Understanding the Aggregate Effects of Disability Insurance*

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Abstract

We study the aggregate consequences of the Social Security Disability Insurance (DI) program, focusing on the role of complementarity between heterogeneous human capital. First, we develop and estimate a wage process in which individuals' human capital comprises (pure) labor and experience, and their efficiencies are affected by disability. We find that older workers are more experience-abundant, and that disability causes a smaller loss in the efficiency of experience than it does in the efficiency of labor. Further, the estimated aggregate production technology shows that labor and experience are complementary inputs. Combining these empirical results with a structural general equilibrium model, we analyze the labor market implications of removing the DI program. Removal of the DI program induces an increase in the relative supply of experience, thus affecting the marginal productivities of inputs and wages of all workers in the economy. Despite the increased labor market entry of disabled workers, the aggregate productivity may increase in the counterfactual economy, thanks to the complementarity between labor and experience.

JEL Codes: J31, J24, E24, I18, I38
Keywords: disability insurance, labor supply, wage risk, skill complementarity, human capital

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1 Introduction

In 2019, approximately 10 million people in the United States benefited from the Social Security Disability Insurance (DI) program (Social Security Administration, 2020), and its growth is accelerating with the aging of the population.[1] Although DI serves as an important safety net against health risks, recent empirical studies (e.g, Maestas et al., 2013 and French and Song, 2014) have found that it suffers from considerable work disincentive effects. Given the large scale of the DI program, understanding the aggregate implications of the labor supply effects of DI is essential. This study addresses this question by evaluating the individual-level effects of disability on workers' productivities and combining the micro-level results with the structural model to measure the effects of DI on aggregate outcomes.

To assess the DI program, we need to measure the productivity of disabled workers, and how the loss of these workers impacts the labor market and aggregate production. Thus, we first estimate the productivity effects of disability on workers. Following the seminal paper of Katz and Murphy (1992) and expanding the work of Jeong et al. (2015), we assume that workers are endowed with two inputs: "(pure) labor" and "experience." Using the detailed micro-level data, we quantify how detrimental the severity of the disability is on the efficiencies of labor and experience, thereby identifying the sources of the low productivity (wage) of disabled workers. Then, we further exploit the time-series variations in the relative price and quantity of labor and experience to measure the substitutability between the two inputs in aggregate production. The modeling of these heterogeneous inputs helps measure both the direct productivity loss and the potential aggregate efficiency consequences from losing workers due to the DI program. Lastly, we use a general equilibrium life-cycle model of workers to evaluate the aggregate labor market effects of DI within our heterogeneous input model and to measure the value of the DI program for workers.

The micro-level estimation of disability effects on productivity uses data from the Panel Study of Income Dynamics (PSID), which contains work history (years of experience) and disability status information. Using the information on the binary indicator of work limitation and the extent to which it limits work, we categorize workers into three disability types: non-disabled, moderately disabled, and severely disabled. Then, using the hourly wage rate as a measure of productivity, we estimate the amounts of efficiency units of labor and experience of workers over the life-cycle and the effects of disability on these human capital after controlling for selection bias using Heckman's two-step procedure. We find that having a moderate (severe) disability lowers the workers' efficiency units of labor by around 27% (40%) and their efficiency units of experience by 4% (17%). That is, the worker's disability is less detrimental to the efficiency of experience

[1] According to Congressional Budget Office (2016), the total benefit payments for DI and Medicare for qualified beneficiaries exceeded $220 billion (5.8% of the federal budget) in 2015.

than that of labor. In conjunction with the fact that the experience is the primary source of human capital for older workers, this finding suggests that the amount of experience lost from the reduced labor market participation of older workers, the majority of DI recipients, might be considerable. Further, if these inputs are imperfectly substitutable in aggregate production, the changes in the relative supply of inputs can cause indirect effects through equilibrium factor prices. To capture the aggregate effect, we estimate the elasticity of substitution between the two inputs, assuming a constant elasticity of substitution (CES) production function. Exploiting the time-series variations in the relative supply and the relative price of experience, we find that labor and experience are gross complements with the elasticity of substitution of 0.40.

Next, we develop a general equilibrium model to quantify the aggregate impacts of the DI program incorporating the empirical findings. Finitely-lived individuals are subject to disability, survival, medical expenditures, and labor market risks. The individuals' disability status affects their survival probabilities, dynamics of future disability status, medical expenditures, preferences, and labor market productivities and opportunities, richly capturing its various impacts on workers. These workers make the endogenous labor supply and saving decisions, and, if disabled, they are allowed to apply to the DI program. Importantly, we model the key features of the DI program, including the application processes and the risks (e.g., acceptance, reassessment, and Medicare qualification) associated with the policy and other social insurance programs (e.g., unemployment insurance) that can affect worker decisions jointly with DI. We calibrate the model to match the life-cycle statistics of worker outcomes by disability statuses, given the estimated wage processes and aggregate production technology. Our model matches the targeted moments (e.g., employment rates and DI beneficiary shares) well and can generate empirically plausible estimates of labor supply elasticities and non-employment elasticities with respect to DI generosity that are not targeted.

Finally, we use the model to evaluate the impact of DI on aggregate outcomes. In the calibrated economy, the removal of the DI program increases the work incentives of all workers, with a more pronounced rise among old and disabled (both moderate and severe) workers. Thus, the relative supply of experience increases by 0.94%, accompanied by 0.53% higher price of labor and 1.80% lower price of experience. These changes in prices are important contributors to wage effects. At the individual level, young workers with abundant labor benefit thanks to the increased price of labor. Old workers benefit from the higher amounts of experience they accumulate in the counterfactual economy despite lower prices. In the aggregate, the employment rate increases by 3.25 percentage points (*pp*) and output by 2.88%.

To understand the role of the input complementarity, we conduct the no-DI counterfactual analysis in a recalibrated economy where labor and experience are perfect substitutes. We find that accounting for the complementarity between inputs is important for gauging the productivity effects of removing the DI program. Thanks to the complementarity between labor and experience and the relatively small detrimental effects of disability on experience, the entry of experience-abundant old workers induced by the removal of DI leads to a 0.08% increase in aggregate productivity (output per hour). This contrasts with the negative productivity effect (–0.03%) of DI removal under the assumption of perfectly substitutable inputs. This finding suggests that disabled (old) workers provide valuable human capital in the labor market, thereby also impacting young workers' productivities.

Lastly, we measure the value of DI to workers. An unexpected temporary (one-period) removal of the DI program generates an overall welfare loss equivalent to 0.65% of the consumption in the benchmark economy with DI. The value of DI is negligible in the early 20s but increases with age, reaching 4% (12%) of consumption for the moderately (severely) disabled in the 60s. While the valuation of DI varies widely across demographic and labor market statuses, ex-ante, workers of all disability types value the DI program.

Overall, our findings can be summarized as follows. First, we find that disability is less detrimental to the efficiency of experience than it is to the efficiency of labor, thereby limiting the productivity losses of old, disabled workers. Second, because of input complementarity, DI impacts the labor market's input composition and their efficiencies, affecting wages of all workers in the economy. Lastly, due to the interaction between inputs, a reduction in the DI program may increase the aggregate productivity (output per hour) of the workforce, whereas an abstraction from this channel would imply a decrease in aggregate productivity. These findings underscore the importance of incorporating heterogeneous human capital of the workforce and their interactions in evaluating and reforming the DI program.

Related Literature Our work is related to several strands of literature studying the role of heterogeneous inputs in production and their interactions in the labor market; the disincentive effects of DI on labor supply; and the effects of social insurance policies in structural models with heterogeneous agents.

First, we build on the literature that studies heterogeneous inputs in production. Similar to the previous literature (e.g., Card and Lemieux, 2001; Krusell et al., 2000; Karabarbounis and Neiman, 2014), we estimate the degree of substitutability across heterogeneous inputs in production using empirical data, assuming a CES production function.[2] In terms of methodology, we are most closely related to Jeong et al. (2015), who extends the work of Katz and Murphy (1992) to estimate the amount of labor and experience, which

[2] Card and Lemieux (2001) uses a CES production function with labor inputs from different skill and age to explain college premium; Krusell et al. (2000) shows that capital-skill complementarity can explain the rise of skilled labor and the skill premium; and Karabarbounis and Neiman (2014) estimates the elasticity of substitution between information technology and labor to explain the decline of the labor share. There are also a few empirical studies that find that young and old workers are complementary in production (e.g., Gruber and Milligan, 2010; Munnell and Wu, 2012). Among them, Munnell and Wu (2012) finds that an increase in employment rate of the old leads to higher employment rate of prime-aged workers.

are two distinct inputs (human capital) a worker is endowed with. They use work experience data along with individual-level characteristics from the PSID. We expand their wage process to estimate the impact of disability on labor and experience over the life cycle after controlling for selection bias.

Second, this paper builds on and expands the studies of the labor supply disincentive effects of DI, which has long been a topic of interest, starting with Bound (1989). Maestas et al. (2013) and French and Song (2014) use random assignments of disability examiners and judges to estimate the disincentive effects of DI on the labor supply of workers, and find substantial disincentive effects.[3] Although these papers use econometric approaches to study individual behavior, Kitao (2014), Low and Pistaferri (2015), and Autor et al. (2019) are among the few who develop life-cycle models to analyze the effects of DI. In particular, Kitao (2014) focuses on the interaction between DI and unemployment insurance, whereas Low and Pistaferri (2015) focuses on the incentive and insurance trade-off that individual workers face. Meanwhile, Autor et al. (2019) evaluates welfare effects of DI by explicitly incorporating household structures and finds that spousal labor supply serves as an important insurance against disability. This paper is distinct from theirs in two dimensions. First, most analyses on disability assume that a worker's human capital is one-dimensional, whereas we explicitly model and estimate the effects of disability on heterogeneous human capital endowments of workers. Thus, our analysis provides an understanding of the sources of the productivity losses that disabled workers face, and how these effects might differ over the life cycle. Second, we further use these micro-level findings and incorporate the interactions between inputs in aggregate production to evaluate the DI program.

Finally, this paper contributes to the broad literature analyzing the effects of social insurance policies, especially concerning health or medical expense risks (e.g., Hubbard et al., 1995; Attanasio et al., 2011; Pashchenko and Porapakkarm, 2017; De Nardi et al., 2018). Some recent papers in the literature include De Nardi et al. (2016) and Braun et al. (2017). Both studies analyze the role of social insurance policies for the old and measure the welfare gains from the policies in the presence of health and medical expenditure risks. Hosseini et al. (2020) studies the role of health risks in accounting for lifetime earnings inequality and finds that DI is an important contributing factor, as it prompts the labor market exit of workers with poor health. We find that when the DI program is removed, workers with disabilities experience a larger increase in their income than non-disabled workers, consistent with their finding. Our study complements these studies by focusing on the role of DI and its aggregate labor market implications.

[3] Maestas et al. (2013) shows that for marginal applicants, the employment rate would have been 28*pp* higher in the absence of the DI program, using the data on behaviors of rejected DI applicants. Similarly, French and Song (2014) also finds that benefit receipt reduced participation rate by 26*pp* three years after the decision. While the focus is different, Low and Pistaferri (2020) uses administrative data to explore broader aspects of the institutional features of the DI program, and finds systematically higher false rejection rates against female applicants during the screening process.

The organization of the paper is as follows. Section 2 outlines our empirical estimation of productivities of workers with different disability statuses and the elasticity of substitution between labor and experience. Section 3 develops a general equilibrium model with DI, which serves as a laboratory for evaluating DI. Section 4 discusses the calibration of the model and its validity. Section 5 uses the calibrated model to conduct counterfactual analyses. Finally, Section 6 concludes.

2 Empirical Analysis

In this section, we estimate the effects of disability on workers' productivities and the degree of complementarity between inputs in aggregate production, using the PSID as our main data source. The detailed data selection process and construction of the variables are described in Appendix A.

2.1 Wage Equation

We consider that workers provide two distinctive inputs—(pure) labor and experience—and empirically examine the relationship between disability and factor productivities. Labor is physical effort or abilities, and experience represents human capital accumulated from participating in labor markets. These concepts correspond to "pure labor" and "pure experience" in the seminal paper of Katz and Murphy (1992), who modeled them as separate inputs exclusively supplied by "young" and "old."

Our wage equation incorporates the disability effects on wages, extending that of Jeong et al. (2015), who generalized the work of Katz and Murphy (1992) to allow all workers to supply a bundle of labor and experience. Through the lens of Jeong et al. (2015), the hourly wage rate (or productivity) of a worker is determined by endowed human capital—labor $\hat{l}$ and experience $\hat{e}$—and their prices R_L and R_E: $w = R_L\hat{l} + R_E\hat{e}$.

We denote the endowed units of labor ($\hat{l}$) for an individual with age j and disability status h as $\lambda_L(j, h)$. Unlike this deterministic life-cycle profile of labor, the amount of experience ($\hat{e}$) can vary within the same demographics as workers may have different employment histories over time. Therefore, we consider that the total amount of experience (in efficiency units) is a product of both the deterministic component $\lambda_E(j, h)$ and a function of a worker's endogenously accumulated work experience $g(e)$. We can interpret that the life-cycle profile $\lambda_E(j, h)$ represents how effectively an individual uses his experience, and the quantity of accumulated experience is captured by the term $g(e)$, a function of the worker's actual years of work e.

Using these notations, the hourly wage rate of a worker with age j and disability status h can be rewritten as

$$w(j,h,e) \quad = \quad R_L \lambda_L(j,h) + R_E \lambda_E(j,h)\, g(e)\,. \tag{1}$$

For specifying the efficiency schedules in Equation (1), we follow the functional form choices of Jeong et al. (2015). The deterministic components of labor and experience are approximated by polynomial functions of age j: $\tilde{\lambda}_X(j) = \exp\left(\lambda_{X,0} + \lambda_{X,1} j + \lambda_{X,2} j^2\right)$ with $X = L$ and E. Further, we incorporate disability effects on labor and experience profiles by including a scaling factor $\phi_X(h)$, so that $\lambda_X(j,h) = \phi_X(h)\,\tilde{\lambda}_X(j)$ for $X = L, E$. Thus, in our implementation, disability proportionately affects the factor profiles. Given the functional form assumptions, the relative efficiency of experience compared to labor is given as $\tilde{\lambda}_E(j)/\tilde{\lambda}_L(j) = \exp\left(\lambda_{E/L,0} + \lambda_{E/L,1} j + \lambda_{E/L,2} j^2\right)$, where $\lambda_{E/L,k} \equiv \lambda_{E,k} - \lambda_{L,k}$ for $k \in \{0,1,2\}$. Moreover, an individual's accumulated experience is determined by $g(e) = e + \zeta_1 e^2 + \zeta_2 e^3 + \zeta_3 e^4$, allowing for possible non-linear effects of years worked on the accumulated experience.[4]

In the empirical estimation, we allow the coefficients of deterministic components to depend on education and disability status. We categorize workers into two education groups, $s_{it} \in \{HS, Col\}$: high school (HS) graduate or less and some college or more (Col). For disability status, we use three groups, $h_{it} \in \{ND, MD, SD\}$. Using the binary variable on work limitation and its extent of limitation, individuals without a work-limiting disability are denoted non-disabled (ND), and those with a work-limiting disability that limits the amount of work "somewhat" or "just a little" are moderately disabled (MD). Meanwhile, if work is limited "completely" or "a lot", they are categorized as severely disabled (SD). Thus, the coefficients are denoted as $\lambda_{X,k}(s_{it})$ and $\phi_X(s_{it}, h_{it})$ for $X \in \{L, E\}$ and $k \in \{0,1,2\}$.

We can rewrite Equation (1) as $w(j,h,e) = R_L \lambda_L(j,h)\left[1 + \Pi_E \cdot \frac{\lambda_E(j,h)}{\lambda_L(j,h)} g(e)\right]$, where $\Pi_E \equiv R_E/R_L$ represents the relative price of experience. Our estimating log-wage equation is

$$\begin{aligned} \ln w_{it} \quad = \quad & d_t + \ln \phi_L(s_{it}, h_{it}) + \left\{\lambda_{L,0}(s_{it}) + \lambda_{L,1}(s_{it})\, j_{it} + \lambda_{L,2}(s_{it})\, j_{it}^2\right\} \\ & + \ln\left[1 + \Pi_{E_t} \frac{\phi_E(s_{it}, h_{it})}{\phi_L(s_{it}, h_{it})} \exp\left(\lambda_{E/L,0}(s_{it}) + \lambda_{E/L,1}(s_{it})\, j_{it} + \lambda_{E/L,2}(s_{it})\, j_{it}^2\right)\right. \\ & \left. \times \left(e_{it} + \zeta_1 e_{it}^2 + \zeta_2 e_{it}^3 + \zeta_3 e_{it}^4\right)\right] + \boldsymbol{\beta} \boldsymbol{X}_{it} + \varepsilon_{it}, \end{aligned} \tag{2}$$

where we replace $\ln R_{L_t}$ with a year-dummy variable d_t, control for individual-level characteristics $\boldsymbol{X}_{it}$, and add a classical measurement error ε_{it}. The individual-level characteristics include region and time-

[4] We construct prior years of work e from the PSID. An individual gains a year of experience if his annual working hours exceed 2000 hours. We describe the detailed data construction process in Appendix A.

specific dummies for college degree, gender, and race. We normalize $\lambda_{L,0}(HS) = \lambda_{E,0}(HS) = 1$ and $\phi_L(s_{it}, ND) = \phi_E(s_{it,}ND) = 1$. Thus, the coefficients $\phi_X(s_{it}, MD)$ and $\phi_X(s_{it}, SD)$, $X \in \{L, E\}$ measure the relative efficiency of human capital supplied by moderately and severely disabled workers compared with non-disabled workers within the same education group.[5]

2.2 Selection Bias and Identification Strategy

One challenge in estimating Equation (2) is that we only observe employed individuals' wages; these workers, especially those who are participating in the labor market despite their disabilities, may systematically differ from non-employed disabled individuals. Therefore, the estimated effects of disability on labor and experience can be biased if we do not correct this potential selection bias.

We address this concern by estimating the wage equation using a standard two-stage procedure described by Heckman (1979). We first estimate the underlying participation decision using a probit model with instrument variables, and then, we estimate the wage equation with the inverse Mills' ratio from the first stage. In line with the idea of simulated IV in public economics (as in Currie and Gruber, 1996a,b and Low and Pistaferri, 2015), we exploit the spatial and time variation of public policies as our first-stage instruments. Specifically, we construct the generosity measures of welfare programs and tax systems by simulating potential transfers and taxes that a "representative" earner would receive from his residential state and year. The generosity of public policies varies by state and year, thus generating heterogeneity in the labor force participation incentives of the representative earner.

Note that both the transfers and taxes are computed for a representative earner, not for each individual using his own characteristics. Indeed, having actual benefits would be inappropriate due to their endogenous relation with wages. With simulated potential transfers, we capture the effects of public policies on labor supply decisions, independent from individual characteristics. Still, to be valid, our identification strategy relies on two assumptions: the policy variations are not systematically related to labor market conditions, and the potential benefits affect individuals' labor market participation decisions but not their wage rates.

For constructing transfers from welfare programs, we use the Earned Income Tax Credit, Unemployment Insurance, the Supplemental Nutrition Assistance Program, and Aid to Families with Dependent Children, which later became Temporary Assistance for Needy Families. Meanwhile, for tax credits, we supplement the PSID data with the Survey of Consumer Finances, which provides rich information on individuals'

[5]Although we estimate the impact of disability on productivity of labor and experience, we do not estimate the full wage processes that include productivity risks as does Low and Pistaferri (2015). However, when we use the wage processes for the structural model, we take as variance of the iid productivity shock, the data-implied residual variances that depend on the disability status of the worker.

financial status, such as mortgage interest payments. Including this information helps us generate a more reliable measure of taxable income, as we can better approximate tax liabilities and credits such as mortgage deductions. Using the predicted taxable income of representative earners, we simulate their taxes using the NBER TAXSIM v.27.[6] Further details of the variable construction and estimation are documented in Appendix B.1.

2.3 Estimation Results

The First-Stage Probit Regression. In the first-stage, we estimate a probit model of labor market participation decision using the entire working-age sample in the data. The independent variables include standard controls for individual characteristics and the two instrumental variables interacted with disability status.[7] Table 1 presents the results from the first-stage probit regression. We observe that a disability has a significant impact on employment probability; for an otherwise-average individual, having a moderate (severe) disability lowers his employment probability by 14.8pp (39.5pp). The averages of marginal effects on employment are 12.4 and 33.2pp for moderately and severely disabled workers, respectively.

Table 1: First-Stage Probit Regression Results

Independent Variables	Coefficients	Effects on Probability of Employment	
		Marginal Effects at the Means	Average Marginal Effects
Moderate Disability	−0.513 (0.036)	−0.148 (0.101)	−0.124 (0.008)
Severe Disability	−1.392 (0.050)	−0.395 (0.014)	−0.332 (0.012)
Number of Obs.	101,335	Pseudo R^2	0.237

Note: Table 1 reports the first-stage probit regression results of Heckman's two-stage estimation for selection correction. The dependent variable is employment status, and the independent variables include individual characteristics (i.e., age, experience, years of schooling, male, race, marital status, state, and time-varying year dummies). We use state- and year-specific amounts of potential transfers and taxes as exclusion restrictions. Individual-level survey weights are used, and standard errors clustered at the individual level are reported in parentheses. The complete list of estimated coefficients is reported in Appendix B.1.

The Role of Disability on Labor and Experience. We now estimate the nonlinear wage equation (Equation (2)), controlling for selection bias. Table 2 reports the estimated coefficients of the wage profile. Based on these estimates, we illustrate the age-efficiency profiles of labor ($\lambda_L(s,j,h)$) and experience ($\lambda_E(s,j,h)$) for high school graduates by disability status in Figure 1.[8] As shown in Figure 1(a), the efficiency units of labor are hump-shaped over the life cycle, peaking in the mid-40s. Meanwhile, their

[6] See Feenberg and Coutts (1993) and http://www.nber.org/taxsim/ for more information regarding the NBER TAXSIM.

[7] Thus, we use a total of six variables to instrument for the labor supply decision estimation. We conduct an over-identification test with the standard linear wage equation and find that the exclusion restriction holds (J-test is not rejected), as detailed in Appendix B.1.

[8] We show the corresponding profiles for college graduates in Appendix B.2 for brevity in the main text.

Table 2: Estimated Coefficients of Wage Profile

		(a) Labor		(b) Experience	(c) Accumulated Experience $g(e)$	
High School	$\lambda_{L,1}$	0.0213 (0.0052)	$\lambda_{E,1}$	0.0034 (0.0142)	ζ_2	-0.0491 (0.0081)
	$\lambda_{L,2}$	-0.0004 (0.0001)	$\lambda_{E,2}$	-0.0002 (0.0003)	ζ_3	0.0013 (0.0004)
College	$\lambda_{L,0}$	-0.2482 (0.0551)	$\lambda_{E,0}$	-0.3814 (0.1826)	ζ_4	-0.00001 (0.0000)
	$\lambda_{L,1}$	0.0534 (0.0056)	$\lambda_{E,1}$	0.0067 (0.0188)	(d) Inverse Mills Ratio	
	$\lambda_{L,2}$	-0.0010 (0.0001)	$\lambda_{E,2}$	-0.0002 (0.0004)	0.2463 (0.0903)	

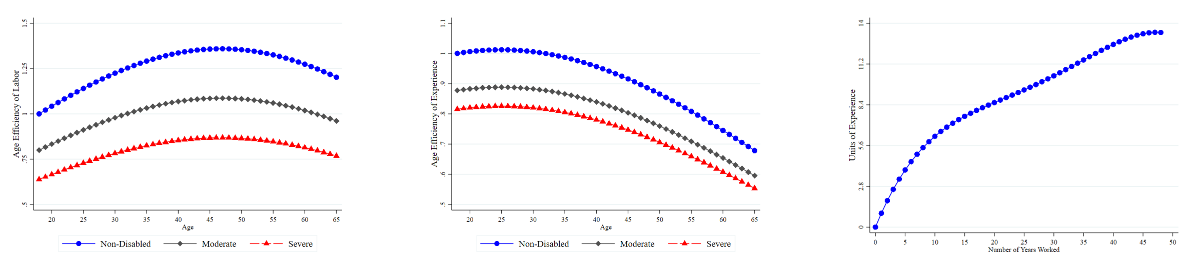
		(e) Disability		(f) Implied Disability Effects	
		$\ln \phi_L(s,h)$	$\phi_E(s,h)/\phi_L(s,h)$	Labor	Experience
High School	Mod.	-0.2238 (0.0691)	1.0977 (0.1828)	0.7994	0.8776
	Sev.	-0.4482 (0.1769)	1.2773 (0.4544)	0.6388	0.8159
College	Mod.	-0.4100 (0.0690)	1.5743 (0.2672)	0.6637	1.0448
	Sev.	-0.5839 (0.1553)	1.5182 (0.5394)	0.5577	0.8471

Note: Table 2 reports the coefficient estimation results of the nonlinear wage process in Equation (2). The control variables include region and year-specific dummy variables for gender, race, and schooling (college). We use individual-level survey weights, and standard errors clustered at the individual level are reported in parentheses. The total number of observations is 83,476. Appendix B.2 reports the complete list of estimated coefficients and the estimated wage profiles by education and disability status and their data counterparts.

experience profile (Figure 1(b)) is downward-sloping, implying that one unit of experience at an early age is more valuable than at a later age. Although the age-efficiency profile of experience decreases over the life cycle, this does not necessarily mean that the worker's effective experience ($\lambda_E \cdot g(e)$) declines as they age. This is because accumulated experience $g(e)$ increases along with years of employment (Figure 1(c)).

Figure 1: Efficiency of Human Capital Over the Life Cycle, High School Graduates

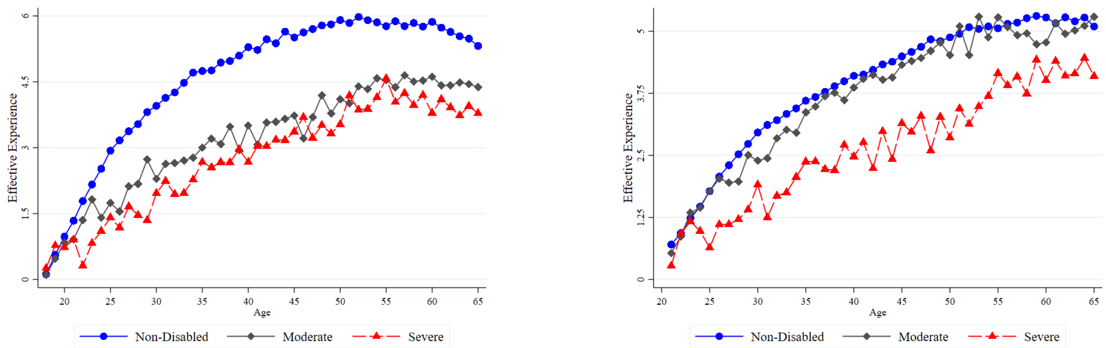
(a): Labor Efficiency, λ_L (b): Experience Efficiency, λ_E (c): Accumulated Experience, $g(e)$



Modeling heterogeneous human capital, we can uncover the sources of productivity losses due to disability. In part (f) in Table 2, we report the implied effects of disability from the estimated coefficients. We find that disability is relatively less detrimental to efficiency units of experience than that of labor. For high school graduates, the efficiency of labor is 20% (36%) lower for moderately (severely) disabled workers compared with their non-disabled counterparts, whereas the efficiency of experience of moderately (severely) disabled workers is 12% (18%) lower than that of non-disabled workers. Meanwhile, the signifi-

Figure 2: Empirical Average of Efficiency Units of Experience by Education

(a): $\lambda_E \cdot g(e)$, High School (b): $\lambda_E \cdot g(e)$, College



cant decline in wage for college-educated workers is driven by the loss in labor efficiency of 34% (44%) for moderately (severely) disabled workers. However, the per-unit efficiency of experience of moderately disabled workers is not necessarily lower than that of non-disabled workers: the estimated coefficient implies a 4% higher efficiency in experience. Similarly, the efficiency effect on the experience of a severe disability is smaller than the effect on labor at 15%.

Figure 2 presents the empirical average of the estimated effective experience $\lambda_E(s, j, h)\, g(e)$, which is determined by both the per efficiency unit effects (λ_E) and the accumulated experience effects ($g(e)$). As shown in Figure 2(b), for college-educated workers, moderately disabled and non-disabled workers have similar amounts of effective experience. This reflects the similar per-unit efficiency in experience between the two groups and higher accumulated experience by non-disabled workers. For low-educated workers, moderately disabled workers' effective experience profiles are similar to those of severely disabled workers, reflecting the similar age-efficiency profile (λ_E) between the two groups relative to non-disabled workers.[9]

The main findings from this wage estimation are, first, a disability impacts the efficiency of both labor and experience and, second, the effect is larger on labor than on experience. Accounting for these heterogeneous effects of disability is important in understanding the sources of the loss in productivity of disabled workers and the potential interaction between workers who exit the labor force and those who stay. For the latter, we now estimate the aggregate production function with labor and experience as inputs.

[9] In Appendix B.2, we report the estimated disability effects without controlling for selection, showing its impact on correctly estimating disability effects. Further, in Appendix B.3, we provide results of robustness analyses that include allowing for education dependence in $g(e)$ and using alternative clustering assumptions in testing for the significance of coefficients. We find that the magnitudes of disability estimates do not vary much with respect to these alternative specifications and are significant at 1% level.

Figure 3: Relative Price and Supply of Experience

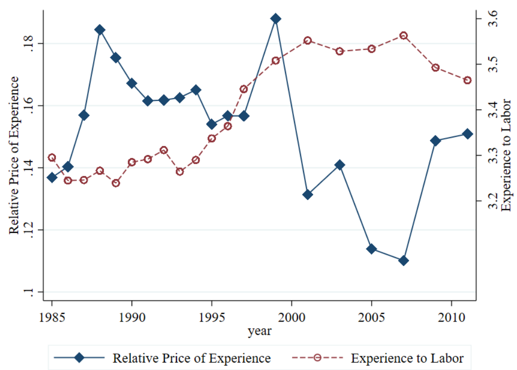


Table 3: Parameter Estimates

Parameters	Coefficient
ρ	-1.5218
	(0.0107)
$\ln\theta$	1.1150
	(0.0129)
Time periods	1985 to 2011
Adjusted R^2	0.3521

2.4 The Elasticity of Substitution between Labor and Experience

We use the time-series variations in the estimated relative supply and price with the parametric assumption to identify the aggregate production function parameters. In the aggregate economy, a representative firm has access to a production technology specified as $Y_t = A_t F(L_t, E_t) = A_t \left(L_t^\rho + \theta E_t^\rho\right)^{1/\rho}$.[10] This function features constant elasticity of substitution (CES) between labor L and experience E, with elasticity of substitution $(1-\rho)^{-1}$. The parameter A_t represents the economy's productivity at time t, and θ is the relative efficiency of E. Under the assumption of competitive factor markets, the factor price is equivalent to its marginal productivity, and the relative price of experience is $\Pi_{E,t} \equiv F_{E,t}/F_{L,t}$.

We construct the total amount of labor and experience in efficiency units based on the wage estimation results from Section 2.3, along with the estimated relative price of experience. Using the observed working hours in the PSID, we obtain aggregate quantities of labor and experience in efficiency units: $\hat{L}_t = \sum_i \hat{\lambda}_L(s,j,h) \cdot \text{hours}_{it}$ and $\hat{E}_t = \sum_i \hat{\lambda}_E(s,j,h)\,\hat{g}(e_{it}) \cdot \text{hours}_{it}$. Figure 3 illustrates the evolution of these two time-series variables: the relative supply of experience to labor ($\hat{E}_t/\hat{L}_t$) and the relative price of experience ($\hat{\Pi}_{E,t}$) from 1985 to 2011.

We then use this data to estimate the two production technology parameters. From $\Pi_{E,t} = \theta\left(\frac{E_t}{L_t}\right)^{\rho-1}$, we have $\ln \Pi_{E,t} = \ln\theta + (\rho-1)\ln(E_t/L_t)$. Therefore, a linear regression using the aggregate time-series data of relative price and quantity delivers the values for θ and ρ (Table 3). We find that the elasticity of

[10] Although this production function is parsimonious, it captures the interaction between heterogeneous human capital, which is the main focus of our paper. Within this production function, we take into account the worker differences by education, by allowing for education-dependent coefficients on labor and experience in individual-level wage estimation procedure. We then aggregate the individual-level labor and experience to construct L and E. However, we do not directly model the potential interaction between workers of low and high education. We could, for example, extend the production function to features CES between workers of high and low education as well as between labor and experience, with more aggregate parameters to be estimated. We also abstract from the role of capital in aggregate production, but our identification strategy can be expanded to more generalized production functions with capital, such as the Cobb-Douglas in capital and composite labor ($Y = K^\alpha\left(\left(L^\rho + \theta E^\rho\right)^{1/\rho}\right)^{1-\alpha}$). We view the benchmark specification as a reasonable starting point.

substitution between the two inputs is 0.40, suggesting that labor and experience are complementary in production. This implies that any policy that impacts the relative supply of inputs has consequences on their marginal productivities. Our goal in the next section is to use a structural general equilibrium model to evaluate the aggregate consequences of DI, incorporating heterogeneous inputs and their complementarities in production.

3 The Model

We construct a stochastic life-cycle general equilibrium model of labor supply and savings, with agents subject to disability and labor market risks. Our model framework extends those used in studies of disability, labor supply, and social insurance programs (e.g., French, 2005; Kitao, 2014) by incorporating the interaction of heterogeneous inputs in the labor market as described in Section 2. We further capture the key features of the DI program similarly to Low and Pistaferri (2015).

3.1 The Model Environment

Demographics, Endowments, and Preferences. Time is discrete, and a model period is a year. Each individual starts his life at age $j = 1$ with a pre-determined education level. For brevity, we abstract from education-dependence in this section but allow for education-dependence in various parameters in the quantitative implementation of the model. All individuals retire at the mandatory retirement age j^R and live until at most age J, at which time assets of the deceased are distributed equally to all surviving members of the economy as an accidental bequest, beq.

An individual's disability status h is either non-disabled (ND), moderately disabled (MD) or severely disabled (SD), and it evolves following an age j-specific Markov chain, $\pi_j^{ab} = \mathbf{Pr}\left(h_{j+1} = b | \, h_j = a\right)$.[11] An individual's disability status impacts his survival probability, medical expenses, preferences, productivities, and labor market risks. Further, it affects his probabilities of receiving benefits from the government. We specify the survival probability of an individual of age j and disability h as $\delta_j^h \in (0, 1)$, with $\delta_J^h = 0$.

The individuals' periodic utility is determined by the amount of consumption c, labor market participation l—zero if not working and one if working—and their disability status h. We use the following

[11]We assume that the disability process is first-order Markov, a commonly used assumption in the literature (e.g., French, 2005; Kitao, 2014). A recent paper (De Nardi et al., 2018) captures both the short- and long-run dynamics of health by allowing for history-dependence of health shocks. Although the rich modeling would be preferable, we adopt a simpler disability transition technology for tractability. Accounting for the rich dynamics could amplify the degree of heterogeneity in the labor market responses to the DI program across disability statuses.

specification

$$u(c,l;h) = \frac{(c \cdot \exp(\eta_h \cdot l))^{1-\gamma}}{1-\gamma}, \tag{3}$$

with the time discount factor of β. The utility specification allows for disability-specific disutility from work through η_h. We assume $\eta_{SD} < \eta_{MD} < \eta_{ND} < 0$, implying that work reduces utility and more so for disabled workers. Individuals incur a disability-dependent fixed monetary cost of F_h, together with the work disutility, when working.[12]

A working-age individual makes a labor supply decision subject to labor market risks. He receives a job offer with probability χ_h that depends on his labor market status in the previous period (e.g., employed, DI applicant). The wage offer is determined by both the worker characteristics following the specification in Section 2.1 and an idiosyncratic productivity shock ν with disability-dependent variance $\sigma^2_{\nu,h}$. After observing the wage offer, the worker decides whether to work or not. Although there is an extensive margin choice for labor supply ($l \in \{0,1\}$), we abstract from the intensive margin decision of individuals and exogenously set the hours worked as disability and age-dependent l^h_j. Thus, the labor income of an employed individual is $w\nu l^h_j$. Importantly, working-age individuals who are moderately or severely disabled can also decide whether to apply for DI benefits. When they do, they need to forego some of their current income; in particular, we assume that a DI applicant's earnings (hours), disutility of work, and fixed costs are a $\kappa < 1$ share of those of employed workers.

Retired individuals receive Social Security benefits from the government. Moreover, all agents have access to risk-free bonds with a time-invariant interest rate r, and they are not allowed to borrow.

Medical Expenditures and Health Insurance. An individual is subject to medical expenditure risks m, which follows an age- and disability-specific stochastic process with mean $\bar{m}^h_j$. The individual's access to the health insurance system depends on their age and labor market status. First, consistent with the employer-sponsored health insurance system in the United States, employed individuals and DI applicants have access to health insurance with an insurance premium of p_{HI} and a coverage rate of q_{HI}.[13] Second, working-age individuals who are unemployed and DI beneficiaries not yet qualified for Medicare benefits have no access to insurance. Third, qualified DI beneficiaries and retirees are eligible for the Medicare program, a public health insurance program with a premium of p_M and a coverage rate q_M.

[12] Low and Pistaferri (2015) shows that these components are necessary for replicating the employment patterns.

[13] Under the Consolidation Omnibus Budget Reconciliation Act (COBRA), workers have the right to continue group health benefits after leaving work for limited periods of time.

Government Policies. The government runs the DI program for working-age individuals. Agents can apply for the DI program if they are moderately or severely disabled, which does not guarantee the receipt of DI benefits. The application process is successful with probability $\pi^{DI,h}$ that differs across disability statuses, and the accepted workers receive DI benefits that replace the recipient's foregone labor income proportional to their previous earnings, $DI\left(\omega_{DI}\right)$. Further, DI recipients become eligible for Medicare after they receive DI benefits for 24 months. For consistency with the institutional feature, we assume that DI recipients receive Medicare benefits with probability π^{M} with an expected waiting period of two years. The beneficiary may receive a reassessment of disability status with probability π^{RE}. If the individual is not deemed eligible to receive DI (i.e., he is non-disabled) upon reassessment, his benefit will be terminated.

Further, unemployed workers receive unemployment insurance (UI) benefits proportional to their labor market income $UI\left(y\right)$ and retired workers are eligible for Medicare and Social Security benefits of the amount $SS\left(\omega_{SS}\right)$. Other welfare programs (e.g., the Supplemental Nutrition Assistance Program) are captured by assuming that the government provides a consumption floor of amount $\underline{c}_f$ and all other government expenditures are denoted as G. These government programs are funded by labor income tax τ_y, capital income tax τ_k, Social Security tax τ_{ss}, and Medicare tax τ_{med}, which we collectively denote as $\boldsymbol{\tau}$.

Production Technology. Representative firms produce output using labor and experience. The production technology is given by a CES production function, $Y = A\left(L^{\rho} + \theta E^{\rho}\right)^{1/\rho}$, as discussed in Section 2.4, and firms trade efficiency units of labor and experience in competitive factor markets at unit prices R_L and R_E.

Timing of Events. At the beginning of the period, each individual with assets and disability status has his medical shock realized. Then, DI reassessment and application results are determined, after which the labor market opens for working-age agents, and labor market productivities are realized. Workers then make labor supply and DI application decisions. The agents receive income, UI, DI benefits, or Social Security payments, after which they pay medical and tax bills, consume, and save. Mortality shock is then realized, and the survived agents receive bequests. In the following, we present the value functions for each type of worker.

3.2 Individual Problems

This section characterizes individual problems in recursive forms. For working-age individuals, the worker may be of four types—employed (W), unemployed (U), DI applicants (A), and DI beneficiaries (B)—and if retired, he is denoted as a retiree (R). These individuals make optimal consumption, saving, labor supply, and DI application decisions (the latter two choices are only applicable if they are of working age) to maximize their discounted utility, given their state variables ($\boldsymbol{x}_{i,}$ for status $i \in \{W, U, A, B, R\}$) and policy parameters of the government.

Employed Workers. An employed ($l = 1$) individual of age j enters a period with asset level a, disability status h, years of work experience e, medical expense m, and idiosyncratic productivity shock ν, and solves the following problem:

$$
\begin{aligned}
W(\boldsymbol{x}_E) &= \max_{c \geq 0, a' \geq 0} u(c + tr, 1; h) + \beta \delta_j^h \pi_j^{h,ND} \begin{bmatrix} \chi_{h'}^W \mathbb{E}_{m',\nu'} L(j+1, a', ND, e+1, m', \nu') \\ + (1 - \chi_{h'}^W) \mathbb{E}_{m'} U(j+1, a', ND, e+1, m') \end{bmatrix} && (4) \\
&\quad + \beta \delta_j^h \sum_{h' \in \{MD, SD\}} \pi_j^{h,h'} \left[\chi_{h'}^W \max \begin{Bmatrix} \mathbb{E}_{m',\nu'} L(j+1, a', h', e+1, m', \nu'), \\ \mathbb{E}_{m',\nu'} A(j+1, a', h', e+1, m', \nu') \end{Bmatrix} \right] && (5) \\
&\quad + \beta \delta_j^h \sum_{h' \in \{MD, SD\}} \pi_j^{h,h'} \left[(1 - \chi_{h'}^W) \max \begin{Bmatrix} \mathbb{E}_{m'} U(j+1, a', h', e+1, m'), \\ \mathbb{E}_{m',\nu'} A(j+1, a', h', e+1, m', \nu') \end{Bmatrix} \right] && (6) \\
s.t. \quad & c + a' + F_h + [p_{HI} + (1 - q_{HI}) m] = \tilde{y}(w \nu l_j^h; \boldsymbol{\tau}) + (1 + \tilde{r}) a + beq, && (7)
\end{aligned}
$$

where $\boldsymbol{x}_E \equiv (j, a, h, e, m, \nu)$. His utility this period is drawn from consumption and disutility from work. The government's welfare program ensures that the worker is able to consume at least the amount of the consumption floor so that $tr = \max\{\underline{c}_f - c, 0\}$ (for all individuals in the economy). In the next period, if he survives (with probability δ_j^h) and turns out to be non-disabled ($\pi_j^{h,h'=ND}$), there are two possibilities (line (4)): he may receive a job offer with probability $\chi_{h'}^W$ or left unemployed with $1 - \chi_{h'}^W$. Note that the job offer arrival rates χ depends on his disability status in the next period and labor market status in the current period to capture the impacts of labor market attachment on future labor market opportunities. When the individual receives the offer and productivity shock, he makes the labor market participation decision, with its value denoted by $L \equiv \max\{W, U\}$. For a worker who becomes moderately or severely disabled, his choice set expands as he can also choose to apply for the DI program (lines (5) and (6)). As an employed worker this period, his experience increases to $e + 1$ at the start of the next period.

As seen in the budget constraint (Equation (7)), expenditures include consumption c, savings a', fixed costs of work F_h, and medical expenditures that consist of premium and out-of-pocket costs $p_{HI} + (1 - q_{HI}) m$. The total resources are from after-tax labor income $\tilde{y}(w \nu l_j^h; \boldsymbol{\tau})$, after-tax capital income $(1 + \tilde{r}) a$ and bequests beq. Given the price of labor (R_L) and experience (R_E) in the market, the base wage of the worker is determined by the worker's current age, disability status, and years of experience (as in Section 2.1). Therefore, the total before-tax labor earnings are $y \equiv w(j, h, e) \nu l_j^h$, where ν is the iid productivity factor and l_j^h is the hours worked. After-tax capital return is denoted as $\tilde{r} \equiv (1 - \tau_k) r$.

Unemployed Workers. The unemployed ($l = 0$) worker's problem is similar to that of the employed, with the state vector of $\boldsymbol{x}_U \equiv (j, a, h, e, m)$:

$$\begin{aligned} U(\boldsymbol{x}_U) &= \max_{c\geq 0, a'\geq 0} u(c+tr, 0; h) + \beta\delta_j^h \pi_j^{h,ND} \begin{bmatrix} \chi_{h'}^U \mathbb{E}_{m',\nu'} L(j+1, a', ND, e, m', \nu') \\ +\left(1-\chi_{h'}^U\right) \mathbb{E}_{m'} U(j+1, a', ND, e, m') \end{bmatrix} \\ &+\beta\delta_j^h \sum_{h'\in\{MD,SD\}} \pi_j^{h,h'} \left[\chi_{h'}^U \max\left\{ \begin{array}{c} \mathbb{E}_{m',\nu'} L(j+1, a', h', e, m', \nu'), \\ \mathbb{E}_{m',\nu'} A(j+1, a', h', e, m', \nu') \end{array} \right\}\right] \\ &+\beta\delta_j^h \sum_{h'\in\{MD,SD\}} \pi_j^{h,h'} \left[\left(1-\chi_{h'}^U\right) \max\left\{ \begin{array}{c} \mathbb{E}_{m'} U(j+1, a', h', e, m'), \\ \mathbb{E}_{m',\nu'} A(j+1, a', h', e, m', \nu') \end{array} \right\}\right] \\ s.t. \quad & c + a' + m = UI(y) + (1+\tilde{r}) a + beq. \end{aligned}$$

The source of income for the unemployed is UI benefits. The individual does not incur work disutility nor monetary costs from work and is without health insurance. Further, he does not accumulate experience; thus, next period's experience stays at e.

DI Applicants. Moderately and severely disabled workers have an option to apply for DI benefits,[14] and their value reads

$$\begin{aligned} A(\boldsymbol{x}_A) &= \max_{c\geq 0, a'\geq 0} u(c+tr, \kappa; h) \\ &+\beta\delta_j^h \sum_{h'} \pi_{j+1}^{hh'} \begin{bmatrix} \pi^{DI,h'} B^{i_M=0}(j+1, a', h', e, m') \\ +\left(1-\pi^{DI,h'}\right) \begin{bmatrix} \chi_{h'}^A \mathbb{E}_{m',\nu'} L(j+1, a', h', e, m', \nu') \\ +\left(1-\chi_{h'}^A\right) \mathbb{E}_{m'} U(j+1, a', h', e, m') \end{bmatrix} \end{bmatrix} \\ s.t. \quad & c + a' + \kappa \cdot F_h + [p_{HI} + (1-q_{HI}) m] = \tilde{y}\left(\kappa \cdot w\nu l_j^h; \boldsymbol{\tau}\right) + (1+\tilde{r}) a + beq, \end{aligned}$$

where $\boldsymbol{x}_A \equiv (j, a, h, e, m, \nu)$ with $h = MD$ or SD. The applicant works for κ share of his time, lowering his labor income, work disutility, and monetary costs from work. As a partially attached worker, he has access to health insurance and does not accumulate experience. In the next period, if successful (with probability $\pi^{DI,h'}$), the worker becomes a DI recipient without Medicare denoted by value $B^{i_M=0}$. If not successful, he becomes unemployed, unless he is given the opportunity to enter the labor market.

[14] We do not allow non-disabled workers to apply; however, it may be that endogenously, it is not in their best interest to do so. In some sense, our notion of disability (from the PSID at least) may extend beyond those who actually receive DI.

DI Beneficiaries with ($i_M = 1$) and without Medicare ($i_M = 0$). The value of being a DI beneficiary depends on whether he receives Medicare benefits ($i_M = 1$) or not ($i_M = 0$). Their values are

$$\begin{aligned}
B^{i_M}(\boldsymbol{x}_B) \quad = \quad & \max_{c\geq 0, a'\geq 0} u(c+tr,0;h) \\
& +\beta\delta_j^h\left(\left(1-\pi^{RE}\right)+\pi^{RE}\left(\pi_{j+1}^{h,MD}+\pi_{j+1}^{h,SD}\right)\right)\ \mathbb{E}_{m'}\boldsymbol{E}B^{i_M}(j+1,a',h',e,m') \qquad (8)\\
& +\beta\delta_j^h\pi^{RE}\ \ \pi_{j+1}^{h,ND}\left[\begin{array}{c}\chi^B\mathbb{E}_{m',\nu'}L(j+1,a',ND,e,m',\nu') \\ +\left(1-\chi^B\right)\mathbb{E}_{m'}U(j+1,a',ND,e,m')\end{array}\right] \qquad (9)\\
s.t. \qquad & c+a'+\left[i_M\left(p_M+(1-q_M)\,m\right)+(1-i_M)\,m\right]=DI(\omega_{DI})+(1+\tilde{r})\,a+beq,
\end{aligned}$$

with $\boldsymbol{x}_B \equiv (j, a, h, e, m)$. In the following period, if the worker is not reassessed $(1 - \pi^{RE})$ or is reassessed and passes the reassessment (i.e., he is moderately or severely disabled in $j + 1$ with probability $\pi^{RE}\left(\pi_{j+1}^{h,MD} + \pi_{j+1}^{h,SD}\right)$), he remains a DI recipient with expected value $\boldsymbol{E}B^{i_M}(a', h', e, m')$ (line (8)). The expected value is $\boldsymbol{E}B^{i_M=1} = B^{i_M=1}$ for already qualified Medicare beneficiaries and $\boldsymbol{E}B^{i_M=0} = \pi^M B^{i_M=1} + \left(1 - \pi^M\right) B^{i_M=0}$ for not-yet-qualified Medicare beneficiaries, the latter of which reflects the future probability of receiving Medicare benefits. If the beneficiary does not pass the reassessment (i.e., he is non-disabled when reassessed), his benefits are terminated (line (9)). Then, he either receives a job offer with probability χ^B or becomes unemployed. Unlike χ_h^W, χ_h^U, or χ_h^A, which are disability-dependent, all workers leaving DI after reassessment are non-disabled and thus face the same job offer arrival rates. As DI beneficiaries only leave the program upon failing the reassessment, non-disabled workers may continue receiving DI benefits. Whether the beneficiary receives Medicare impacts his medical expenditures through the budget constraint.

Retirees. Once retired, the individual receives Social Security benefits based on his earnings history ω and makes optimal consumption and saving decisions:

$$\begin{aligned}
R(\boldsymbol{x}_R) \quad = \quad & \max_{c\geq 0, a'\geq 0} u(c+tr,0;h)+\beta\delta_j^h\mathbb{E}_{h',m'}R(j+1,a',h',\omega,m') \\
s.t. \qquad & c+a'+\left[p_M+(1-q_M)\,m\right]=SS(\omega_{SS})+(1+\tilde{r})\,a+beq,
\end{aligned}$$

with $\boldsymbol{x}_{\boldsymbol{R}} \equiv (j, a, h, \omega, m)$. In the last period of the working life, the individual's Social Security benefit is determined by his past average earnings ω, which becomes a state variable that does not change for the rest of his life.

3.3 Competitive Equilibrium

Denote the vector of the state space of all types of individuals as $\boldsymbol{x} \equiv \{\boldsymbol{x}_W, \boldsymbol{x}_U, \boldsymbol{x}_A, \boldsymbol{x}_B, \boldsymbol{x}_R\}$. Given the government's policy parameters, the competitive equilibrium of the economy consists of individuals' policy functions and value functions; factor prices of labor and experience; the size of bequest transfers; and the distribution of individuals over the state space $\mu(\boldsymbol{x})$ such that the following conditions hold.

1. The individual policy functions solve their optimization problems as defined in Section 3.2.
2. Factor prices for labor (R_L) and experience (R_E) are determined competitively: $R_L = A\left(L^\rho + \theta E^\rho\right)^{(1-\rho)/\rho} L^{\rho-1}$ and $R_E = \theta A\left(L^\rho + \theta E^\rho\right)^{(1-\rho)/\rho} E^{\rho-1}$.
3. Factor markets clear: $L = \sum_{\boldsymbol{x}} \lambda_L(j,h) \cdot \left(l(\boldsymbol{x})\, l_j^h\right) \cdot \mu(\boldsymbol{x})$ and $E = \sum_{\boldsymbol{x}} \lambda_E(j,h)\, g(e) \cdot \left(l(\boldsymbol{x})\, l_j^h\right) \cdot \mu(\boldsymbol{x})$, where $\lambda_L(\cdot)$ and $\lambda_E(\cdot)$ are defined as in Section 2.1.
4. The bequest transfer equals the amount of assets left by the deceased: $beq = \sum_{\boldsymbol{x}} a(\boldsymbol{x})\left(1-\delta_j^h\right)\mu(\boldsymbol{x})$.
5. The government budget is satisfied:

$$\sum_{\boldsymbol{x}} \left\{SS(\boldsymbol{x}) + DI(\boldsymbol{x}) + UI(\boldsymbol{x}) + tr(\boldsymbol{x}) + q_M \bar{m}_j^h \mathbb{I}_M(\boldsymbol{x})\right\}\mu(\boldsymbol{x}) + G \quad = \sum_{\boldsymbol{x}} T\left(y(\boldsymbol{x}), a(\boldsymbol{x})\right)\mu(\boldsymbol{x})$$

   in which $\mathbb{I}_M(\boldsymbol{x})$ is an indicator for whether the individual qualifies for Medicare (either DI recipients with Medicare or retirees), and $T\left(y(\boldsymbol{x}), a(\boldsymbol{x})\right)$ denotes the total tax (labor and capital income, Social Security, and Medicare) paid by agents with labor income $y(\boldsymbol{x})$ and assets $a(\boldsymbol{x})$.

4 Calibration

This section describes how we map our model to the data to evaluate the impacts of the DI program quantitatively. For the empirical implementation of the model, we allow for two education (s) types consistent with Section 2: workers with less than or equal to 12 years of education (high school graduates, "HS") and those with more than 12 years of education (college, "Col"). In particular, we allow for education-dependence in the variance of iid productivity shock $\sigma^2_{\nu,\{h,s\}}$, work disutility $\eta_{h,s}$, fixed costs of work $F_{h,s}$, and offer arrival rates $\chi^X_{h,s}$ for labor market statuses $X \in \{W, U, A, B\}$.

We first document the parameters calibrated outside the model, describe the within-model calibration process and the model's performance on targeted moments, and then externally validate the model.

4.1 Exogenously Calibrated Parameters

The unit of time in our analysis is a year, and the unit of analysis is an individual.[15] High school graduates start their lives at 18, whereas college graduates start their lives at 22. All workers retire at the mandatory age of 65 and live at most to 100.[16] The constant relative risk aversion (CRRA) parameter γ in the utility function is set exogenously at 2, and risk-free bonds earn a 3% annual return.

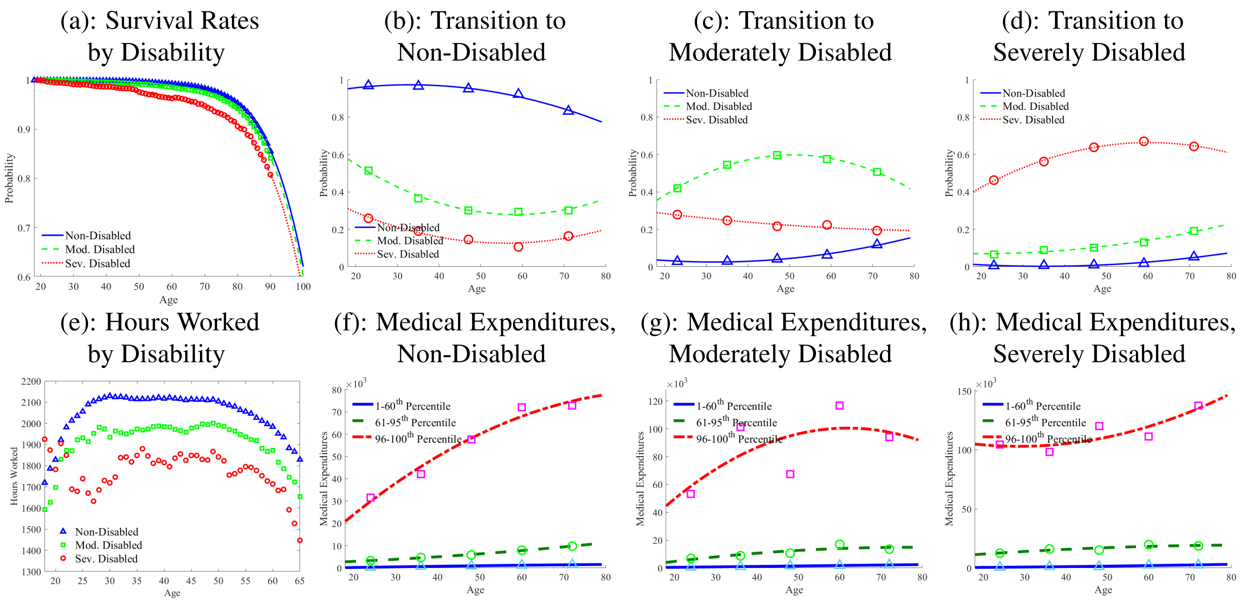
Disability, Survival, and Hours. We classify disability status (h) into three categories, namely, non-disabled (ND), moderately disabled (MD) and severely disabled (SD), based on the binary indicator of work limitation and the work-limiting degree of disability, which is consistent with the empirical specification presented in Section 2. Disability status in the model impacts the worker's (i) survival probability; (ii) evolution of future disability statuses; (iii) medical expenditures; earnings through (iv) hours worked and (v) wage profiles; (vi) job offer arrival rates; and (vii) disutility and fixed costs from work. We exogenously calibrate the parameters relating to (i) through (iv), and use the estimated wage coefficients summarized in Table 2 and the residual variances from the regression to specify wage profiles ((v)). The last two sets of parameters in (vi) and (vii) are endogenously calibrated within the model, which we discuss in Section 4.2. In the following, we describe how we determine parameters for survival probabilities, the evolution of disability statuses, and hours worked.

First, following the strategy of Attanasio et al. (2011), we estimate conditional survival probabilities by disability status using the life table from the Social Security Administration and micro-level data from the PSID. The estimated probabilities are plotted in Figure 4(a), and the procedure is documented in Appendix C.1. Second, the disability status in the model evolves stochastically and depends on the worker's age and current disability status. We use the panel dimension of the PSID to find the transition probabilities for five age groups (18–29, 30–41, 42–53, 54–65, and 66 years and older) and fit these moments to a quadratic function of age to produce smooth transitions over the life cycle. As shown in Figures 4(b)–4(d), disability statuses are persistent, and older workers are more likely to transition to severely disabled than young workers. Lastly, conditional on working, we assume that individuals work for a fixed number of hours. For each age and disability status, we construct working hours as the average working hours among the employed with more than 700 hours per year (Figure 4(e)).

[15] We abstract from gender in the analysis. This is a simplifying assumption in our quantitative model and is a consistent assumption with the benchmark empirical wage analysis, where we use both genders and control for gender-specific effects.

[16] We take the 2015 demographic composition of the U.S. population from the National Population Projections by the U.S. Census Bureau, which we detail in Appendix C.1.

Figure 4: Externally Calibrated Parameters



Note: In Figures 4(a)–4(d), 4(f)–4(h), markers are data points from the PSID, which we use to estimate survival, transition probabilities, and medical expenditures by disability and age. Due to sample size issues, we use the same parameters for disability transition and medical expenditures for those aged 80 years and older. For average hours in Figure 4(e), we smooth out variations from small sample sizes by using average hours (conditional on disability) of workers between age $j-2$ and $j+2$ to construct age-j worker's hours.

Medical Expenditures and Health Insurance. Medical expenditure risks differ by age and disability statuses. We use adult-equivalent medical expenditures from the PSID to construct these variables. Following Attanasio et al. (2011), we use three medical expenditure bins representing the averages in the 1st–60th percentile, 61st–95th percentile, and 96th–100th percentile. Similar to the approach used for disability transitions, we fit medical expenditures using a quadratic function in age. The calibrated parameters are presented in Figures 4(f)–4(h).

We assume that employed workers and DI applicants have access to employer-sponsored health insurance (ESHI) with a constant coverage rate q_{HI} of 60% and a premium p_{HI} of \$2,500, which are values similar to those used by Imrohoroglu and Kitao (2012). The constant health insurance premium captures that ESHI is a group insurance (workers do not pay the actuarially fair premium by age and health). However, this is a simplifying assumption as we do not impose the break-even condition of the health insurance system.[17] To deal with this issue, we assume that the government pays the differences in expenditures and premia. As these ESHI premia are tax-exempted and thus partially funded by taxes, our assumption may be reasonable. Moreover, the quantitative magnitude of the differences in expenditures and premia turn out to

[17] If we imposed the break-even condition, we would need to solve for a fixed-point for equilibrium premium, increasing the computational burden. We choose to simplify the modeling of the ESHI in order to enrich the model in key dimensions, e.g., endogenous experience accumulation and a more detailed DI program.

be small.

Government Policies. We discuss parameters for government policies: Disability Insurance, Unemployment Insurance, Social Security, Medicare, tax policies, and welfare programs.

Disability Insurance. Five parameters fully describe the DI program: application penalty parameter κ, application success probability π^{DI}, the probability of qualifying for Medicare benefits π^{M}, reassessment probability π^{RE}, and benefit schedule as a function of previous earnings $DI(\omega)$.

DI applicants have a waiting period of around five months to receive DI benefits; thus, we assume that applicants earn 60% of their labor income and that their disutility and monetary costs of work are also scaled down by the same proportion. The DI receipt probabilities are set at 18% for moderately disabled workers and 45% for severely disabled workers, within the ranges estimated by Low and Pistaferri (2015).[18] The Medicare receipt probability is 50% to capture the beneficiary's expectation to qualify for the benefits after two years. Further, the reassessment probability is set at 6%, similar to that used by Low and Pistaferri (2015). Lastly, the DI payments are determined by the following Primary Insurance Amount (PIA) formula (in 2011 dollars):

$$PIA(\omega) = \begin{cases} 0.90 \times \omega & \text{if } \omega < \$8,988 \\ \$8,089 + 0.32 \times (\omega - \$8,988) & \text{if } \$8,988 \leq \omega < \$54,204 \\ \$22,559 + 0.15 \times (\omega - \$54,204) & \text{if } \omega \geq \$54,204, \end{cases} \tag{10}$$

where ω reflects the worker's average indexed monthly earnings (AIME) out of his 35 highest years of earning. Given the large state space, it is difficult to keep track of each worker's earnings.[19] Hence, we approximate ω_{DI} using state variables instead. Specifically, we use the average labor earnings of the workers, given their education, age, and years of experience, such that $\omega_{DI}(j,s,e) = \mathbb{E}_h\left[w(j,s,h,e)\cdot l_j^h\right]$. To better reflect the average previous earnings, we disregard the iid shock ν and take the average across the disability status distribution at age j. Thus, ω_{DI} reflects the heterogeneity in AIMEs by workers' education, age, and experience. Although this method is not perfect, it reasonably approximates the past earnings of individuals with heterogeneous earnings profiles with a reduced computational burden. Finally, we follow the policy cap on AIME for benefit calculation, imposing $DI(\omega) = \min\{PIA(\omega_{DI}), \$30,448\}$.

[18]Unlike in our model, Low and Pistaferri (2015) only uses high school graduates. Although their DI acceptance probability is age-dependent (younger or older than 45), we use constant probabilities that are approximately the average of their estimates.

[19]To be more accurate, one could keep AIME as an additional state variable, an approach taken by Kitao (2014). However, as we keep track of the years of work experience, the additional state variable would be too burdensome computationally. Thus, we choose to exploit experience as an additional observable reflecting workers' previous earnings and show in Section 4.3 that we are able to match the average DI benefit amounts of workers over the life cycle in the calibrated model.

Unemployment Insurance. UI benefits are paid to unemployed workers. With about a 45% replacement rate that pays up to six months, the overall yearly replacement rate is set at 23% of the worker's annual income.

Social Security and Medicare Benefits. The PIA in Equation (10) also determines Social Security payments. For ω_{SS}, we use a similar approximation as that for DI, but we require 35 years of work experience.[20] Medicare benefits are provided to all retirees and qualified DI recipients. Beneficiaries pay a premium of $p_M = \$1,157$, and its coverage rate q_M is 50%.

Taxes and Welfare Programs. Labor income is taxed at rate $\tau_y = 0.26$ and the capital income tax rate is $\tau_k = 0.1$.[21] Social Security taxes are set at $\tau_{ss} = 0.104$, levied on labor earnings, with maximum taxable earnings of $y_{ss} = \$106,800$. Meanwhile, the Medicare tax rate is $\tau_M = 0.029$, levied on labor earnings. We set the consumption floor as $\underline{c}_f = \$3,150$ to capture other un-modeled government's welfare programs.[22]

Production Technology. The values for ρ and θ in the aggregate production function $Y = A\left(L^\rho + \theta E^\rho\right)^{1/\rho}$ are taken from the estimated values reported in Section 2.4.

We summarize the values of all exogenously calibrated parameters in Table 4.

Table 4: Parameters Calibrated Outside the Model

Parameters	Description	Values	Parameters	Description	Values
Demographics, Preferences, Technology			Policies: UI, SS, Medicare, Tax		
$\{\delta_j^h\}$	Survival rates	Fig. 4(a)	b	UI replacement rate	0.23
γ	Risk aversion	2	τ_y	Labor income tax	0.26
r	Interest rate	0.03	τ_k	Capital income tax	0.10
$\{\rho, \theta\}$	Agg. production	-1.52; 3.05	τ_{SS}	SS tax	0.104
Health, Medical Expenditures, and Health Insurance			y_{SS}	Max. taxable earnings	$106,800
$\{\pi_j\left(h'\|h\right)\}$	Health transition	Fig. 4(b)–4(d)	τ_M	Medicare tax	0.029
$\{m_j^h\}$	Medical expenditures	Fig. 4(f)–4(h)	$\{p_M, q_M\}$	Medicare prem., coverage	$1,157; 0.5
$\{p_{HI}, q_{HI}\}$	HI prem., coverage	$2,500; 0.6	$\underline{c}_f$	Consumption floor	$3,200
Wage and Hours			Policy: Disability Insurance		
$w\left(j, h, s, e\right)$	Wage coefficients	Table 2	κ	Application penalty	0.6
$\sigma^2_{\nu,\{ND,HS/Col\}}$	iid shock var., non-dis.	0.65; 0.71	$\left\{\pi^{DI,MD/SD}\right\}$	DI receipt prob.	0.18; 0.45
$\sigma^2_{\nu,\{MD,HS/Col\}}$	iid shock var., mod.	0.79; 0.78	π^M	Medicare benefit prob.	0.5
$\sigma^2_{\nu,\{SD,HS/Col\}}$	iid shock var., sev.	1.06; 0.87	π^{RE}	Re-examination prob.	0.06
$\{l_j^h\}$	Hours	Fig. 4(e)	$\{PIA\left(\omega\right)\}$	Primary Insurance Amount	Eq. (10)

[20] As years of experience is our state variable, we can capture the impact of years of experience on workers' Social Security benefit determination: if a worker worked for 20 years, for example, we use (as does the U.S. policy) zero as earnings for 15 years. The work requirement for DI benefits are a lot more relaxed; thus, we do not impose such experience restrictions for the approximation of ω_{DI}.

[21] We assume a constant capital income tax rate, similar in level to the long-term capital gains tax rate.

[22] This is within the range used in the literature: the annual consumption floor is set at $4,000 in Kitao (2014) and estimated to be $1,540 (in 2003 dollars) in Pashchenko and Porapakkarm (2017) and $3,593 in De Nardi et al. (2018).

4.2 Parameters Calibrated within the Model

A total of 34 parameters remain: $\left\{A, \beta, \eta_{h,s}, F_{h,s}, \chi^W_{h,s}, \chi^U_{h,s}, \chi^A_{h,s}, \chi^B_s\right\}$ for $h \in \{ND, MD, SD\}$ and $s \in \{HS, Col\}$. We calibrate these parameters to match employment rates by education, disability, and age group[23]; share of DI recipients by age group; average labor income by education and disability; average consumption by education and disability (75 moments). Given the rich modeling of the labor market, the preferences and labor market parameters jointly match the life-cycle employment rates by education and disability. We also directly target the share of DI recipients by age group to ensure that the model replicates the life-cycle share of DI recipients. The latter pattern is determined by disabled workers' labor market opportunities controlled by offer arrival rates for DI recipients and applicants. Further, although the relative efficiency of experience θ and the elasticity of substitution between labor and experience $1/(1-\rho)$ are exogenous, we use the average total factor productivity (TFP) parameter A to match the level of the wage rate in the model. Lastly, the time preference of individuals β informs the consumption level of workers.

Table 5 presents the values of calibrated parameters. We observe that disabled workers have higher disutility and fixed costs of work. Our estimates imply that working lowers the marginal utility of non-disabled by 9% (11%), moderately disabled workers by 15% (15%), and severely disabled workers by 23% (18%) for high school graduates (college). The job offer arrival rates differ across education, disability status, and labor market status. Conditional on education and disability status, the estimated offer arrival rates are highest for the employed, lower for the unemployed and DI applicants, and lowest for DI recipients. The low offer arrival rates for DI recipients (despite them being non-disabled) captures the difficulty of returning to the labor market after being a DI recipient. These trade-offs are key determinants in workers'

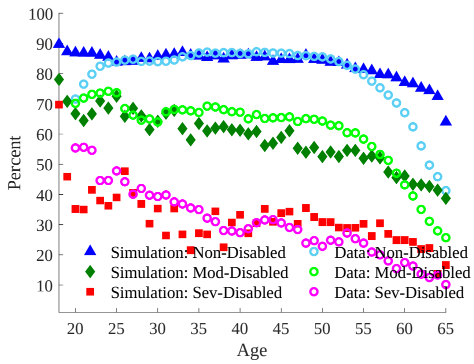
Table 5: Parameters Calibrated within the Model

Parameters	Description	Value					
A	TFP	0.650					
β	Time discount factor	0.953					
		High School			College		
		Non-Disabled	Moderate	Severe	Non-Disabled	Moderate	Severe
$\eta_{h,s}$	Disutility of work	-0.089	-0.157	-0.264	-0.115	-0.161	-0.198
$F_{h,s}$	Fixed cost of work	1142.532	1210.811	1295.115	783.908	830.683	1743.583
$\chi^W_{h,s}$	Offer arrival rate: Employed	0.896	0.765	0.420	0.939	0.905	0.545
$\chi^U_{h,s}$	Offer arrival rate: Unemployed	0.727	0.452	0.355	0.772	0.581	0.504
$\chi^A_{h,s}$	Offer arrival rate: Applicants	0.694	0.452	0.178	0.936	0.641	0.256
χ^B_s	Offer arrival rate: DI beneficiaries	0.271	-	-	0.543	-	-

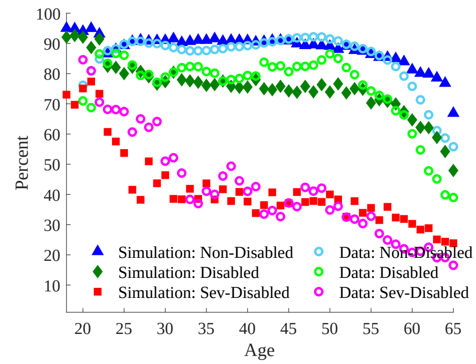
[23]To calculate employment rates in the simulated model, we include employed workers and 60% of applicants, as our model assumes that applicants work 60% of their time. We use nine age groups: under 25, 25–29, 30–34, 35–39, 40–44, 45–49, 50–54, 55–60, and 61–65.

Figure 5: Calibrated Model Fit

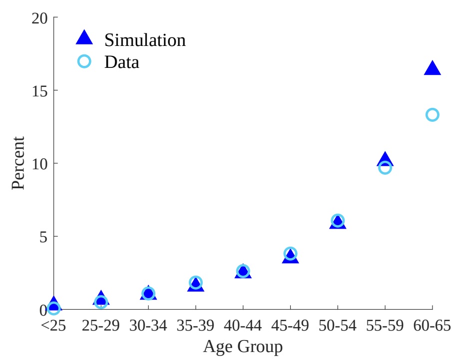
(a): Employment, High School



(b): Employment, College



(c): DI Recipient Share



(d): Income and Consumption

	High School		College	
	Data	Simulation	Data	Simulation
Income				
Non-Disabled	39,073	37,077	59,293	51,373
Moderate	32,458	31,302	44,147	39,232
Severe	24,954	23,291	36,818	24,853
Consumption				
Non-Disabled	16,941	14,727	26,428	22,540
Moderate	14,863	13,082	22,498	20,487
Severe	13,642	12,504	18,245	17,598

Note: We obtain DI recipient share data in Figure 5(c) from Social Security Administration (2013), where only the specified age group (the nine age groups used in this paper) level data are available. The average income and consumption by disability statuses in (d) are based on the PSID (in 2011 US dollars).

decisions to apply for DI.

In Figure 5, we compare our targeted moments and their data counterparts, including employment rates by disability status and education,[24] DI recipient shares, and the average consumption and earnings by education and disability status. Overall, the simulated model fits the targeted moments well.

4.3 Model Validation

Before conducting counterfactual analyses, we validate the model by evaluating its performance on non-targeted moments among working-age individuals who are the primary focus of this study.

[24]Although we target employment rates by disability and education for nine age groups, we here present the full life-cycle pattern to show the model's performance at a more disaggregated age level. Our model generates higher employment rates near retirement. This might be because we assume that all workers retire at the mandatory age of 65, not permitting workers to claim Social Security benefits (albeit with penalty) earlier.

Life-Cycle Patterns of Earnings, Consumption, and Labor Supply Elasticity. We first compare workers' earnings and consumption by disability statuses over the life cycle. Although we only target the average earnings and consumption by disability status and education, as shown in Figure 6, our model broadly matches the life-cycle patterns in the data. The model under-estimates consumption at earlier ages that might be due to the lack of consumption insurance for the young (e.g., inter-vivos transfers from parents) in the model, unlike in the data. However, starting in the late 30s, the model generates the life-cycle consumption levels close to the data.

Figure 6: Earnings and Consumptions over the Life Cycle, Data vs. Model

(a): Non-Disabled (b): Moderately Disabled (c): Severely Disabled

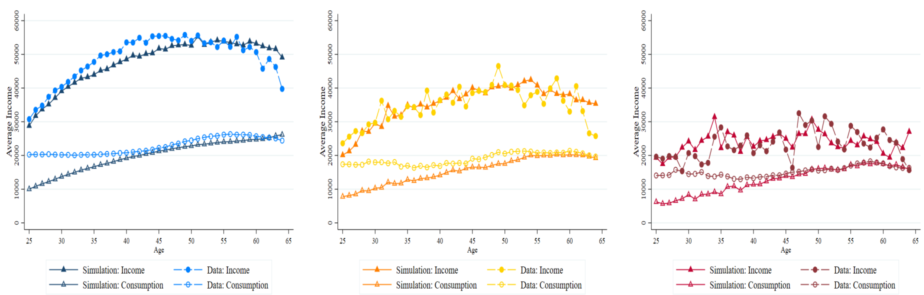
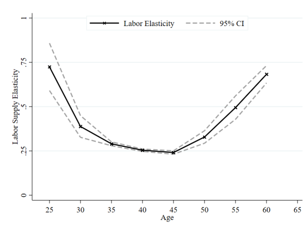


Figure 7: Elasticity



Note: In Figure 6, triangular markers represent the average earnings of the simulated economy, and circular markers are their empirical counterparts from the PSID (in 2011 dollars). Consumption data are constructed using the PSID for 1999–2013. The data include food, utilities, transportation, education expenses, childcare, clothing, trips, and recreation categories. We use individuals older than 25 years for sample size and control for family size using an equivalence scale with 0.5 weight on an additional adult and 0.3 on an additional child.

One of the main focuses of our paper is analyzing labor market effects; thus, we verify whether the model is able to generate reasonable labor supply elasticities. To compute the labor supply elasticity, we conduct experiments in which individuals of age j experience an unanticipated wage change for one period. Figure 7 illustrates the simulated labor supply elasticities. As we do not model intensive margin (hours are assumed to be fixed by age and disability), the results are extensive margin elasticities. The average labor supply elasticity is 0.41 and U-shaped over the life cycle, which is consistent with recent findings of Erosa et al. (2016).[25]

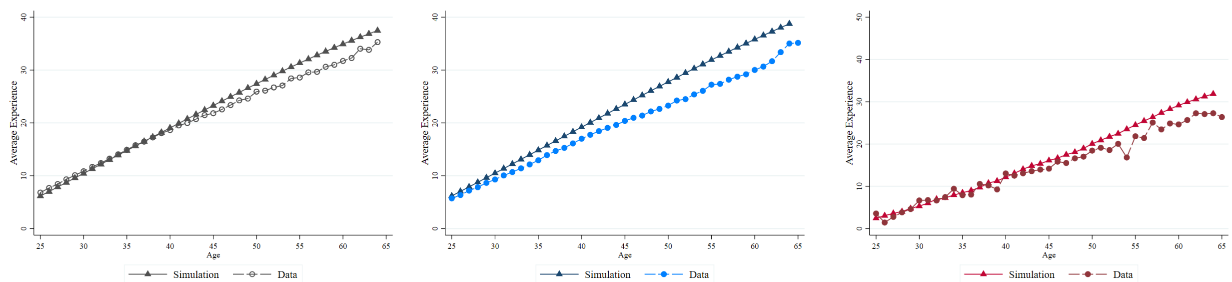
Life-Cycle Patterns of Experience. We document the model's performance in replicating the empirical life-cycle patterns of workers' years of experience, which are important aspects of our model. In Figure 8,

[25] Erosa et al. (2016) studies the aggregate labor supply elasticities in a rich heterogeneous agents model. Additional to features similar to ours (e.g., life cycle, labor productivity shocks, fixed costs), they also model preference heterogeneity and non-linearity in earnings with respect to hours worked. Our average model-implied extensive margin elasticity from a temporary wage change is smaller than theirs (1.08). According to their decomposition exercises, this may well be due to the lack of preference heterogeneity in our model. Overall, however, we believe that our model is able to broadly replicate the key features of the labor elasticities, similar to their findings.

we plot average experience profiles for all population, and by DI recipiency status in the simulated model and in the data. The profiles in Figures 8(b) and 8(c) show that DI recipients near the retirement age have work experiences around 10 years lower than non-DI recipients. Although our model somewhat overestimates the experience of workers, it generates similar differences in the years of experience by DI status.

Figure 8: Experience Profiles

(a): Average Experience (b): Non-SSDI Recipients (c): SSDI Recipients



Note: We identify DI recipients using the PSID's question on the type of Social Security received, which is available in 1984–1992 and from the year 2005 onward. We use those aged 25 and older for sample size issues and also report summary statistics of DI recipients in Appendix A.

DI Applicants and Beneficiaries. Now, we examine the behaviors of DI applicants in our model. Figure 9 plots the model-predicted share of DI applicants that underlie the DI recipient shares in Figure 5(c). In Figure 9(a), we plot the model-predicted share of DI applicants by disability status. A larger share of severely disabled workers apply for DI with a peak during the 50s. Moderately disabled workers with DI receipt probability of 18% have less incentives to apply for the benefits. Given the risks and the opportunity costs, the application rate among moderately disabled workers is very small around the prime-working ages (40–50), which increases later in life. We also note that severely disabled workers' application rates start dropping near retirement age and precipitously two years before retirement, as the benefit from applying is lower: the expected DI duration is shorter and they have to wait (in expectation) two years to receive medical benefits. Overall, although DI receipt probability in the model is constant over the life cycle, a steep increase in the applicant share occurs among workers in their late 40s (Figure 9(b)). This shows that the model is able to capture the trade-offs that workers face in their decision to apply for DI that depends on their labor market opportunities.

Second, we check the rate at which rejected DI applicants return to employment. The model endogenously generates this rate through job offer arrival rates, wage processes, and the participation choice of workers. We find that in the model, on average, about 63% of applicants become employed the next period conditional on rejection, which is similar to the data pattern documented by Maestas et al. (2013) (see Figure

Figure 9: DI Applicant Share

(a): Share by Disability (b): Share of Population

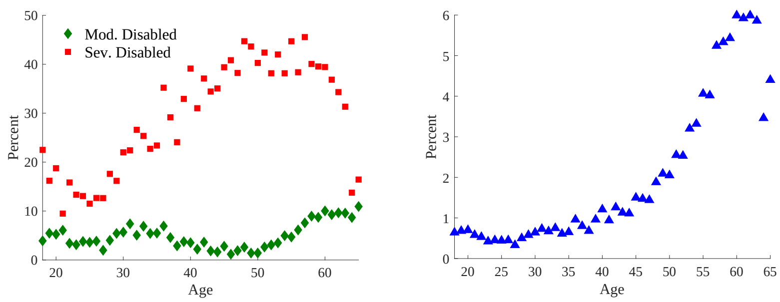
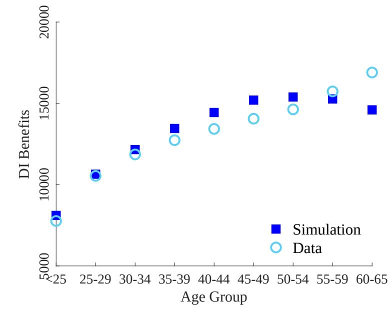


Figure 10: DI Benefit Amounts



Note: In Figure 10, data are obtained from Social Security Administration (2013) that documents the average DI benefit amounts by the plotted age group.

2 for initially denied applicants' employment probabilities).[26]

Finally, we examine the behaviors of DI beneficiaries in the model and compare them to the data. First, Figure 10 shows the average DI payment by age in the simulated model compared to data. The model matches DI benefits by age group well. The average DI benefit amount is $13,250 in the model and $13,100 in the data, implying that the way we approximate the PIA for DI benefit is reasonable. Second, DI recipients in the model are strongly attached to the program: about 5% of surviving working-age DI recipients (thus excluding exiting due to retirement or death) exit the program. As we assume that benefits are terminated upon failing a reassessment and that workers do not leave the program voluntarily, this rate is determined exogenously by reassessment and transition probabilities of disability status. According to the Social Security Administration (2020), around 10% of DI recipients had their benefits terminated, 87% of them due to reaching retirement age or death (1.3% termination rate for reasons other than death or retirement). Moreover, about 2% of recipients have their benefits withheld yearly. If we include both as flows off the DI program, the exit rate among surviving working-age beneficiaries is around 4%, close to the level in the model.[27] Third, the model-implied elasticities of non-employment with respect to DI benefit generosity are 0.24 for moderately disabled workers and 0.05 for severely disabled workers, which are within the ranges documented in Bound and Burkhauser (1999) and similar to those of Low and Pistaferri (2020). This ensures that the model is able to capture the behaviors of marginal DI beneficiaries well, which are important features for our counterfactual analysis to be plausible.

[26] Maestas et al. (2013) uses the behaviors of marginal DI applicants to estimate the labor supply effects of DI. They suggest that applicants who are rejected are more likely to work after two years. We also plot the life-cycle patterns of applicant-to-employment transition among the rejected in Appendix C.2.

[27] In the data, the termination rates among workers have been around 8-10% in the recent years. The benefit may be withheld for reasons such as administrative issues (address unknown) or due to pending determination of continuing disability. These statistics are drawn from Tables 48, 49, and 50 of Social Security Administration (2020). Since our model implies a higher exit rate, we could potentially target this exit rate by assuming that a share of the population is permanently disabled and thus never leaves the DI program. Although we do not take that approach, we think that overall, we are able to broadly replicate the strong attachment to the DI program and the behaviors of DI recipients.

Overall, we believe that our model is able to capture the key labor market behaviors of workers—not only of DI applicants and recipients but also of healthier individuals—over the life cycle showing that it is a plausible laboratory for policy experiments.

5 Quantitative Analysis

We now use the calibrated model to study the labor market effects of the DI program, the role of accounting for imperfect substitutability, and the value of the policy.[28]

5.1 Labor Market Effects of DI

To evaluate the labor market impact of the DI program in the U.S., we simulate an economy without DI, imposing budget-neutrality using lump-sum transfers.[29] In the following, we first discuss the employment effects of removing the DI program, the effects on effective labor and experience of the workforce that, along with prices of labor and experience, determine the average wage and income. We then discuss the macroeconomic effects.

Figure 11 presents the percentage point (pp) changes in workers' employment rates by disability status. When the DI program is removed, the employment rates increase, with magnitudes larger for older workers whose employment rates in the benchmark economy (with DI) are low. Non-disabled workers increase their labor supply across all ages, due to the lack of social insurance program and also because their wages depend on their accumulated experience. For young disabled workers, we see a small drop in employment rates as previous DI applicants drop out of the labor force. Further, the employment rate of moderately disabled workers, who were at the margin of entering the DI program, increases the most. As a result, the experience distribution of workers at retirement (age 65) in the counterfactual analyses shifts right relative to that in the benchmark as shown in Figure 12.

To understand the wage and income effects from DI, we plot the percentage changes in average effective labor ($\lambda_L \nu$) and experience ($\lambda_E g\left(e\right)\nu$) per hour by disability status (Figures 13(a)-13(c)).[30] When the DI program is removed, DI applicants and beneficiaries become either employed or unemployed (and previ-

[28] Since there are few disabled workers younger than 25 (both in the data and the model), we focus on individuals older than 25. With the main text focusing on the average effects across education, the education-specific analysis are relegated to Appendix C.3.

[29] An elimination of a DI program may be an extreme policy reform. In Appendix C.4, we complement this analysis by conducting two relatively moderate policy reforms: lowering DI benefit amounts and lowering DI acceptance rates. In both cases, the labor market effects are quantitatively smaller but qualitatively similar to the results from the counterfactual analysis without DI.

[30] For the analysis of effective labor, effective experience, wage, and income (but not employment), we drop top and bottom 1% in the wage distribution to ensure that outliers do not drive the results. Further, we use five-year averages for each age (between age $j-2$ and $j+2$ for age-j worker) to compensate for small sample size, especially for young, severely disabled workers. The percent changes are of the aggregate average of the corresponding variable.

Figure 11: Employment Effects by Disability

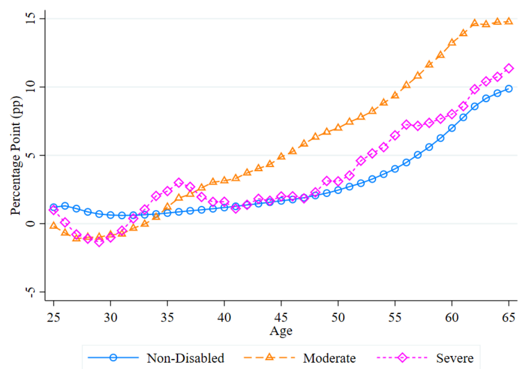
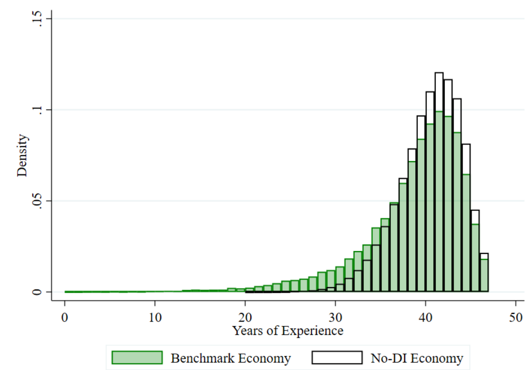


Figure 12: Distribution of Experience at Retirement



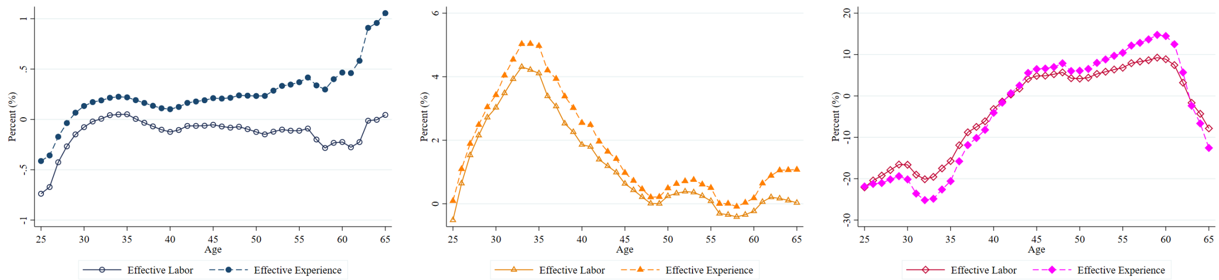
ously employed and unemployed workers may also change their decisions). As seen in Figure 13(c), the average effective human capital of young severely disabled workers falls as new entrants are of lower productivity. On the other hand, the average productivity of young moderately disabled workers increases in the no-DI economy (Figure 13(b)), which is driven by the behaviors of DI applicants. In the benchmark economy, moderately disabled workers face a large opportunity cost from applying for DI, as their acceptance rate is low (18%). Thus, moderately disabled applicants are either those with a low productivity shock ν (because of their poor labor market prospects) or a very high productivity shock (because their high earnings allow them to incur the application cost). Without DI, the latter choose to work, whereas the former drops out of the labor force, leading to an increase in the moderately disabled workers' average human capital. These effects become smaller as workers reach their prime working age, during which time, the application rate among moderately disabled workers are very low (Figure 9(a)), and as they reach retirement age, because by then, higher share of new entrants are previous DI beneficiaries. Lastly, among non-disabled workers, per-hour efficiency of experience increases as they age, whereas the per-hour efficiency of labor changes little (Figure 13(a)). Unlike moderately (and severely) disabled workers, the selection effect from the DI program for non-disabled workers are absent as they are not allowed to apply for the DI program. However, they still supply more labor due to the lack of social insurance, increasing their accumulated experience. This manifests as the higher effective experience among the old non-disabled workers in the no-DI economy.

Although the employment responses in the counterfactual economy lead to higher supplies of both effective labor and experience, the relative supply of experience increases due to the disproportionate increase in older workers in the labor force.[31] As a result, the price of experience drops 1.80%, whereas the price of

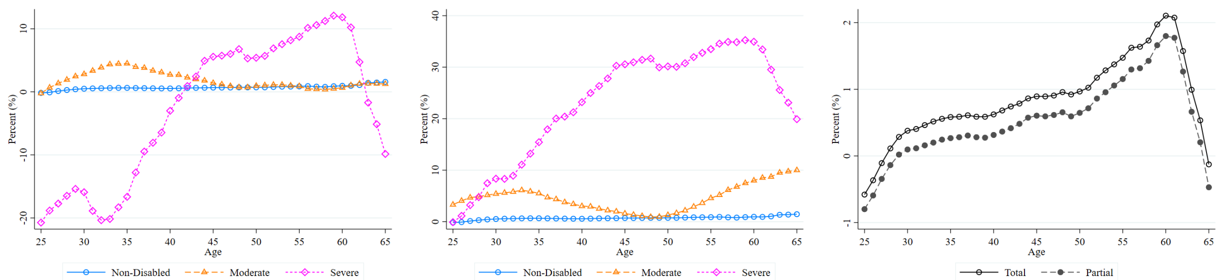
[31] Although we model the concurrent disutility of work and its impact on future wages (through increased experience), we do not model that work might impact the health of workers. The research on this issue is inconclusive. Case and Deaton (2005), for

Figure 13: Effects of Removing DI over the Life-Cycle by Disability

(a): Efficiency, Non-Disabled (b): Efficiency, Moderately Disabled (c): Efficiency, Severely Disabled



(d): Wage Effects (e): Income Effects (f): Wage Effect Decomposition



labor increases 0.53% (Table 6). These price changes, in conjunction with the changes in effective labor and experience, lead to the changes in average wages ($w = (R_L \lambda_L + R_E \lambda_E g(e)) \nu$) and income ($w \cdot$ hours) (Figures 13(d) and 13(e)). Overall, the pattern and the size of wage effects closely follow those of the average human capital, and the income effects reflect the increased hours of the DI-applicants-turned-employed.[32]

As the average wage changes are driven both by price and human capital, we gauge the size of the general equilibrium effect by conducting a partial equilibrium analysis where the factor prices are fixed to the benchmark values. In Figure 13(f), we plot the average changes in wages in the general and partial equilibrium. Although partial equilibrium effects are dominant, explaining 74.6% of the total wage change (61.8% of the total income change), the size of price effects are non-negligible. For young workers, with most human capital in labor, a larger fraction of wage changes are driven by the price changes. For older workers, their increased accumulated experience dominantly determines their wages, and thus, the price effect plays a smaller role. Further, for severely disabled workers, almost all effects are driven by partial effects, whereas a higher share of wage changes for non-disabled workers are due to price changes, which

example, reports that self-reported health status worsens for workers in manual occupations. On the other hand, there are others (e.g., Schaller and Stevens, 2015; Sullivan and von Wachter, 2009) that find that job loss leads to higher mortality and worse self-reported health. We acknowledge that our abstraction from this additional channel could bias our quantitative results: over (under)-estimating the increase in aggregate supply of inputs, if working deteriorates (improves) health.

[32] Even though the percent change in wage for severely disabled workers at early ages is large, the absolute magnitude is around \$2–\$4.

we discuss in Appendix C.3.

Table 6: Labor Market Effects of DI Reforms

	Change from DI to No-DI		Change from DI to No-DI
Employment	+3.25pp	Hours	+2.80%
Output	+2.88%	Output per Hour	+0.08%
Labor	+2.66%	Labor per Hour	-0.13%
Experience	+3.62%	Experience per Hour	+0.80%
Price of Labor	+0.53%	Relative Supply, E/L	+0.94%
Price of Experience	-1.80%	Relative Price, R_E/R_L	-2.32%

Lastly, we summarize the macroeconomic effects of the removal of the DI program in Table 6. The aggregate employment rate increases by 3.25pp and aggregate hours by 2.80%. As a relatively large share of new entrants to the labor force is disabled workers with lower efficiency of labor, the effective labor per hour decreases by 0.13%. However, because of the endogenous accumulation of experience and the small detrimental effect of disability on experience, per hour effective experience increases by 0.80%. Overall, the aggregate productivity as measured by output per hour increases 0.08% that leads to output growth of 2.88%.

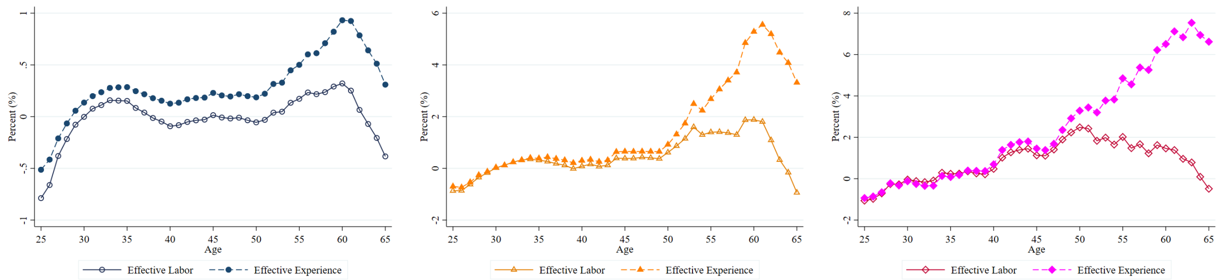
Analysis by Lifetime Health Status Our previous analysis captures the effects of removing DI on a worker of specific disability type at a given age. Among other things, the application decision only depends on the worker's current disability status; therefore, the disability-based analysis shows the trade-off between the application and labor supply decision and its consequences. Although this analysis is useful, it is limited in fully capturing the changes in work histories by disability type in the two economies. Importantly, wage of a worker in our model is determined by the *history* of his disability and labor market outcomes through his years of accumulated experience.

To better analyze the life-cycle income changes that reflect policy-induced worker-history effects, we construct an alternative measure called *lifetime health.* We define a worker to be *healthy* if he is non-disabled for more than 33 years out of 44 working years between 22 and 65, *less healthy*, if non-disabled between 28 and 32 years, *unhealthy* if non-disabled for less than 27 years. According to this categorization, about 84% of workers are healthy, 12%, less healthy, and 4%, unhealthy, similar to the population distribution of the disability status.[33] It is important to note that as the lifetime health status is constructed using the full disability history of workers, it does not directly measure a worker's disability status at a certain age. That

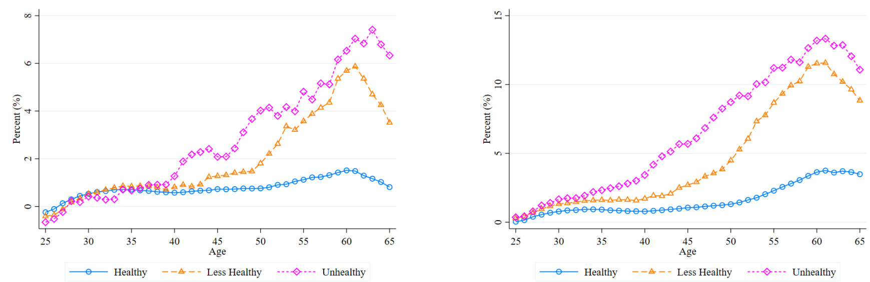
[33]Because of persistence in disability statuses, even though we only condition on periods in which a worker is non-disabled in categorizaing workers, the number of periods when workers are moderately and severely disabled also vary monotonically across lifetime health status. For healthy workers, average years as non-disabled, moderately, and severely disabled are 39.2, 3.4, and 1.4 years respectively; for the less healthy, they are 30.4, 8.5, and 5.1 years; and for the unhealthy, they are 24.3, 11.4, and 8.3 years.

Figure 14: Effects of Removing DI over the Life-Cycle by Lifetime Health

(a): Efficiency, Healthy (b): Efficiency, Less Healthy (c): Efficiency, Unhealthy



(d): Wage Effects (e): Income Effects



is, a "healthy" worker could have been severely disabled at age 35, just as an "unhealthy" worker could have been non-disabled at age 35. However, it is the case that a healthy worker's average life-cycle earnings profile differs from that of an unhealthy worker.[34]

Using the lifetime health measure, we plot the changes in average efficiency of human capital, wage, and income in Figure 14. The labor efficiency of all lifetime health types is not impacted much by the removal of DI because it is determined only by demographic characteristics (age, education, and disability status), and because the lifetime health status does not directly reflect the selection of workers into employment at a specific age as does the disability-based analysis. However, unlike the labor efficiency, a monotonic increase in effective experience occurs as workers age, exactly reflecting the increased experience during lifetime due to the DI removal. A healthy worker's effective experience increases by around 1% near retirement, and this magnitude is larger for unhealthy workers at 8% as they are the most impacted workers by the policy change. The corresponding wage and income changes are plotted in Figures 14(d) and 14(e). We observe that all types of workers, with the exception of very young, experience higher wage and income during their lifetime. The magnitudes of income changes are larger for healthy workers than those of non-disabled, but smaller for unhealthy workers than those of severely disabled. This analysis complements the disability-based analysis,

[34]We show the life-cycle employment and income profiles by lifetime health in Appendix C.3. Overall, they are monotonic in lifetime health. Compared to disability-status-specific profiles however, employment and income differences across lifetime health statuses are smaller when young, as all types are more likely to be non-disabled when young.

by providing lifetime earnings effects from the accumulation of experience driven by the DI removal.

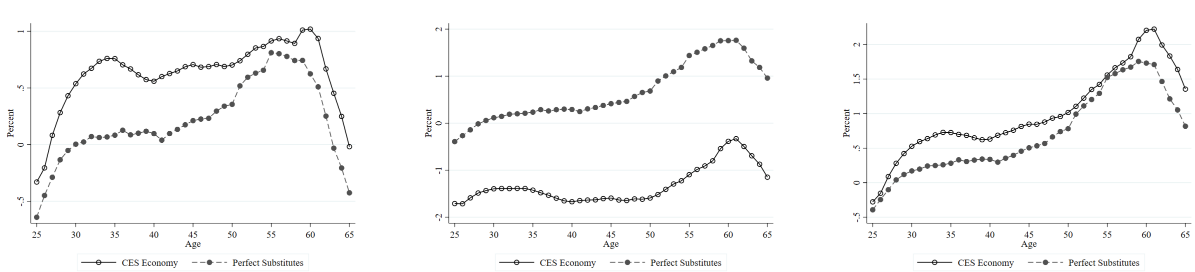
5.2 Role of Imperfect Substitutability

This section aims to evaluate the role of imperfect substitutability between labor and experience on labor market effects of DI. To do so, we abstract from the assumption that labor and experience are imperfect substitutes in aggregate production.[35] Instead, we assume that these two inputs are perfectly substitutable by imposing that ρ, the parameter controlling the elasticity of substitution, is equal to one; thus, the aggregate production function now reads $Y = A(L + \theta E)$. We then re-estimate the wage process, re-calibrate the model economy, and conduct the counterfactual experiment of removing the DI program.[36]

In Figures 15(a) and 15(b), we plot the changes in the average life-cycle *values* of labor ($R_L \cdot \lambda_L \nu$) and experience ($R_E \cdot \lambda_E g(e) \nu$) in the CES and the perfect substitutability ($\rho = 1$) economies.[37] In both cases, workers' choice to work in each period and consequentially, their accumulated experiences affect their human capital. The key feature of the CES-economy relative to the perfect-substitutes economy is the equilibrium price effects from the removal of DI: the price of labor R_L increases and the price of experience R_E decreases, due to the increase in relative supply of experience. Absent from these price changes, in the perfect-substitutes economy, the effects of DI removal on the value of labor is lower, whereas the effect of DI removal on the value of experience is higher compared to those in the CES-economy. As the endowments of these human capital vary over the life-cycle, these effects yield heterogeneous wage effects as shown in 15(c). In particular, with most of their human capital in labor, young workers enjoy higher increase in wages

Figure 15: Human Capital and Wage Effects of Removing DI

(a): Value of Labor (b): Value of Experience (c): Wage



[35] Although the two inputs are perfectly substitutable, we still maintain the assumption that individuals are endowed with labor and experience, which evolve over the life cycle.

[36] We start by re-estimating the wage equation (Equation (2)), with the restriction that the experience premium, $\Pi_{E,t}$, is equal to one for all years, the implication of imposing $\rho = 1$. Then, we use the re-estimated wage equation parameters and re-calibrate the model with an additional parameter θ, the relative efficiency of experience in aggregate production. We summarize the calibrated parameters of this economy in Appendix C.5.

[37] We take the averages across lifetime health statuses as they reflect the effects of work history on human capital better than disability status as we discuss in Section 5.1. The qualitative and quantitative results do not change much when we take averages across disability statuses.

Table 7: Labor Market Effects of DI under Perfect Substitutability between Inputs

	Change from DI to No-DI			Change from DI to No-DI	
	CES Production	Perfect Substitutes		CES Production	Perfect Substitutes
Employment	+3.25pp	+3.12pp	Hours	+2.80%	+2.59%
Output	+2.88%	+2.56%	Output per Hour	+0.08%	-0.03%
Labor	+2.66%	+2.38%	Labor per Hour	-0.13%	-0.21%
Experience	+3.62%	+3.33%	Experience per Hour	+0.80%	+0.72%
Price of Labor	+0.53%	-	Relative Supply, E/L	+0.94%	+0.92%
Price of Experience	-1.80%	-	Relative Price, R_E/R_L	-2.32%	-

in the no-DI, CES-economy than they would have in the no-DI, perfect-substitutes economy, thanks to the increased price of labor. As workers age, despite the lower price of experience in the no-DI, CES-economy, workers receive higher wage rates because of the increase in accumulated experience.

Given the micro-level effects, Table 7 compares the aggregate effects under $\rho = 1$ with those under the benchmark production specification. In the CES-economy, the elimination of DI leads to larger increases in employment, output, labor, and experience. Further, productivity effects of removing the DI program, as measured by effective labor, effective experience, and output per hour, are higher than in the perfect substitutes economy. In particular, the removal of DI increases output per hour by 0.08% in the CES-economy, whereas in the perfect substitutes economy, the removal of DI decreases output per hour by 0.03%. This implies that when we account for the complementarity between labor and experience, despite the large share of new workforce having disabilities, the productivity of the workforce increases, in contrast to when we ignore the linkages between these two inputs. Put differently, thanks to the complementarity between old (experience) and young (labor) workers, the increased supply of old workers leads to higher productivity (output per hour) in equilibrium.

5.3 Value of DI

We analyze the value of DI by conducting the following counterfactual experiment. For each worker of age j, the DI program becomes unexpectedly unavailable for one period so that the age-j worker's labor market choices are restricted to between working and not working. All other aspects of the model are identical to the benchmark economy up to age $j-1$ and starting again at age $j+1$.[38] Then, we calculate the consumption equivalent variation (CEV) as the percentage of consumption an age-j worker needs to be compensated for to be as well off as in the benchmark economy with DI; thus, the CEV represents how valuable DI is for an

[38] We consider this experiment more suitable for measuring the value of DI, rather than calculating the welfare in the economy with the complete removal of DI, because the complete removal of the program is a large reform that also leads to, for example, significant changes in government budget and the lump-sum transfers that workers receive. These confounding factors make it difficult to isolate the welfare effects from the removal of DI alone.

age-j worker.[39]

Figure 16: Value of DI by Disability Status in j

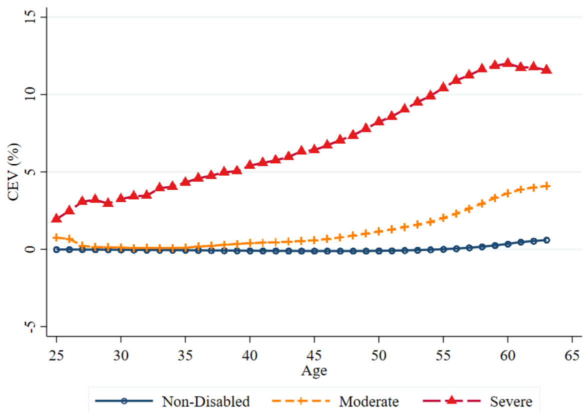


Table 8: CEV (%) by Subgroups

Disability in $j-1$	Labor status in $j-1$	(a) Disability in j: Non-Disab.	(b) Disability in j: Mod.	(c) Disability in j: Sev.	(d) Expected CEV
Non-Disabled	Employed	0.0	0.16	3.35	0.13
	Unemployed	0.0	0.46	5.22	0.19
	DI Recipient	-0.21	13.96	20.33	0.93
Mod. Disabled	Employed	0.0	0.06	3.65	0.90
	Unemployed	0.0	0.34	4.95	1.24
	DI Applicant	0.0	1.76	9.31	2.79
	DI Recipient	0.80	15.06	21.84	11.58
Sev. Disabled	Employed	0.0	0.44	2.58	2.19
	Unemployed	0.0	0.57	4.38	3.20
	DI Applicant	0.0	1.27	8.17	6.01
	DI Recipient	1.07	15.21	22.03	17.25
Average		1.5e-6	1.60	8.67	0.65

First, in Figure 16, we illustrate the average CEVs by age and current disability status in age j. We find that the value of DI increases as workers age, and more so for disabled workers: the CEV reaches 4.1% for the moderately disabled and 12% for the severely disabled in their 60s. Next, in Table 8, we further detail the CEVs by past disability and labor market statuses to better evaluate the heterogeneity in the value of DI. Conditional on disability and labor market status in $j-1$, the more severe a worker's realized disability status is (moving from columns (a) to (c)), the higher the CEV is. Moreover, conditional on disability status in j, disabled workers who are more attached to the DI program (and less attached to the labor market) have higher CEVs. An exception is non-disabled DI recipients with a small but negative CEV, indicating they prefer to be in the labor market instead of receiving DI.[40]

Finally, to illustrate the insurance value of the program, we compute the expected CEV in column (d), taking into account the mortality risks and disability transition probabilities from age $j-1$ to j. For instance, a worker who is employed in $j-1$ and non-disabled in both periods does not value DI (CEV is zero) as his choice is unaffected by the DI removal in age j. However, prior to the realization of their disability status in j, we see positive valuations of DI from the non-disabled workers as they could potentially transition to a disability status. Still, as the probability of being disabled (and thus utilizing the DI program) increases

[39] Let the utility of worker age j in the benchmark economy be $\bar{V}_j$; and in the counterfactual economy, $\tilde{V}_j$, where in age j, the DI program is removed. Then, consider a proportional consumption increase of Δ_j to this worker in every period (from today onward) in the counterfactual economy, which given our utility preferences equals $(1+\Delta_j)^{1-\gamma}\tilde{V}_j$. Then we solve for Δ_j such that $\bar{V}_j = (1+\Delta_j)^{1-\gamma}\tilde{V}_j$.

[40] In the model, as a DI recipient only returns to the labor market if he fails the reassessment test, there are non-disabled workers among DI recipients.

with the severity of disability in $j-1$, the ex-ante value of DI is higher for disabled workers.[41]

6 Conclusion

The Social Security Disability Insurance program is an important social safety net for workers facing disability risks. However, empirical findings suggest that it creates sizable disincentives for the labor supply of workers. This study aims to understand the aggregate implications of DI. Toward that goal, we estimated the productivity effects of disability regarding the two kinds of human capital possessed by a worker, (pure) labor and experience, and the interaction of these two inputs in aggregate production. A key empirical finding is that although disability lowers overall productivity, it is less detrimental to the productivity of older workers whose human capital primarily consists of experience (than labor). Our counterfactual analyses from a calibrated life-cycle model of workers are used to evaluate the impact of removing the DI program and to measure the value of DI to workers of heterogeneous characteristics. Removal of the DI program has broad effects on the labor market, increasing the wages of young workers through general equilibrium effects, and those of older workers through an increase in accumulated experiences. Also, the aggregate productivity may increase when the DI program is removed, thanks to the complementarity between human capital. The welfare benefits of the DI program are heterogeneous, with higher valuations from the old workers and those less attached to the labor market.

Our findings on the effects of the DI program suggest potential gains from encouraging disabled individuals to work, not only at the individual-level (as their loss in human capital might be small) but also at the aggregate level (as they might complement the human capital of other workers). Thus, the joint design of DI with labor market policies might be valuable.[42] In general, analyzing the effects of policies with aggregate interactions between heterogeneous human capital (inputs) modeled in this paper is not limited to the context of DI. For example, the recent demographic changes from the aging of the U.S. population would impact the relative supply of labor and experience, affecting workers across all ages and the aggregate productivity of the workforce. Thus, it would be interesting to study the role of policies that influence the labor supply decisions of workers, such as an increase in the mandatory retirement age or changing the Social Security payment schedule, within our model framework. We leave these important questions to future research.

[41] In Appendix C.6, we also show the CEVs by asset, disability, education, and age.

[42] Aizawa et al. (2020) studies the joint DI and labor market policy design problem. Although its focus is not on aggregate labor market efficiency, it incorporates both worker and firm responses to DI and labor market policies for their optimal design.

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Appendix

A Data Appendix

Sample Selection Criteria. We use the PSID for years 1985–2011 as the main data source for wage process estimation. Our sample consists of individuals of working age (age 18 to 65), male and female, at all education levels. We keep observations regardless of their employment status to control for selection. We exclude observations missing key information for our analysis. First, we drop observations without the two variables on work-limiting health conditions in the PSID that we use to construct our indicator of disability status (which we detail below). We also drop observations missing prior years of work (experience) if we are unable to fill the gaps even after exploring the past observations in panel data. Finally, we do not use observations missing information for constructing instrumental variables. As a result, our sample includes 101,335 observations, which consists of 17,859 non-employed (5,301 men, 12,558 women) observations and 83,476 employed (40,255 men, 43,221 women) observations with their wage information. Table 9 summarizes the selection results. In all analyses, we use core individual weights.

Table 9: Sample Selection

	Sample size
original sample	137,583
# of drops for missing:	
(1) disability	496
(2) experience	967
(3) welfare and tax (for instrumental variable construction)	34,785
total # of dropped obs.	36,248
remaining sample	101,335

Construction of the Disability Variable. We use two survey questions from the PSID to categorize workers' disability status: (a) "*Do you have any physical or nervous condition that limits the type of work or the amount of work you can do?*" and (b) "*For work you can do, how much does it limit the amount of work you can do?*" The former is a binary question (Yes or No), and the latter has four possible choices (A lot, Somewhat, Just a little, or Not at all). We define a worker to be non-disabled, if his answer is either a "No" on (a) or "Not at all" on (b); severely disabled, if his answer is "Yes" on (a) and "A lot" on (b); and moderately disabled, otherwise.

Construction of the Experience and Wage Variables. We follow Jeong et al. (2015) in constructing experience and wage variables. For measuring prior years of work (experience), we take the number of years reported by the PSID (which directly asked respondents for years of prior work) as its basis and construct the experience variable by adding experience when an individual reported working hours above 2000 hours per year.[43] Jeong et al. (2015) uses 1500 annual hours worked as the threshold for accumulating one year of experience, thus we use a more strict measure in our analysis. When an individual's first reported experience variable was larger than one he had at the age of 18 or older, we retrogressively construct the experience variable in time for his younger working life. Starting from year 1999, the PSID changed its survey frequency from annual to biennial, and we adjust the gap accordingly by adding two years of experience when he worked 2000 hours last year. Supplementing the yearly measure, we construct the accumulated working hours and compare the two experience variables. Table 10 shows that both measures

[43] The PSID asked for the number of years of experience in 1974, 1975, 1976, and 1985 for every head of household and wife of household. In subsequent sample years, the PSID has collected this information for new heads and wives.

Table 10: Accumulated Experience and Hours in the PSID by Disability Trajectory

Variable		Accumulated Working Hours			Accumulated Years of Experience		
Disability Trajectory		less than 20%	more than 20%	ratio (%)	less than 20%	more than 20%	ratio (%)
age	18-29	6,730	5,946	88.4	4.6	3.8	82.6
	30-39	18,708	14,992	80.1	10.8	8.9	82.4
	40-49	35,433	26,827	75.7	18.3	14.0	76.5
	50-59	48,123	34,523	71.7	25.1	17.7	70.5

Note: We compute the share of reported disabilities of individual's survey periods and categorize the samples into (i) those who reported disabilities less than 20% of their survey periods and (ii) those who reported disabilities more than 20% of their survey periods.

share quantitatively similar features. We compute the hourly wage rate using total annual earnings and total annual hours worked provided in the survey, and apply CPI to obtain real wage rates. We consider those who report more than 700 hours of work as employed and classify all others as non-participants. We use both types of workers in the first-stage where we control for selection, and only the economically active population (more than 700 hours of reported work) for the second-stage wage estimation.

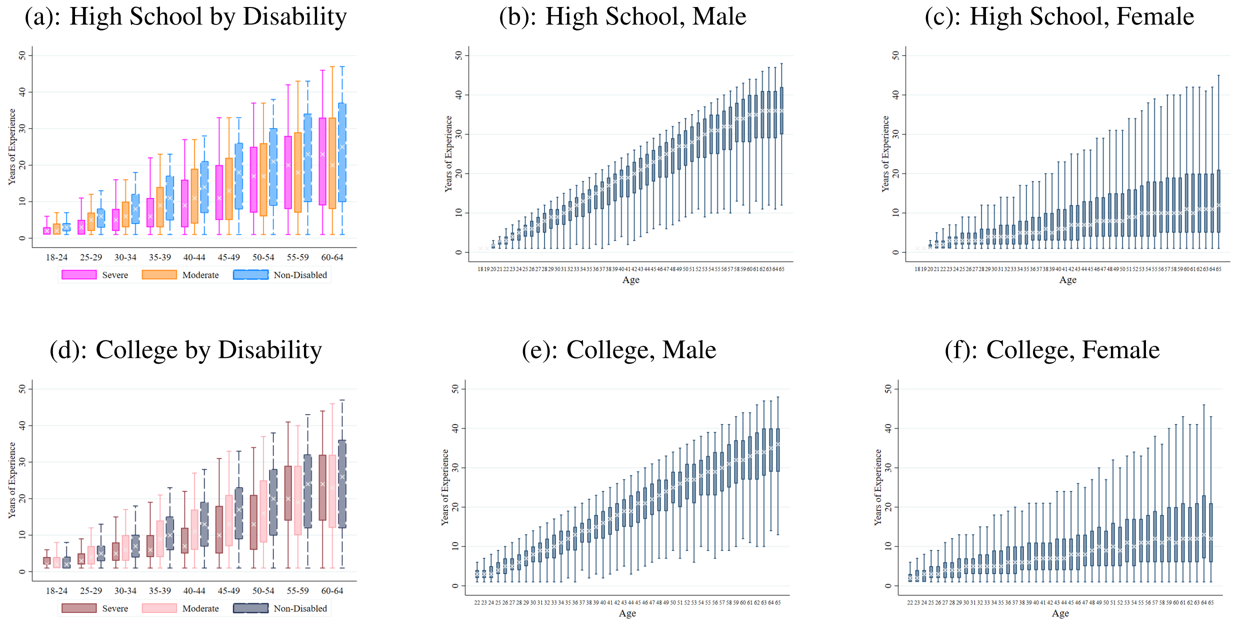
Descriptive Statistics. Table 11 reports the summary statistics by disability status. In general, workers with a more severe disability are older, obtained less education, report worse subjective health evaluation, and work less both extensively (employment rate) and intensively (hours). Even though the average age of disabled workers are higher, their average years of experience are similar to those who are non-disabled. For individuals younger (older) than 40, the average work experience decreases in severity of disability. We further detail the experience heterogeneity in Figure 17, presenting the distributions of experience by education, gender, and disability. We see sizable differences in experience by disability status, gender, and to a lesser degree across education. Lastly, in Table 12 are additional characteristics of workers by the SSDI receipt status. We identify DI recipients using the PSID's question on the type of Social Security received, which is available during the years 1984–1992 and from the year 2005 onward. We use this data to externally validate our model performance in Section 4.3.

Table 11: Summary Statistics by Disability Status

Variable	Non-Disabled Mean (St.Dev.)	Moderately Disabled Mean (St.Dev.)	Severely Disabled Mean (St.Dev.)
male	0.48 (0.50)	0.42 (0.49)	0.46 (0.50)
age (yr)	41.06 (12.17)	46.55 (12.36)	49.86 (11.48)
schooling (yr)	13.69 (2.08)	13.13 (2.29)	12.21 (2.48)
subjective health	2.11 (0.89)	3.17 (0.98)	4.01 (0.98)
employment	0.87 (0.33)	0.70 (0.46)	0.33 (0.47)
working hrs (yr)	1,949.1 (728.9)	1,732.5 (802.6)	1,342.4 (858.7)
experience (yr)	11.49 (10.04)	12.00 (10.60)	11.54 (10.61)
age $<$40	7.07 (4.89)	6.02 (5.08)	4.18 (4.25)
age $\geq$40	16.26 (10.94)	14.57 (10.81)	13.29 (10.70)
number of obs.	87,418	8,846	5,071

Note: Table presents the summary statistics, weighted by individual survey weights. Subjective health measure is a category variable ranging from 1 (excellent) to 5 (very poor). The average working hour is for individuals with positive labor earnings.

Figure 17: Prior Years of Work Experience



Note: The charts (a) and (d) are the life-cycle patterns of experience by disability and education. Solid lines (gray) and dashed lines (red) represent the 95% distribution of the non-disabled and the disabled workers. The charts (b), (c), (e), and (f) illustrate the variation in experience variable by gender and education. Boxes show the range of samples between 25% and 75% percentiles. Marker × denotes the median years of experience.

Table 12: Summary Statistics by SSDI Status

Variable	SSDI Recipients Mean (St. Dev.)	Non-SSDI Recipients Mean (St. Dev.)
age	51.17 (10.87)	40.53 (12.08)
schooling (year)	11.94 (2.55)	13.58 (2.13)
marital status (married)	0.44 (0.50)	0.60 (0.49)
subjective health	3.80 (1.04)	2.25 (0.99)
work limitation	0.823 (0.38)	0.11 (0.31)
experience (year)	12.71 (10.57)	11.00 (10.07)
mean assets (2011 dollars)	71,559.0 (270,189.1)	175,274.1 (971,452.2)
median assets (2011 dollars)	10,699.9 (17,394.8)	38,469.7 (52,738.2)
number of obs.	1,290	50,115

Note: The statistics are weighted by individual survey weights. Subjective health is a category variable ranging from 1 (excellent) to 5 (very poor).

B Estimation of Wage Equation

B.1 First Stage

Construction of Potential Benefits and Taxes. To address the selection bias in our wage process estimation, we adopt Heckman's two-stage estimation (Heckman, 1979) and run a probit regression using potential government transfers and taxes as our exclusion restriction. Similar to the simulated IV method in Currie and Gruber (1996a,b) and Low and Pistaferri (2015), we construct the magnitude of potential benefits from the state government and their interaction with disability status as our exclusion restrictions. Unlike the actual transfer amounts, which are endogenous, these potential benefits are exogenous by construction.

Following Low and Pistaferri (2015), we compute the potential benefits for a representative household enrolled in the following welfare programs: the Earned Income Tax Credit (EITC), Unemployment Insurance (UI), the Supplemental Nutrition Assistance Program (SNAP), Aid to Families with Dependent Children (AFDC), and Temporary Assistance for Needy Families (TANF). We start from the welfare benefit calculations available in Online Appendix C.1 of Low and Pistaferri (2015) and update the benefit formulas when more recent policy changes occurred. We then apply each policy formula to a representative household to compute the potential benefits for the years from 1985 to 2011.

To construct the potential tax liabilities by state and year, we use the NBER TAXSIM program v.27, which calculates federal and state income taxes given a household's financial circumstances. As a first step, we construct a financial statement of a representative household using the Survey of Consumer Finances (SCF), a triennial cross-sectional survey providing rich information on the financial status of U.S. households, e.g., information on earnings (including business income, dividends, and capital gains) by source. The SCF also includes respondents' mortgage balance and payment records, which we use to approximate mortgage interest payments.[44] We combine 9 waves of the SCF from the years 1986 to 2010 with the PSID for years 1985-2011, which contains variables such as childcare expenses, UI and SSI benefit payments, rents, and house prices.[45] Conjointly, we construct a profile of a representative household for tax-filing via NBER TAXSIM. For tax liability calculations, we use the nominal values of expenditures and earnings variables from both the SCF and PSID. We convert these tax liabilities into 2011 U.S. dollar using the CPI before we estimate a probit regression.

Table 13: Coefficient Estimation Results of Instrumental Variables

Dependent variable: employment	high school + college		high school only		college only	
potential benefits	-0.0790***	(0.0090)	-0.0740***	(0.0133)	-0.0915***	(0.0119)
potential benefits×moderate disability	0.0559	(0.0225)	0.0599**	(0.0303)	0.0548	(0.0349)
potential benefits×severe disability	0.0098	(0.0352)	-0.0252	(0.0473)	-0.0487	(0.0534)
potential taxes	2.95e-06***	(5.34e-07)	1.80e-06***	(6.69e-07)	4.43e-06***	(8.37e-07)
potential taxes×moderate disability	4.87e-07	(6.74e-07)	-2.26e-07	(8.43e-07)	1.26e-06	(1.14e-06)
potential taxes×severe disability	2.01e-07	(9.82e-07)	-8.84e-08	(1.26e-06)	6.18e-07	(1.52e-06)

Instrumental Variables and Probit Estimation Results. Since our sample includes both high school and college graduates, we choose to have wide range of potential welfare benefits/taxes as our instrumental variables.[46] Intuitively, we can infer the validity of our instruments based on the coefficient estimation results. Table 13 shows that the potential tax liabilities are statistically significant across education and disability groups. We also find that more generous benefit programs are negatively related to employment. We also examine whether our choice of exclusion restrictions is proper using the J-test, which evaluates the null hypothesis that an additional instrument is structurally correlated with error terms. For computational simplicity, instead of the nonlinear wage equation discussed in the main text, the test statistics are derived

[44]Specifically, income variables include WAGEINC, BUSSEFARMINC, INTDIVINC, KGINC, INCOME, and SSRETINC. These are wage and salary income, business income, interest, capital gains/losses, family income, and pensions, respectively. Mortgage balances, house value, and mortgage payments (MORTPAY, HOUSES, and NH_MORT) are conjointly used to predict mortgage interest payments, assuming a standard 30-year mortgage schedule.

[45]Since the PSID has been conducted biennially since 1997, these two surveys are simultaneously available every six years. In our case, except for the years 2001 and 2007, we merge the two data sets by matching the most recent SCF to the PSID. Thus, some components of taxable incomes from the SCF may have, at most, a one-year gap with the variables in the PSID. This gap has no specific direction in the sense that it could be either proceeding or lagging.

[46]Low and Pistaferri (2015) focused on samples with high school education to study trade-offs between welfare benefits from disability insurance and its costs from limiting work-incentives.

based on a standard linear log-wage equation. As reported in Table 14, the null hypothesis is rejected, indicating that our instruments are jointly valid. Table 15 reports the complete probit regression results.

Table 14: Over-Identification Test for Labor Supply Decision

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		high school + college			high school only			college only	
J-test	5.0547	1.9686	0.1955	3.1790	1.6417	0.4885	5.9041	0.0969	0.7171
p-value	0.4092	0.3737	0.9069	0.6724	0.4401	0.7833	0.3157	0.9527	0.6987
potential benefits	×	×		×	×		×	×	
potential taxes	×		×	×		×	×		×
number of obs.		83,476			36,197			47,279	

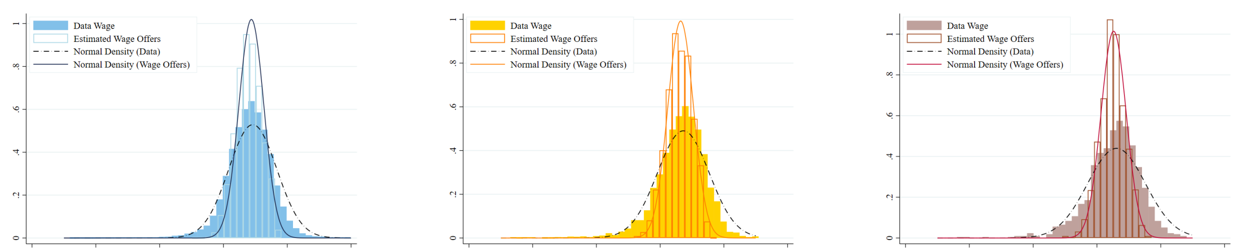
Table 15: First-Stage Probit Regression Results

Variable	Coefficients		Variable	Coefficients	
moderate disability	-0.5128***	(0.0356)	age	0.0027	(0.0030)
severe disability	-1.3979***	(0.0496)	age^2	-0.0009***	(0.0001)
experience (e)	0.2128***	(0.0065)	married	-0.0786***	(0.0223)
e^2	-0.0091***	(0.0004)	male	0.1382***	(0.0218)
e^3	0.0001***	(6.92e-6)	black	-0.0582***	(0.0240)
years of schooling	0.0671***	(0.0048)			
Number of obs.			101,335		
Pseudo R^2			0.2365		

Note: Table 15 reports the first-stage probit regression results of Heckman's two-stage estimation. The dependent variable is the employment status of an individual. Independent variables also include year dummies. We use individual-level survey weights for our analysis. Standard errors are clustered at the individual level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Figure 18: Observed Wage vs. Estimated Wage Offers

(a): Non-Disabled Workers (b): Moderately Disabled Workers (c): Severely Disabled Workers



Note: The hourly wage (2011 US dollars) in the PSID (years 1985 to 2011) is labor income divided by the annual working hours.

B.2 Nonlinear Wage Equation Estimation

Selection Control. As shown in Table 2, the coefficient on the inverse Mills' ratio is significant. Table 16 reports the estimated effects of disability on productivities with and without selection control. Without selection control, the estimated productivities of a moderately disabled worker relative to a non-disabled worker are 0.87 (0.71) and 0.90 (1.22) for labor and experience respectively for high school graduates (some college). For severely disabled workers, the results are 0.84 (0.75) and 0.92 (0.84) for labor and experience. Figure 18 illustrates the selection bias by comparing the log-wage and wage offer distributions by disability. The offer distributions are constructed by applying the estimated coefficients on observable characteristics. As seen in Figure 18, the distributions show differences, notably more so for disabled workers.

Detailed Estimation Results. In Figure 19, we plot the estimated coefficients of the dummy variables in wage estimation; in Figure 20, we plot the estimated life-cycle profiles of labor and experience efficiency for college educated workers using the estimated coefficients of Equation (2) (the analogues of Figure 1); and in Figure 21, we plot the predicted log wages along with the original data.

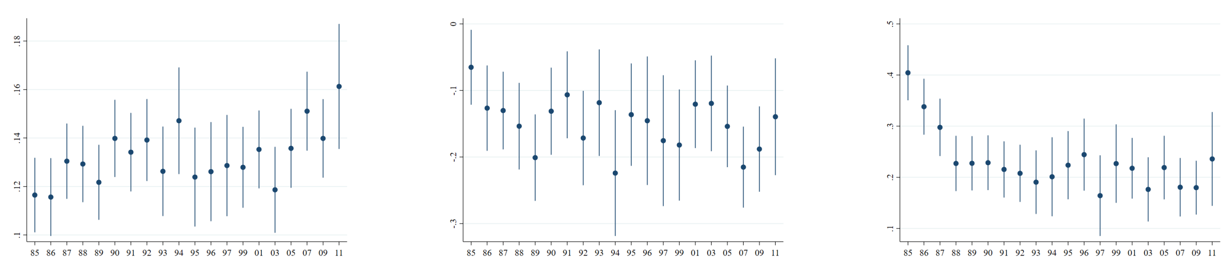
Table 16: Effect of Disability on Wage: With and Without Selection Control

Coefficients			(1) benchmark	(2)
Inverse Mils Ratio			0.2463 (0.0903)	
Labor Profile		$\lambda_{L,1}\,(HS)$	0.0213 (0.0052)	0.0200 (0.0050)
		$\lambda_{L,2}\,(HS)$	-0.0004 (0.0001)	-0.0002 (0.0001)
		$\lambda_{L,0}\,(Col)$	-0.2481 (0.0551)	-0.2501 (0.0542)
		$\lambda_{L,1}\,(Col)$	0.0534 (0.0056)	0.0522 (0.0051)
		$\lambda_{L,2}\,(Col)$	-0.0010 (0.0001)	-0.0009 (0.0001)
	Moderate	$\ln\phi_L\,(HS)$	-0.2237 (0.0691)	-0.1358 (0.0560)
		$\ln\phi_L\,(Col)$	-0.4100 (0.0690)	-0.3355 (0.0574)
	Severe	$\ln\phi_L\,(HS)$	-0.4481 (0.1769)	-0.1718 (0.1286)
		$\ln\phi_L\,(Col)$	-0.5841 (0.1553)	-0.2918 (0.1192)
Experience Profile		$\lambda_{E,1}\,(HS)$	0.0034 (0.0142)	-0.0046 (0.0203)
		$\lambda_{E,2}\,(HS)$	-0.0002 (0.0003)	-0.0003 (0.0004)
		$\lambda_{E,0}\,(Col)$	-0.3821 (0.1826)	-0.3663 (0.2432)
		$\lambda_{E,1}\,(Col)$	0.0067 (0.0188)	-0.0116 (0.0258)
		$\lambda_{E,2}\,(Col)$	-0.0002 (0.0003)	0.00003 (0.0005)
	Moderate	$HS:\phi_E/\phi_L$	1.0975 (0.1828)	1.0289 (0.2228)
		$Col:\phi_E/\phi_L$	1.5743 (0.2673)	1.7035 (0.3606)
	Severe	$HS:\phi_E/\phi_L$	1.2769 (0.4543)	1.0885 (0.5074)
		$Col:\phi_E/\phi_L$	1.5191 (0.5396)	1.1254 (0.6413)
Accumulated		ζ_2	-0.0491 (0.0081)	-0.0531 (0.0112)
Experience		ζ_3	0.0013 (0.0004)	0.0016 (0.0005)
		ζ_4	-0.00001 (5.47e-6)	-0.00002 (7.50e-6)
Number of Obs.				83,476

Note: The control variables (other than the functional specification) include region and year-specific dummies for gender, race, and schooling (college). We use individual-level survey weights. Standard errors in parentheses are clustered at the individual level.

Figure 19: Estimation Results: The Dummy Variables

(a): Schooling: College (b): Race: Black (c): Gender: Male



Note: Dots are the estimates, and the lines are their 95% CI. The x-axis is the year, and the y-axis is the productivity measured by log hourly wage (2011 US dollar). Standard errors are clustered at the individual level.

Figure 20: The Efficiency Schedules over the Life-cycle, Workers with College Education

(a): Labor Efficiency, λ_L (b): Experience Fficiency, λ_E

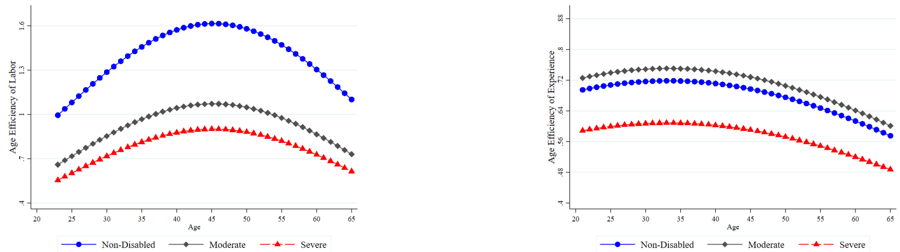
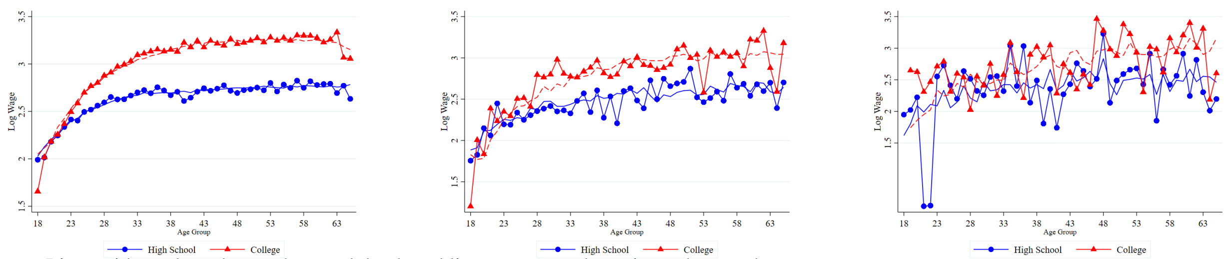


Figure 21: Estimation Results, Data Fit

(a): Non-Disabled (b): Moderately Disabled (c): Severely Disabled



Note: Lines with markers denote data, and the dotted lines represent the estimated wages by age.

Table 17: Effects of Disability with Alternative Specifications

Coefficients			(1) $\phi_X(s) = \phi_X$	(2) $\lambda_X(s) = \lambda_X$	(3) Benchmark	(4) $g(e;s)$
Labor Profile	moderate	$\phi_L(HS)$	0.7095	0.7885	0.7994	0.8000
		$\phi_L(Col)$		0.6911	0.6637	0.6658
	severe	$\phi_L(HS)$	0.5830	0.6399	0.6388	0.6420
		$\phi_L(Col)$		0.6072	0.5577	0.5620
Experience Profile	moderate	$\phi_E(HS)$	0.9621	0.9568	0.8776	0.8776
		$\phi_E(Col)$		0.9844	1.0448	1.0469
	severe	$\phi_E(HS)$	0.8237	0.9459	0.8158	0.8145
		$\phi_E(Col)$		0.7949	0.8471	0.8450
Education-Specific	ϕ_L and ϕ_E			$\times$	$\times$	$\times$
Components	λ_L and λ_E		$\times$		$\times$	$\times$
	$g(e)$					$\times$

B.3 Robustness Analyses

Our benchmark specification allows for the education-dependence of the disability effects (ϕ_L and ϕ_E) and the age-efficiency schedules of labor and experience (λ_L and λ_E). Table 17 reports the effects of disability under alternative specifications. In column (1), we relax the education-dependence and find that we might have over-estimated the effects of disability on labor and under-estimated its effects on experience for high school graduates, had we not included education-dependent disability effects. We further check whether suppressing the education-dependence on efficiency profiles while allowing for education-specificity on disability effects (column (2)) and whether the education-specific accumulated experience function (column (3)) impact the estimation outcomes. The estimated effects of disability are similar to benchmark estimates under these alternative specifications. The estimates underlying Table 17 are documented in Table 18. We also test the significance of the coefficient estimates under alternative clustering assumptions and find that the results are significant at the 1% level under various assumptions (Table 19).

Table 18: Robustness Analyses: Estimated Labor and Experience Efficiencies with Alternative Specifications

Coefficients			(1)	(2)	(3) benchmark	(4)
Labor Profile		$\lambda_{L,1}\,(HS)$	0.0216 (0.0053)	0.0397 (0.0041)	0.0213 (0.0052)	0.0217 (0.0053)
		$\lambda_{L,2}\,(HS)$	−0.0004 (0.0001)	−0.0007 (0.0001)	−0.0004 (0.0001)	−0.0004 (0.0001)
		$\lambda_{L,0}\,(Col)$	−0.2592 (0.0548)	-	−0.2481 (0.0551)	−0.2401 (0.0561)
		$\lambda_{L,1}\,(Col)$	0.0532 (0.0057)	-	0.0534 (0.0056)	0.0532 (0.0058)
		$\lambda_{L,2}\,(Col)$	−0.0010 (0.0001)	-	−0.0010 (0.0001)	−0.0009 (0.0001)
	Moderate	$\ln\phi_L\,(HS)$	−0.3432 (0.0527)	−0.2376 (0.0679)	−0.2237 (0.0691)	−0.2226 (0.0692)
		$\ln\phi_L\,(Col)$	-	−0.3695 (0.0659)	−0.4100 (0.0690)	−0.4076 (0.0687)
	Severe	$\ln\phi_L\,(HS)$	−0.5396 (0.1315)	−0.4464 (0.1717)	−0.4481 (0.1769)	−0.4431 (0.1761)
		$\ln\phi_L\,(Col)$	-	−0.4989 (0.1518)	−0.5841 (0.1553)	−0.5762 (0.1548)
Experience Profile		$\lambda_{E,1}\,(HS)$	0.0047 (0.0090)	0.0023 (0.0151)	0.0034 (0.0142)	0.0018 (0.0154)
		$\lambda_{E,2}\,(HS)$	−0.0003 (0.0002)	−0.0002 (0.0003)	−0.0002 (0.0003)	−0.0002 (0.0003)
		$\lambda_{E,0}\,(Col)$	-	-	−0.3821 (0.1826)	−0.4588 (0.1919)
		$\lambda_{E,1}\,(Col)$	-	-	0.0067 (0.0188)	0.0074 (0.0221)
		$\lambda_{E,2}\,(Col)$	-	-	−0.0002 (0.0003)	−0.0002 (0.0004)
	Moderate	$HS:\phi_E/\phi_L$	1.3560 (0.1568)	1.2134 (0.2211)	1.0975 (0.1828)	1.0964 (0.1832)
		$Col:\phi_E/\phi_L$	-	1.4244 (0.2307)	1.5743 (0.2673)	1.5737 (0.2695)
	Severe	$HS:\phi_E/\phi_L$	1.4129 (0.3491)	1.4782 (0.5515)	1.2769 (0.4543)	1.2687 (0.4498)
		$Col:\phi_E/\phi_L$	-	1.3091 (0.4837)	1.5191 (0.5396)	1.5035 (0.5400)
Accumulated		$\zeta_2\,(HS)$	−0.0490 (0.0079)	−0.0493 (0.0087)	−0.0491 (0.0081)	−0.0526 (0.0095)
Experience		$\zeta_3\,(HS)$	0.0012 (0.0004)	0.0013 (0.0004)	0.0013 (0.0004)	0.0015 (0.0004)
		$\zeta_4\,(HS)$	−0.00001 (5.36e-6)	−0.00001 (5.83e-6)	−0.00001 (5.47e-6)	−0.00001 (6.35e-6)
		$\zeta_2\,(Col)$	-	-	-	−0.0445 (0.0141)
		$\zeta_3\,(Col)$	-	-	-	0.0009 (0.0007)
		$\zeta_4\,(Col)$	-	-	-	-6.50e-6 (9.78e-6)
Education-Specific		ϕ_L and ϕ_E		×	×	×
Components		λ_L and λ_E	×		×	×
		$g\,(e)$				×
Number of Obs.				83,476		

Note: The control variables (other than the functional specification) include region and year-specific dummies for gender, race, and schooling. We use individual-level survey weights. Standard errors in parentheses are clustered at the individual level.

C Quantitative Analysis

C.1 Details on Exogenously Calibrated Parameters

Demographics. We use the 2014 Population Projections Program from the Census for the demographic distribution in the economy. The 2014 Population Projections Program provides projected estimates of demographic composition by age, sex, race, and ethnicity using the 2010 Census, and the analysis was conducted in 2013 based on the cohort method under the assumptions on future fertility, mortality, and migration rates (Figure 22).

Survival Probability. We estimate the impact of health on conditional survival probabilities, using the life table from the Social Security Administration and micro-level data from the PSID. Following the strategy of

Table 19: Robustness Analyses, Estimated Coefficients with Alternative Clustering

Coefficients			(1)	(2)	(3)	(4) benchmark
Inverse Mils Ratio			0.2463 (0.5577)	0.2463 (0.1411)	0.2463 (0.0570)	0.2463 (0.0903)
Labor Profile		$\lambda_{L,1}\,(HS)$	0.0213 (0.0043)	0.0213 (0.0054)	0.0213 (0.0037)	0.0213 (0.0052)
		$\lambda_{L,2}\,(HS)$	−0.0004 (0.0001)	−0.0004 (0.0002)	−0.0004 (0.0001)	−0.0004 (0.0001)
		$\lambda_{L,0}\,(Col)$	−0.2482 (0.0424)	−0.2482 (0.0615)	−0.2482 (0.0394)	−0.2481 (0.0551)
		$\lambda_{L,1}\,(Col)$	0.0534 (0.0041)	0.0534 (0.0052)	0.0534 (0.0033)	0.0534 (0.0056)
		$\lambda_{L,2}\,(Col)$	−0.0010 (0.0001)	−0.0010 (0.0001)	−0.0010 (0.0001)	−0.0010 (0.0001)
	Moderate	$\ln\phi_L\,(HS)$	−0.2238 (0.0612)	−0.2238 (0.0745)	−0.2238 (0.0511)	−0.2237 (0.0691)
		$\ln\phi_L\,(Col)$	−0.4100 (0.0622)	−0.4100 (0.0613)	−0.4100 (0.0495)	−0.4100 (0.0690)
	Severe	$\ln\phi_L\,(HS)$	−0.4482 (0.1190)	−0.4482 (0.2720)	−0.4482 (0.1360)	−0.4481 (0.1769)
		$\ln\phi_L\,(Col)$	−0.5839 (0.0972)	−0.5839 (0.1840)	−0.5839 (0.1116)	−0.5841 (0.1553)
Experience Profile		$\lambda_{E,1}\,(HS)$	0.0034 (0.0096)	0.0034 (0.0133)	0.0034 (0.0088)	0.0034 (0.0142)
		$\lambda_{E,2}\,(HS)$	−0.0002 (0.0002)	−0.0002 (0.0002)	−0.0002 (0.0002)	−0.0002 (0.0003)
		$\lambda_{E,0}\,(Col)$	−0.3814 (0.1079)	−0.3814 (0.1608)	−0.3814 (0.1220)	−0.3821 (0.1826)
		$\lambda_{E,1}\,(Col)$	0.0067 (0.0140)	0.0067 (0.0208)	0.0067 (0.0111)	0.0067 (0.0188)
		$\lambda_{E,2}\,(Col)$	−0.0002 (0.0003)	−0.0002 (0.0004)	−0.0002 (0.0002)	−0.0002 (0.0003)
	Moderate	$HS:\phi_E/\phi_L$	1.0977 (0.1533)	1.0977 (0.2192)	1.0977 (0.1314)	1.0975 (0.1828)
		$Col:\phi_E/\phi_L$	1.5743 (0.2118)	1.5743 (0.2409)	1.5743 (0.1961)	1.5743 (0.2673)
	Severe	$HS:\phi_E/\phi_L$	1.2773 (0.2764)	1.2773 (0.5058)	1.2773 (0.3665)	1.2769 (0.4543)
		$Col:\phi_E/\phi_L$	1.5182 (0.2733)	1.5182 (0.4721)	1.5182 (0.4007)	1.5191 (0.5396)
Accumulated		ζ_2	−0.0491 (0.0048)	−0.0491 (0.0071)	−0.0491 (0.0046)	−0.0491 (0.0081)
Experience		ζ_3	0.0013 (0.0003)	0.0013 (0.0004)	0.0013 (0.0002)	0.0013 (0.0004)
		ζ_4	−0.00001 (4.07e-6)	−0.00001 (5.24e-6)	−0.00001 (3.41e-6)	−0.00001 (5.47e-6)
Cluster		year	×		×	
		state		×		
		id			×	×
Number of Obs.				83,476		

Note: The control variables (other than the functional specification) also include region and year-specific dummies for gender, race, and schooling. We use individual-level survey weights for our analysis.

Attanasio et al. (2011), we obtain age-dependent survival probabilities ($\bar{\delta}_j$) from the life table, and obtain the empirical disability distribution by age (p_j^h) and survival rates by disability status and age δ_j^h from the PSID. Then, we use the following equations to obtain disability-dependent conditional survival probabilities that are consistent with the life tables: $\bar{\delta}_j = \sum_{h\in\{ND,MD,SD\}} p_j^h \delta_j^h$ and $\Delta_j^h = \delta_j^{ND} - \delta_j^h$ for $h \in \{MD, SD\}$. The latter equations represent the survival premia of being non-disabled, relative to having moderate or severe disability. Given the small samples in the PSID, we smooth out survival premia (Δ_j^h) by fitting polynomials to age, and extrapolate them for individuals older than 90.[47]

C.2 Calibrated Model Performance

Figure 23 shows the share of population by disability status in the simulated model and in the data. We see that the model fits the data shares well. Figure 24 is the share of rejected applicants that become employed in the subsequent period by age, supplementing the applicant-to-employment transition rate discussed in

[47] Attanasio et al. (2011) uses the Health and Retirement Study (HRS) to calculate health-dependent survival probabilities for individuals older than 50. The magnitudes of our survival premia are similar to theirs.

Figure 22: Population Share by Age

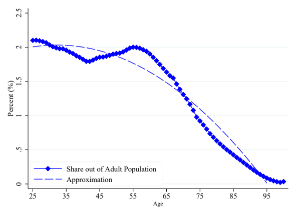


Figure 23: Population Share by Disability Status

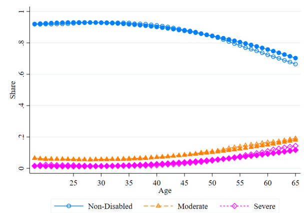


Figure 24: Applicant to Employment Transition Rate

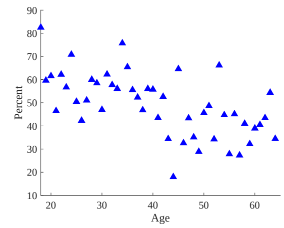
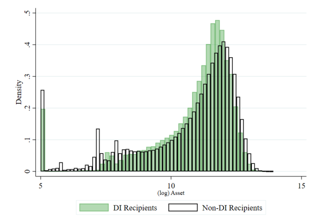


Figure 25: Asset Distribution by DI Status



Note: In Figure 23, hollow markers represent the share of population by disability status in the simulated model, and filled markers, corresponding shares in the data. In Figure 25, assets less than \$150 has been collapsed to \$150 for plotting purposes only.

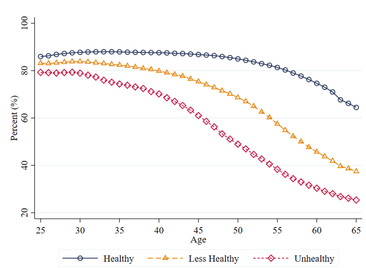
Section 4.3. Lastly, we plot the asset distribution by DI status in Figure 25, where we clearly see that DI recipients have lower average asset than non-DI recipients, as in the data documented in Table 12.

C.3 Labor Market Effects of DI

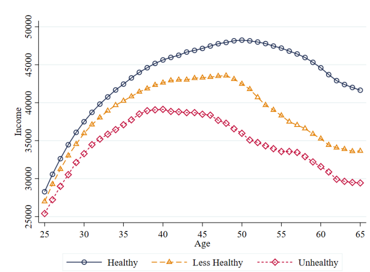
Life-Cycle Profiles by Lifetime Health. Figure 26 shows employment and income profiles by lifetime health status, a new measure we introduced in Section 5.1 to complement the analysis by disability. Since lifetime health statuses are constructed based on the disability history during the working life, there is a smaller variation in the labor market outcomes among young workers, as all lifetime health types are less likely to be severely (or moderately) disabled when young. However, the variations in their employment rates and labor income diverge as they age, reflecting their heterogeneous experiences in the labor market.

Figure 26: Employment and Income Profiles by Lifetime Health

(a): Employment Rate



(b): Labor Income

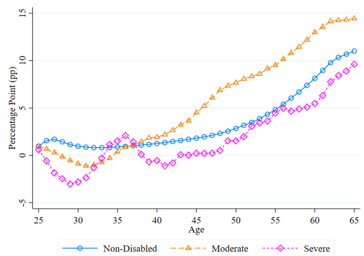


Effects by Education. Figure 27 shows the life-cycle effects of the DI removal on employment rates and wages by education and two measures of health statuses—disability and lifetime health. Unlike high-school educated workers, starting in their 40's, the employment rates of severely disabled workers with college education increase as much as those of moderately disabled workers. This may be due to the fact that even severely disabled workers do not suffer a large productivity effect on experience: the productivity declines by 15% (18%) for high school (college). Therefore, individuals without the DI option choose to work, rather than stay unemployed. The wage changes by disability are larger for high-school graduates than they are for college-educated workers, but their patterns are qualitatively similar. Lastly, consistent with a large increase in employment among college-educated workers, which results in high amounts of accumulated experience, the unhealthy workers experience the largest increase in their wage.

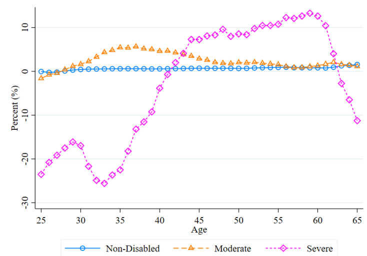
Figure 27: Effects of Removing the DI Program by Education

A. High School

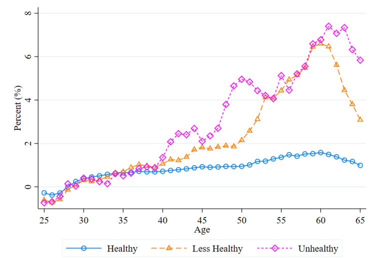
(a): Employment by Disability



(b): Wage by Disability

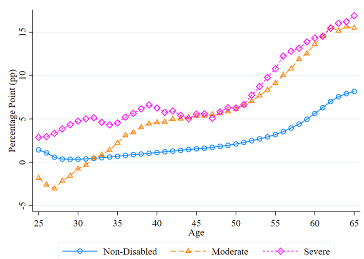


(c): Wage by Lifetime Health

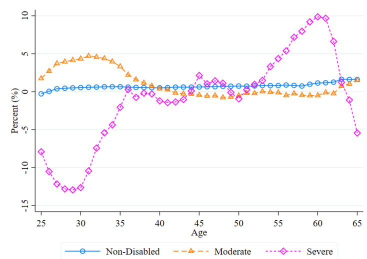


B. College

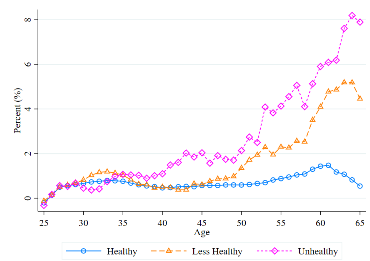
(d): Employment by Disability



(e): Wage by Disability



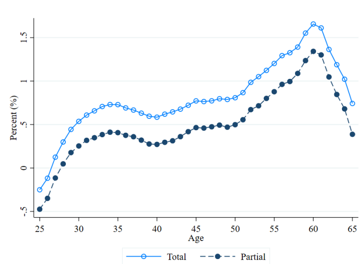
(f): Wage by Lifetime Health



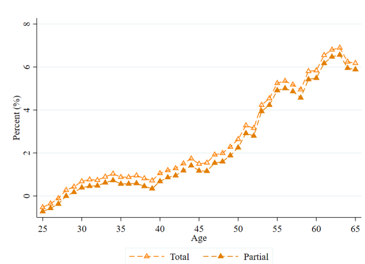
Partial Equilibrium Analysis of DI Removal. The decomposition of wage effects by lifetime health statuses are plotted in Figure 28. Although a large share of wage changes is due to price effects for healthy individuals (who consist 84% of the total population and a even higher share among employed workers), it is not the case for less healthy and unhealthy workers. For the latter two types of workers, it is mostly the changes in their labor market participation behaviors that impact their wages over the life-cycle, that is, partial effects explain almost all of the changes in their wage rates.

Figure 28: Wage Effect Decomposition by Lifetime Health

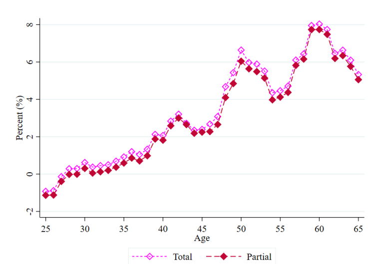
(a): Healthy



(b): Less Healthy



(c): Unhealthy



C.4 Labor Market Effects of Moderate Reforms

In order to analyze the effects of more moderate DI reforms, we conduct experiments in which the DI benefit amounts are lowered by 20% and the DI acceptance probabilities are lowered by 30%, which yield similar shares of DI recipients. Table 20 summarizes the aggregate effects of the reforms and compare the share of DI applicants and recipients in the counterfactual economies with those of the benchmark DI economy.

Table 20: Labor Market Effects of DI Reforms

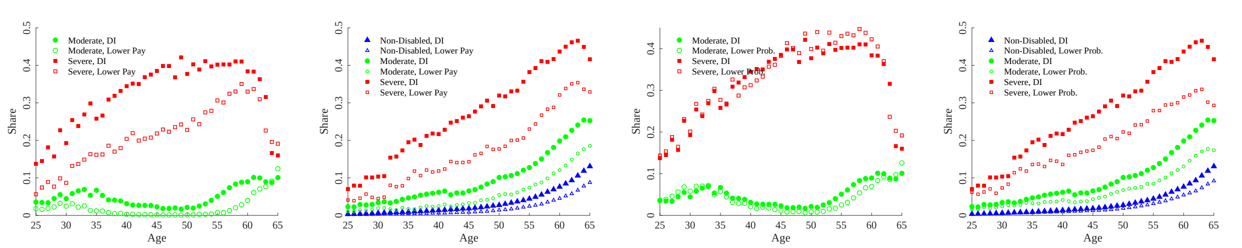
	Change from the Benchmark DI Economy, %				Bench-	Lower	Lower
	(a) No DI	(b) ↓ Benefits	(c) ↓ Probability		mark	Benefit	Prob
Employment (Hours)	+3.25*pp* (+2.80)	+0.42*pp* (+1.14)	-0.36*pp* (+0.63)	DI Applicant Share, %			
Output (per Hour)	+2.88 (+0.08)	+1.20 (+0.06)	+0.62 (-0.01)	Moderate	5.57	2.69	4.58
Relative Supply, E/L	+0.94	+0.32	+0.08	Severe	33.47	24.80	34.88
Labor (per Hour)	+2.66 (-0.13)	+1.13 (-0.01)	+0.61 (-0.03)				
Experience (per Hour)	+3.62 (+0.80)	+1.45 (+0.31)	+0.68 (+0.05)	DI Recipient Share, %			
Relative Price, R_E/R_L	-2.32	-1.09	-0.20	Non-Disabled	2.82	1.58	1.98
Labor	+0.53	+0.25	+0.04	Moderate	12.14	7.31	8.23
Experience	-1.80	-0.83	-0.15	Severe	34.89	23.54	24.74

Note: All units are in percentage terms, with the exception of employment rates which are in percentage points. In (a), we completely remove the DI program; (b), lower DI benefits by 20%; and (c), lower DI acceptance probability by 30%. In all economies, we impose budget neutrality relative to the benchmark (DI) economy using lump-sum transfers.

Under both reforms, smaller shares of the population receive DI benefits. However, while the benefit reform reduces applicants, lowering the success probability does not necessarily do so. In fact, as shown in Figure 29, when probabilities are lower, the applicant share increases among the old, severely disabled workers, but decreases among the old, moderately disabled workers. These heterogeneous responses lead to a reduction in employment rate but an increase in hours under the low-probability reform (since moderately disabled workers work more hours). In the aggregate, while the quantitative magnitudes are smaller than that of a DI removal, the qualitative effects from reforms aimed at decreasing the size of the DI programs increases the relative supply and decreases the relative price of experience. The benefit reform increases output per hour, similar to the no-DI reform case. On the other hand, the output and output per hour effects are smaller when only the acceptance probabilities are lowered.

Figure 29: DI Applicant and Beneficiary Shares under DI Reforms

(a): Applicants: Lower Benefits | (b): Beneficiaries: Lower Benefits | (c): Applicants: Lower Probability | (d): Beneficiaries: Lower Prob.



C.5 Role of Imperfect Substitutability

Wage Estimation and Calibration. In Section 5.2, we re-estimate the wage equation and re-calibrate the quantitative model under the assumption that $\rho = 1$ to study the effects of incorporating the role of heterogeneous inputs. Table 21 summarizes the estimated wage parameters and parameters calibrated within the model in this economy.

Table 21: Estimated Coefficients with Perfect Substitutability

(a): Wage Estimation

(a) Labor			(b) Experience		(c) Accumulated Experience $g(e)$	
High School	$\lambda_{L,1}$	0.0227 (0.0053)	$\lambda_{E,1}$	0.0010 (0.0143)	ζ_2	-0.0494 (0.0079)
	$\lambda_{L,2}$	-0.0004 (0.0001)	$\lambda_{E,2}$	-0.0002 (0.0003)	ζ_3	0.0013 (0.0004)
College	$\lambda_{L,0}$	-0.2393 (0.0558)	$\lambda_{E,0}$	-0.3818 (0.1792)	ζ_4	-0.00001 (0.0000)
	$\lambda_{L,1}$	0.0529 (0.0058)	$\lambda_{E,1}$	0.0069 (0.0186)		
	$\lambda_{L,2}$	-0.0010 (0.0001)	$\lambda_{E,2}$	-0.0002 (0.0004)	(d) Inv. Mills	0.2485 (0.0920)

(e) Health Effects		$\ln\phi_L(s,h)$		$\phi_L(s,h)/\phi_E(s,h)$	Implied Effects	Mod.	Sev.
High School	Mod.	-0.2107 (0.0705)	Mod.	1.0580 (0.1896)	Labor	0.8100	0.6435
	Sev.	-0.4408 (0.1775)	Sev.	1.2411 (0.4512)	Experience	0.8570	0.7987
College	Mod.	-0.3930 (0.0698)	Mod.	1.4902 (0.2623)	Labor	0.6750	0.5464
	Sev.	-0.6044 (0.1567)	Sev.	1.6023 (0.5539)	Experience	1.006	0.8755

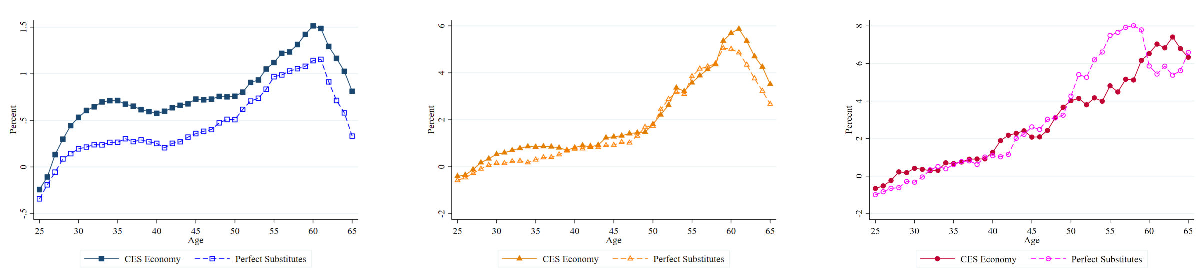
(b): Parameters Calibrated within the Model

Parameters	Description	Value					
A	Aggregate productivity	0.446					
θ	Efficiency of experience	0.051					
β	Time discount factor	0.959					
		High School			College		
		Non-Disabled	Moderate	Severe	Non-Disabled	Moderate	Severe
$\eta_{h,s}$	Disutility of work	-0.137	-0.219	-0.282	-0.140	-0.196	-0.215
$F_{h,s}$	Fixed cost of work	1233.799	1377.822	1507.883	702.897	747.957	821.883
$\chi^W_{h,s}$	Offer arrival rate: Employed	0.904	0.776	0.434	0.937	0.895	0.556
$\chi^U_{h,s}$	Offer arrival rate: Unemployed	0.584	0.476	0.356	0.662	0.532	0.556
$\chi^A_{h,s}$	Offer arrival rate: Applicants	0.685	0.438	0.010	0.931	0.657	0.060
χ^B_s	Offer arrival rate: DI beneficiaries	0.101	-		0.543	-	

Effects of Removing the DI Program by Lifetime Health Status. In Figure 30, we plot the wage effects from removing the DI program under the CES and perfect substitutes economies by lifetime health status.

Figure 30: Wage Effects by Lifetime Health by Aggregate Production Technology

(a): Healthy (b): Less Healthy (c): Unhealthy



C.6 Value of DI

In Figure 31(a), we plot the CEV distributions by asset and in Figure 31(b), the share of population in specific asset levels by age and health. As seen in the plots, there is a significant share of workers with low assets, for whom DI is more valuable (high CEV).

Figure 31: Value of Disability Insurance by Asset

(a): CEVs by Asset

(b): Distribution of Asset