional research appears highest, given both the persistence of the gap for this group and its disproportionate weight in current disability programs.

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Appendix D. Welfare and Fiscal Analysis

This appendix documents the inputs, sources, and arithmetic underlying the welfare and fiscal magnitudes reported in Section 8.

D.1 Population Aggregates

The working-age population reporting a disability is constructed from the U.S. Census Bureau, American Community Survey 2022 1-Year Public Use Microdata Sample (PUMS), restricted to the civilian non-institutionalized population aged 18 to 64. The disability indicator is $DIS = 1$, which equals one for any of six disability types (hearing, vision, cognitive, ambulatory, self-care, or independent living difficulty). Person weights are applied throughout. The 2022 ACS implies approximately 21.4 million working-age adults with a disability, consistent with BLS (2023), which reports that persons with a disability accounted for 12 percent of the civilian non-institutionalized population in 2022. The employment-population ratio for working-age adults with a disability was 34.8 percent in 2022, compared with 74.4 percent for those without a disability (BLS 2023, USDL-23-0351, Table A; Current Population Survey, ages 16 to 64). The population denominator of 21.4 million is from the ACS; the employment rate is from the CPS, which uses a similar but not identical disability definition. The implied employed working-age population with disabilities is approximately 7.5 million.

The composition of the working-age disability population by impairment type is constructed from the same ACS extract, with $DREM = 1$ identifying cognitive difficulty and combinations of $DPHY$, $DEAR$, $DEYE$, $DDRS$, and $DOUT$ identifying non-cognitive types. Workers with cognitive (mental) disability represent approximately 5.2 percent of the working-age population. The diagnostic-group composition of SSDI disabled-worker beneficiaries is reported in the Annual Statistical Report on the Social Security Disability Insurance Program (SSA 2023, Chart 6). For December 2022, mental disorders combined account for 28.8 percent of disabled-worker beneficiaries (12.7 percent depressive, bipolar, and related disorders; 3.8 percent intellectual disorders; 12.3 percent other mental disorders), with musculoskeletal disorders accounting for 34.1 percent, nervous system and sense organs for 10.0 percent, circulatory system for 7.6 percent, and

all other nonmental impairments for 19.4 percent. The implied overrepresentation ratio for mental disabilities is $28.8 / 5.2 \approx 5.5$, the largest of any disability category.

D.2 Per-Worker Earnings Gap in Dollar Terms

Mean earnings of workers with and without disabilities in our NLSY97 sample, reported in 2017 dollars in manuscript Table 2, are inflated to 2022 dollars using the BLS Consumer Price Index for All Urban Consumers (CPI-U) annual averages, with the 2022/2017 ratio of $292.655 / 245.120 \approx 1.194$. Mean earnings of workers without disabilities are \$40,589 in 2017 dollars, or \$48,463 in 2022 dollars; mean earnings of workers with disabilities are \$33,814 in 2017 dollars, or \$40,374 in 2022 dollars.

The per-worker dollar gap implied by a log-point coefficient β is computed as $(1 - \exp(\beta))$ multiplied by mean earnings of workers without disabilities in 2022 dollars. Applying this conversion to the four columns of manuscript Table 4, Panel A yields per-worker dollar gaps of \$10,963 (baseline, $\beta = -0.256$), \$8,790 (column 2, $\beta = -0.200$), \$7,328 (column 3, $\beta = -0.164$), and \$6,069 (column 4, $\beta = -0.134$). The mechanism-attributable per-worker contributions—obtained by differencing across columns—are \$2,173 for pre-market skills, \$1,462 for education beyond skills, \$1,259 for occupational sorting beyond education, and \$6,069 for the within-occupation residual.

D.3 Aggregate Annual Earnings Shortfall

The aggregate earnings shortfall is the per-worker dollar gap multiplied by the relevant population denominator. Under our preferred specification, which restricts attention to employed working-age adults with disabilities, the denominator is approximately 7.5 million and the baseline aggregate is approximately \$82 billion. The decomposition by mechanism, reported in manuscript Table 9, allocates approximately \$16 billion to pre-market skills, \$11 billion to education beyond skills, \$9 billion to occupational sorting beyond education, and \$45 billion to the within-occupation residual.

An alternative aggregation that applies the per-worker gap to the full working-age population reporting a disability—including those not currently employed—yields approximately \$235 billion. The choice of denominator is consequential and depends on the counterfactual being

considered. The employed-only base is appropriate for thinking about the gap as a wage penalty among employed workers; the all-working-age base captures the broader shortfall that includes implicit zero-earnings observations among those out of the labor force. We report both magnitudes and use the employed-only figure as the headline.

D.4 Foregone Tax Revenue

Tax revenue calculations rest on effective tax rates published by the Congressional Budget Office (CBO 2026). The middle-quintile household earnings range, in which workers with disabilities are concentrated, is subject to a comprehensive federal effective tax rate of approximately 14 percent in 2022, including individual income tax, payroll tax, and other federal taxes. Applied to the \$82 billion aggregate shortfall, the comprehensive federal rate yields approximately \$12 billion in foregone federal revenue. Decomposing the comprehensive rate into components yields an individual income tax rate of approximately 4.0 percent at the middle quintile and a combined employee-plus-employer payroll tax rate of 15.3 percent, which together imply approximately \$16 billion in federal foregone revenue. We use the higher figure as the headline because it makes the payroll-tax component explicit.

State and local effective tax rates for middle-income households average 10.5 percent (Institute on Taxation and Economic Policy 2024), which yields approximately \$8.6 billion in foregone state and local revenue. Combined foregone tax revenue is therefore approximately \$20 to \$24 billion. These figures are upper bounds because they assume the entire earnings shortfall would translate one-for-one into additional taxable income absent the gap. Behavioral responses to higher earnings, including labor supply changes and offsetting reductions in transfer income, would reduce the realized fiscal gain.

D.5 Federal Disability Program Expenditures

The DI Trust Fund paid \$143.6 billion in benefits in 2022, an increase of 2.5 percent over the \$140.1 billion paid in 2021 (SSA 2023, Highlights). In December 2022, 8.96 million people received Social Security disability benefits as disabled workers (7,604,098), disabled adult children (1,139,775), or disabled widow(er)s (211,301). Average monthly benefits were \$1,628

for male disabled workers and \$1,338 for female disabled workers. Disabled-worker beneficiaries aged 18 to 64 accounted for 3.9 percent of the U.S. population aged 18 to 64.

Total federally-administered SSI payments were \$55.8 billion in 2022, of which \$52.9 billion were federal payments. In December 2022, 7,542,222 people received federally-administered SSI payments, including 4,195,789 blind or disabled recipients aged 18 to 64. The working-age disabled portion of federal SSI payments is approximately \$31 billion, calculated as 55.6 percent of the \$55.8 billion total. SSDI plus the working-age portion of SSI together totaled approximately \$175 billion in 2022.

Disability-related Medicaid expenditures are larger still: federal and state Medicaid spending on disabled enrollees totaled approximately \$225 billion in fiscal year 2022 (CMS 2023). Decomposing this expenditure between costs that would be incurred regardless of labor-market participation and costs that depend on disability program enrollment is beyond the scope of our analysis.

D.6 Implied SSDI Savings

French and Song (2014) and Maestas, Mullen, and Strand (2013) provide direct elasticity estimates of 0.30 to 0.35 using examiner-assignment designs. Applied to the 23 percent earnings gap, these elasticities imply application reductions of 6.9 to 8.1 percent and savings of approximately \$10 to \$12 billion annually.

D.7 Combined Fiscal Stakes and Sensitivity

Under the most conservative inputs (employed-only denominator, CBO comprehensive federal rate, French-Song elasticity), the combined fiscal stakes are approximately \$25 billion. Under the all-working-age denominator with the same assumptions, combined fiscal stakes rise to approximately \$90 billion. The reasonable range is therefore \$25 to \$90 billion, with the headline central estimate of \$30 to \$35 billion.

D.8 ACS-Based Aggregate Earnings Shortfall

The NLSY97 coefficients used for the headline calculation reflect a single birth cohort observed during ages 23 to 40. Section 5 of the manuscript establishes that within-occupation

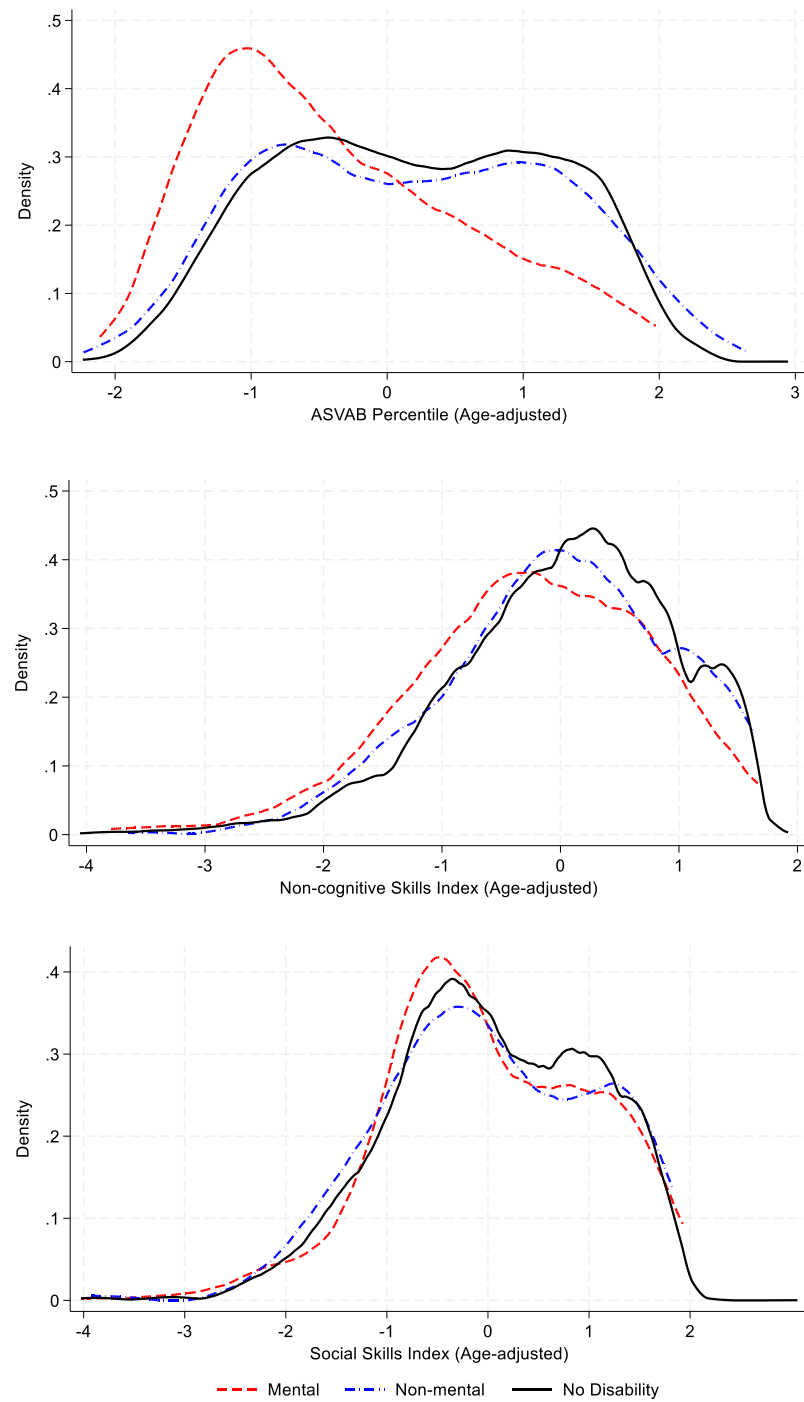
earnings gaps grow over careers, so NLSY97-based aggregates understate the lifetime gap. As a robustness exercise, we compute the aggregate using ACS earnings differentials directly, which capture older workers across the lifecycle. Restricting the ACS 2022 PUMS sample to civilian non-institutionalized adults aged 18 to 64 with positive wage and salary income, the raw earnings gap is approximately \$19,400 per worker in 2022 dollars. Conditioning on education narrows the gap to approximately \$15,300; and the fully adjusted gap conditional on both education and occupation is approximately \$12,300. Multiplying by 7.5 million employed workers with disabilities yields aggregate shortfalls in the \$92 to \$145 billion range, larger than the NLSY97-based estimate of \$82 billion but consistent with the lifecycle widening of within-occupation gaps documented in Section 5.

D.9 Section 14(c) Subminimum Wage Context

The U.S. Department of Labor (2024) reports that approximately 40,500 workers were employed under Section 14(c) certificates as of 2024, with a median hourly wage of \$3.50 and approximately 14 percent earning less than \$1.00 per hour (U.S. Government Accountability Office 2023).

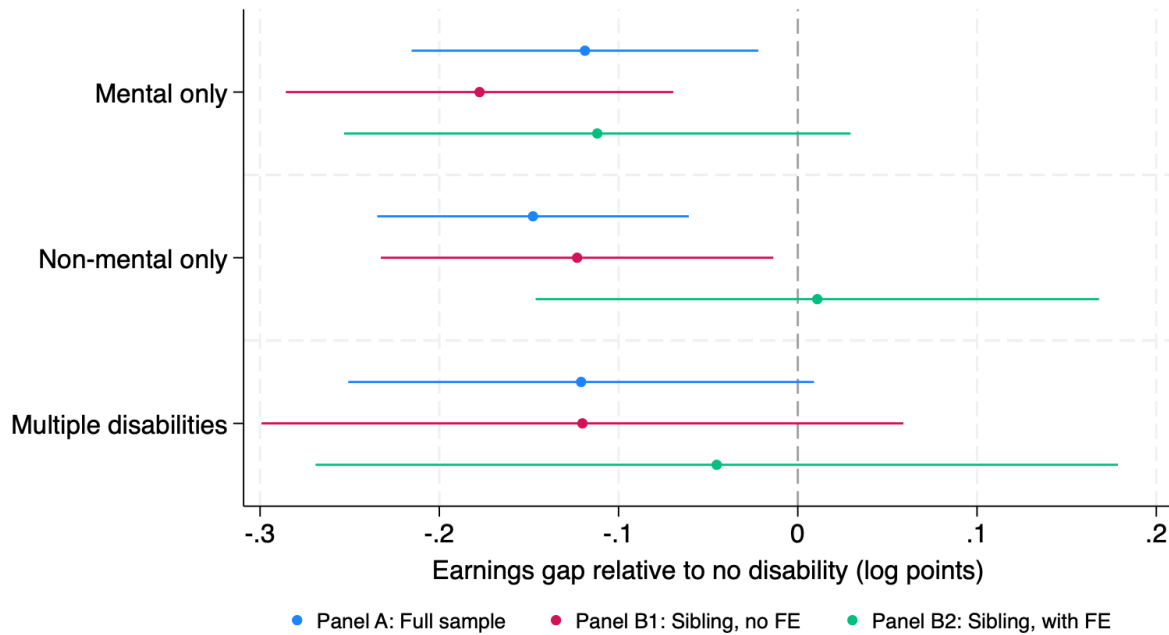
Figures

Figure 1: Distribution of skills for youths with and without disabilities in 1997



Notes: The above figures show the distribution of the corresponding skill proxy for youth with any mental disability, non-mental disability, and no disabilities (based on parents' reports in 1997) using NLSY97 data.

Figure 2: Estimates of the earnings disability gap by disability type (fully adjusted model; full results in Appendix Table C.5)



Notes: Estimates from fully adjusted model (demographics, premarket skills, education, occupation). 95% confidence intervals shown. SE clustered at individual level. Reference group: no limiting disability. Full results in Appendix Table 5.

Figure 3: Estimates of the earnings disability gap by gender (fully adjusted model; full results in Appendix Table C.6)

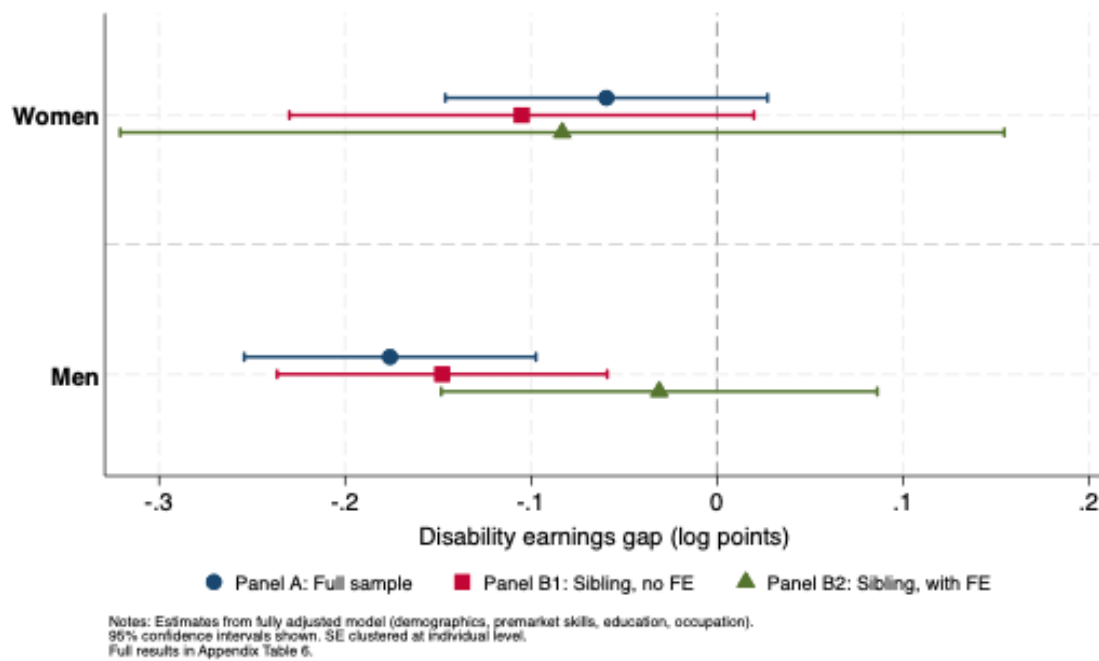


Figure 4: Estimates of the earnings disability gap by race/ethnicity (fully adjusted models; full estimates in Appendix Table C.7)

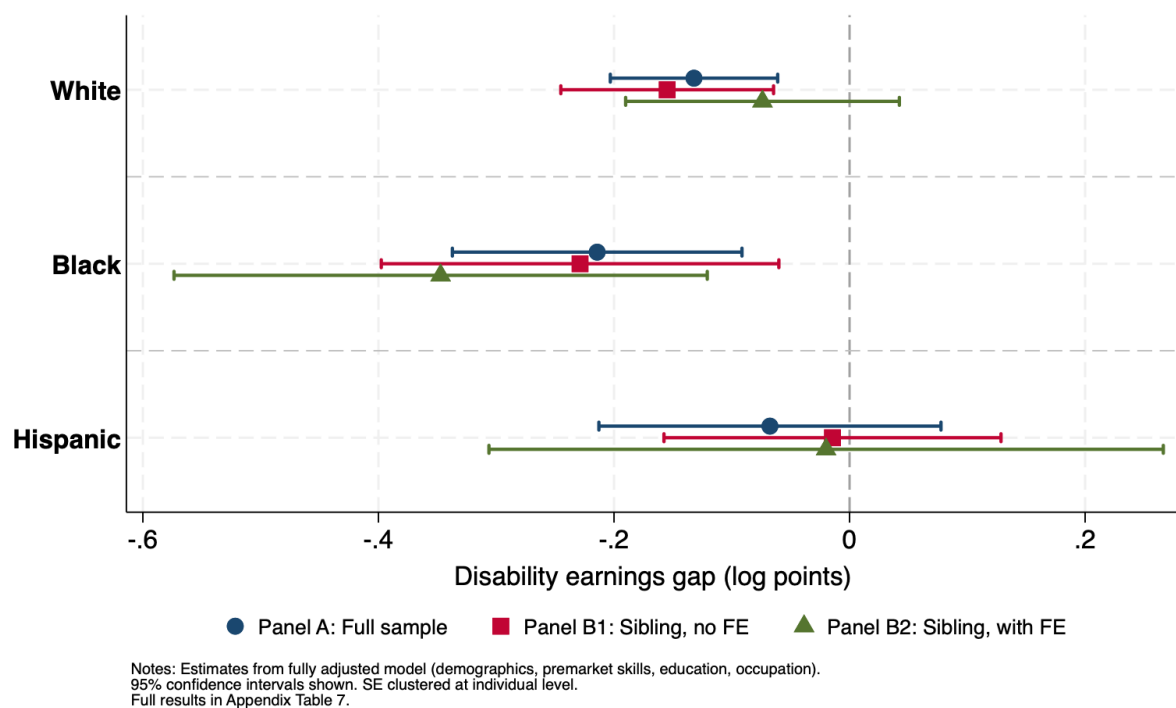
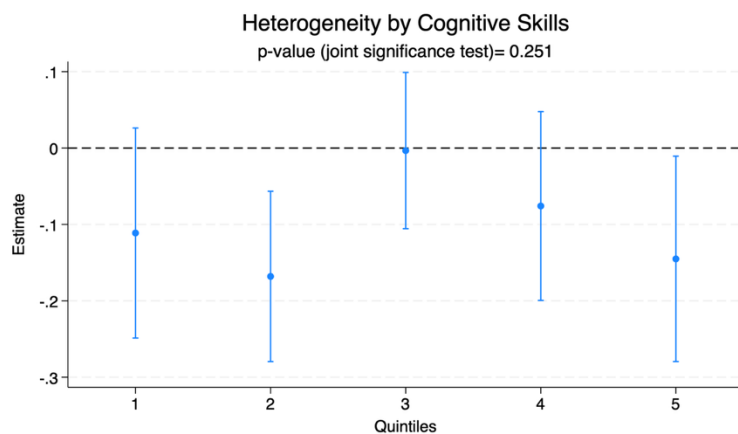
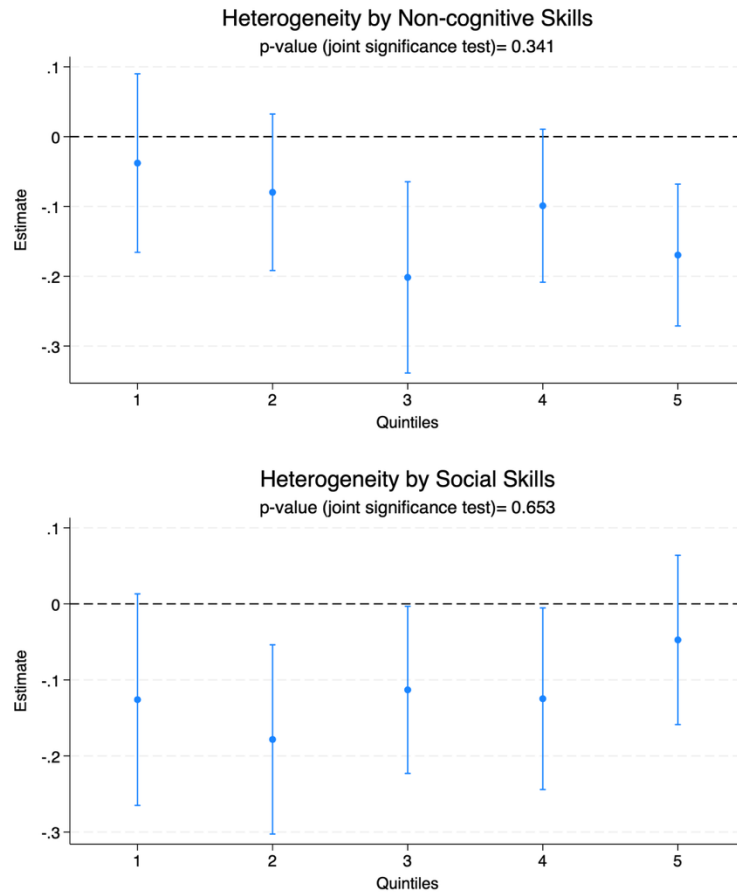


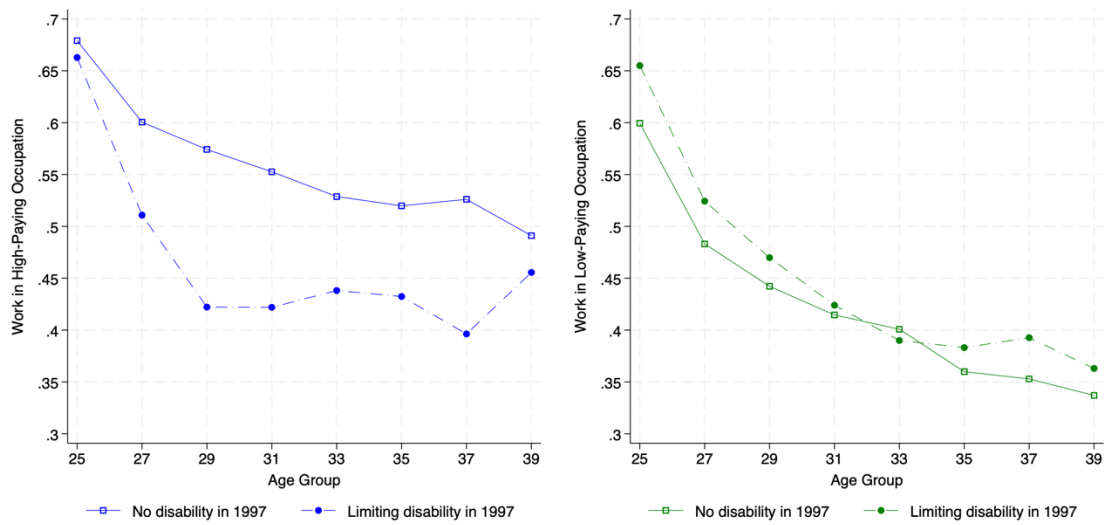
Figure 5: Estimates of the earnings disability gap by quintiles of the skill distribution





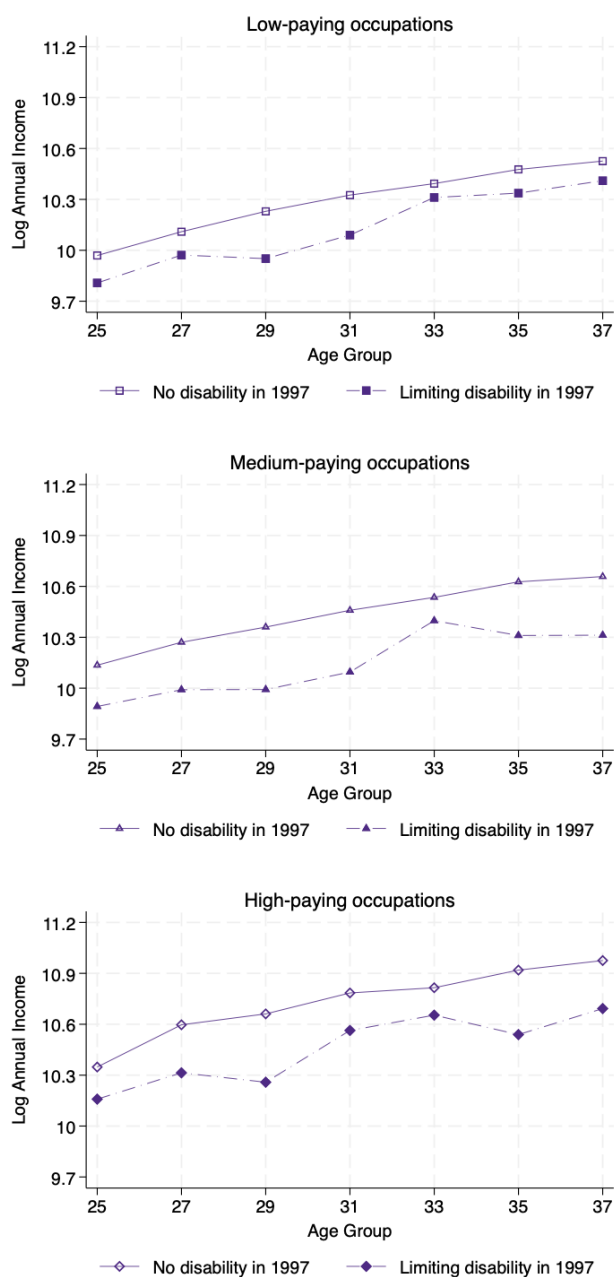
Notes: Each plot displays the earnings disability gap for each quintile of the corresponding skill distribution. We estimate Equation (3) and plot the coefficients β_q . Solid lines correspond to 95% confidence intervals. The reported p-value corresponds to a joint test of equality of all coefficients. See the main text for details.

Figure 6: Probability of working in a high-paying and low-paying occupation conditional on early occupational group



Notes: The figures above display the average probability of remaining employed in a high-paying occupation (on the left) or a low-paying occupation (on the right) at different ages, conditional on disability status in 1997 and the occupational category in which the worker was observed between ages 23-24. We group three-digit occupations into low-paying, medium-paying, and high-paying based on average earnings observed in the ACS. See the main text for details.

Figure 7: Earnings trajectories conditional on disability status in 1997 and initial occupational group



Notes: The figures above display average earnings at different ages, conditional on disability status in 1997 and the occupational category in which the worker was observed between ages 23-24. Solid lines represent earnings trajectories for workers without disabilities, while dashed lines display earnings trajectories for workers with disabilities. We group three-digit occupations into low-paying, medium-paying, and high-paying based on average earnings observed in the American Community Survey. See the main text for details.

Tables

Table 1: Questions on Physical and Mental Impairments in NLSY97

A. Round 1 Parent Questionnaire (1997)

Impairment	Question
Sensory	Does [this youth] now have or has [he/she] ever had trouble seeing, hearing, or speaking?
Chronic	Does [this youth] now have or has [he/she] ever had any other chronic health condition or life-threatening disease such as asthma, heart condition, anemia, diabetes or cancer?
Learning/Emotional	Does [this youth] now have or has [he/she] ever had a learning or emotional problem that limits or has limited the kind of schoolwork or other daily activities [he/she] can perform, the amount of time [he/she] can spend on these activities or [he/she] performance in these activities?
Physical	Does [this youth] now have or has [he/she] ever had a part of [his/her] body that [is/was] deformed or missing?

B. Rounds 6, 11-13 Youth Questionnaires (2002, 2007-2009)

Impairment	Question
Sensory	Have you ever had trouble seeing, hearing, or speaking?
Chronic	Have you been diagnosed with asthma, a heart condition, anemia, diabetes, cancer, epilepsy, HIV/AIDS, sexually transmitted disease other than HIV/AIDS, or other?
Learning/Emotional	Have you ever had an eating disorder, a learning or emotional problem or a mental condition that has limited your ability to attend school regularly, do regular school work, or work at a job for pay?
Physical	Have you ever had a part of your body that was deformed or missing?

Table 2: Summary statistics of the analytic sample by baseline disability status

	Any disability in 1997	No disability in 1997	Difference	P-value
A. Individual Level Characteristics				
Female	0.44	0.51	-0.08	0.000
Hispanic	0.14	0.20	-0.08	0.000
Black	0.25	0.27	-0.01	0.369
Years of education	13.1	14.3	-1.19	0.000
ASVAB score (percentile)	36.8	46.7	-10.7	0.000
Noncognitive skills (s.d.)	-0.12	0.01	-0.15	0.000
Social skills (s.d.)	-0.07	0.03	-0.09	0.022
Disability in 1997: Physical	0.04			
Disability in 1997: Chronic	0.33			
Disability in 1997: Sensory	0.33			
Disability in 1997: Mental	0.51			
More than one disability	0.19			
Congenital disability	0.11			
N	644	5,397		
B. Individual-Year Level Characteristics				
Employed	0.70	0.78	-0.07	0.000
Full-time employment	0.70	0.75	-0.05	0.000
Annual income (US\$2017)	33,814	40,589	-6,775	0.000
Hourly wage rate (US\$2017)	19.34	22.37	-3.03	0.000
Hourly compensation (US\$2017)	21.82	26.27	-4.45	0.000
Hours worked per week	37.85	38.48	-0.63	0.000
N	7,609	64,192		

Notes: This table presents summary statistics for our NLSY97 full sample by disability status as reported by parents in 1997. Panel A shows individual-level characteristics. Panel B describes labor market outcomes considering all person-year observations available between 1997 and 2021.

Table 3: Average skill differences between youth with and without disabilities by disability type

	All Disabled		Mental		Non-Mental	
	Difference	p-value	Difference	p-value	Difference	p-value
Cognitive Skills	-0.307	0.000	-0.580	0.000	-0.021	0.686
Non-cognitive Skills	-0.147	0.000	-0.257	0.000	-0.021	0.667
Index						
Social Skills Index	-0.035	0.346	-0.027	0.598	-0.030	0.559

Notes: This table shows the difference in means for each skill measure between each disability category and youth with no disabilities (based on parents' reports in 1997) using NLSY97 data. Estimates reported in bold indicate statistically significant differences at the 5% level.

Table 4: Estimates of the association between disability status in 1997 and annual income

	(1)	(2)	(3)	(4)
A. All sample				
Disability in 1997	-0.256*** (0.032)	-0.200*** (0.035)	-0.164*** (0.035)	-0.134*** (0.030)
N observations	53,920	42,158	41,791	40,474
N individuals	8,068	5,844	5,786	5,711
R-squared	0.14	0.18	0.21	0.33
B1. Siblings (no family FE)				
Disability in 1997	-0.225*** (0.044)	-0.177*** (0.048)	-0.141*** (0.046)	-0.143*** (0.037)
N observations	24,219	19,431	19,283	18,660
N individuals	3,624	2,690	2,666	2,629
N sibling families	1,818	1,448	1,444	1,438
R-squared	0.14	0.18	0.22	0.37
B2. Siblings (with family FE)				
Disability in 1997	-0.111** (0.049)	-0.054 (0.055)	-0.047 (0.055)	-0.053 (0.049)
N observations	24,178	19,406	19,257	18,633
N individuals	3,583	2,665	2,640	2,602
N sibling families	1,777	1,423	1,418	1,411
R-squared	0.44	0.46	0.47	0.55
Premarket Skills	No	Yes	Yes	Yes
Education	No	No	Yes	Yes
Occupation	No	No	No	Yes

Notes: Each column presents a different regression using data from the NLSY97. All regressions control for background characteristics, including race-by-gender, census regions, and urbanicity indicators. They also include age-level and year-level fixed effects. Education corresponds to a full set of indicators for years of education. Person-level weights were incorporated and standard errors (displayed in parenthesis) were clustered at the person-level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Estimates of the association between disability status in 1997 and educational attainment (fully adjusted model; full results in Appendix Table C.11)

	All Disability	Mental Disability	Non-Mental Disability
	(1)	(2)	(3)
A. All sample			
Disability in 1997	-0.579*** (0.117)	-0.723*** (0.160)	-0.429*** (0.159)
N observations	5,603	5,308	5,298
N individuals	5,603	5,308	5,298
R-squared	0.34	0.33	0.33
B1. Siblings (no family FE)			
Disability in 1997	-0.537*** (0.186)	-0.831*** (0.250)	-0.071 (0.257)
N observations	2,235	2,055	2,013
N individuals	2,235	2,055	2,013
N sibling families	1,048	965	947
R-squared	0.35	0.36	0.34
B2. Siblings (with family FE)			
Disability in 1997	0.051 (0.237)	-0.363 (0.341)	0.593* (0.306)
N observations	2,235	2,055	2,013
N individuals	2,235	2,055	2,013
N sibling families	1,048	965	947
R-squared	0.76	0.76	0.76
Premarket Skills	Yes	Yes	Yes
Education	Yes	Yes	Yes
Occupation	Yes	Yes	Yes

Notes: Each column presents a different regression using data from the NLSY97. All regressions control for background characteristics, including race-by-gender, census regions, and urbanicity indicators. Person-level weights were incorporated. Heteroskedasticity-robust standard errors are shown in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Estimates of the association between disability status in 1997 and occupational group (fully specified models; full results in Appendix Table C.12)

	Low-paying occupations	Medium-paying occupations	High-paying occupations
	(1)	(2)	(3)
A. All sample			
Disability in 1997	0.026 (0.022)	-0.011 (0.022)	-0.066*** (0.019)
N observations	5,548	5,548	5,548
N individuals	5,548	5,548	5,548
R-squared	0.06	0.02	0.18
B1. Siblings (no family FE)			
Disability in 1997	0.050 (0.034)	0.053 (0.036)	-0.057** (0.029)
N observations	2,178	2,178	2,178
N individuals	2,178	2,178	2,178
N sibling families	1,023	1,023	1,023
R-squared	0.08	0.03	0.20
B2. Siblings (with family FE)			
Disability in 1997	0.069 (0.053)	-0.009 (0.053)	-0.024 (0.043)
N observations	2,178	2,178	2,178
N individuals	2,178	2,178	2,178
N sibling families	1,023	1,023	1,023
R-squared	0.54	0.53	0.63
Premarket Skills	Yes	Yes	Yes
Education	Yes	Yes	Yes
Occupation	Yes	Yes	Yes

Notes: Each column presents a different regression using data from the NLSY97. All regressions control for background characteristics, including race-by-gender, census regions, and urbanicity indicators. Person-level weights were incorporated. Heteroskedasticity-robust standard errors are shown in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Average Differences in Annual Earnings and Hourly Wages by Initial Occupational Group.

	Log annual earnings			Log hourly wages		
	(1)	(2)	(3)	(4)	(5)	(6)
Disability in 1997 × low-paying early occupation	-0.174*** (0.046)	-0.121** (0.052)	-0.110** (0.051)	-0.103*** (0.026)	-0.054** (0.027)	-0.044* (0.026)
Disability in 1997 × medium-paying early occupation	-0.114* (0.065)	-0.120 (0.074)	-0.100 (0.073)	-0.040 (0.038)	-0.052 (0.042)	-0.043 (0.040)
Disability in 1997 × high-paying early occupation	-0.026 (0.075)	-0.057 (0.084)	-0.027 (0.085)	-0.080* (0.048)	-0.110** (0.050)	-0.080 (0.050)
Premarket Skills	No	Yes	Yes	No	Yes	Yes
Education	No	No	Yes	No	No	Yes
N	53,920	42,158	41,791	64,521	49,679	49,174
R-squared	0.17	0.20	0.22	0.18	0.21	0.24

Notes: Each column presents a different regression using data from the NLSY97. All regressions control for background characteristics, including race-by-gender, census regions, and urbanicity indicators. They also include age-level and year-level fixed effects. Person-level weights were incorporated and standard errors (displayed in parenthesis) were clustered at the person-level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Changes in the disability gap for annual earnings across birth cohorts (ACS).

	(1)	(2)	(3)	(4)	(5)	(6)
	Born before 1985		Born between 1985 and 1990		Born after 1990	
Any disability	-0.547*** (0.012)	-0.444*** (0.010)	-0.515*** (0.010)	-0.425*** (0.008)	-0.439*** (0.010)	-0.355*** (0.009)
Background	Yes	Yes	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes	Yes	Yes
Year and Age FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	No	Yes	No	Yes	No	Yes
N	1,140,434	1,140,434	1,605,067	1,605,067	1,617,832	1,617,832
R-squared	0.18	0.30	0.20	0.32	0.16	0.28

Notes: Each column presents a different regression using data from the American Community Survey 2008-2022 limiting the sample to individuals aged 23-33 years old. All regressions control for background characteristics, including race by gender, citizenship, English proficiency, and parenting indicators. They also include fixed effects for age, state, and year. Columns (2), (4), (6) incorporate a full set of three-digit occupation fixed effects. Education includes a full set of indicators using reported education attainment. Person-level weights were incorporated and standard errors (displayed in parenthesis) were clustered at the occupation-age level * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9. Aggregate Annual Earnings Shortfall Associated with the Disability Pay Gap

	Per-worker gap (2022\$)	Share of total gap	Aggregate shortfall (7.5M employed)
Baseline disability earnings gap	\$10,963	100%	\$82.2
<i>Attributable to:</i>			
Pre-market skills	\$2,173	19.8%	\$16.3
+ Education	\$1,462	13.3%	\$11.0
+ Occupational sorting	\$1,259	11.5%	\$9.4
Within-occupation residual	\$6,069	55.4%	\$45.5

Notes: Mechanism attributions computed from Table 4, Panel A. Per-worker dollar gap = $(1 - \exp(b)) \times \$48,463$, where \$48,463 is mean earnings of workers without disabilities in 2022 dollars (\$40,589 in 2017 dollars x CPI-U ratio 1.194). Employed working-age adults with disabilities: approximately 7.5 million (BLS 2023; ACS 2022). All dollar amounts in 2022 USD. Shares sum to 100% by construction.

Table 10. Foregone Tax Revenue Associated with the Disability Earnings Gap

Tax component	Effective rate	Foregone revenue
<i>Federal</i>		
Comprehensive effective rate (CBO 2026)	14.4%	~\$11.8B
Income tax + payroll tax, itemized (CBO 2026)	19.3%	~\$15.9B

(Individual income tax 4.0%; employee + employer payroll tax 15.3%)		
State and local (ITEP 2024)	10.5%	~\$8.6B
Combined: low estimate (federal comprehensive + state/local)		~\$20B
Combined: high estimate (federal itemized + state/local)		~\$24B

Notes: Calculations apply effective tax rates to the \$82.2 billion aggregate earnings shortfall for 7.5 million employed working-age adults with disabilities (Table 9). Federal effective tax rates for middle-quintile households from CBO (2026). State and local effective tax rate from ITEP (2024).

Table 11. Disability Category Composition of SSDI Disabled-Worker Beneficiaries and the Working-Age Population

Disability category	% SSDI beneficiaries	% Working-age population	Overrepresentation ratio
Mental disorders (total)	28.8%	5.5%	5.2×
Depressive, bipolar, and related disorders	12.7%	—	—
Intellectual disorders	3.8%	—	—
Other mental disorders	12.3%	—	—
Musculoskeletal disorders	34.1%	—	—
Nervous system and sense organs	10.0%	—	—
Circulatory system disorders	7.6%	—	—
All other non-mental impairments	19.4%	—	—
Total	100%	—	—
<i>SSDI disabled-worker beneficiaries (2022)</i>	<i>7.6 million</i>	<i>21.4 million working-age</i>	

Notes: SSDI beneficiary composition from SSA Annual Statistical Report on the Social Security Disability Insurance Program, Chart 6 (SSA 2023), December 2022 disabled-worker beneficiaries. Working-age population with cognitive (mental) disability from ACS 2022; all working-age adults with disability from BLS (2023).