Three Essays on Social Security Disability Insurance Participation

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Abstract

Three Essays on Social Security Disability Insurance Participation

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Over the last three decades, the U.S. labor force has increased by less than thirty percent, while the number of Social Security Disability Insurance (DI) beneficiaries has almost tripled, despite improvements in overall labor force health. This thesis examines individual-level DI participation using micro-public surveys and a blend of empirical and theoretical dynamic models, presented in three chapters.

The first chapter explores the relationship between DI participation, skill level, and labor market outcomes. By extending the Diamond-Mortensen-Pissarides framework to include heterogeneous skills and endogenous DI participation, the model examines the effects of aggregate productivity, health-related eligibility criteria, and DI application success rates. Key findings include: (1) economic downturns prompt higher-skilled individuals to seek disability benefits, narrowing the wage gap; (2) relaxed health-related eligibility criteria increase DI participation among less skilled workers, widening the wage gap; and (3) higher DI application success rates boost participation with minor effects on skill composition.

The second chapter investigates how health, productivity, and labor market outcomes influence DI participation. Using the Panel Study of Income Dynamics (PSID), the study finds that better health conditions are associated with higher wage growth and lower DI participation probability. An equilibrium search model incorporating health-driven productivity, endogenous DI participation, and job separation reveals that health shocks significantly impact DI participation and labor market outcomes. Policy evaluations show that shorter initial determination periods raise unemployment, while shorter appeal processes reduce it. The persistence and volatility of individual health conditions are critical for understanding DI participation levels.

The third chapter analyzes the impact of non-health factors, such as DI and Unemployment Insurance (UI) benefit replacement rates and unemployment duration, on DI participation using an empirical logistic model. This chapter provides the first microdata-based evidence on these factors. Results indicate that higher DI benefit replacement rates and longer unemployment duration strongly increase DI participation, especially among less educated and older workers.

In summary, this thesis offers a comprehensive analysis of DI participation, highlighting the roles of economic conditions, health dynamics, and policy factors in shaping labor market and DI outcomes.

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I am forever indebted to my parents for their constant support and belief in my capabilities. Their encouragement has been a guiding light throughout my academic pursuits. Additionally, I express my gratitude to my brothers, whose gentle encouragement and support have been a consistent source of strength. I feel truly blessed to be part of such a close and loving family.

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Dedication

I dedicate this Ph.D. thesis to my late father, Bayarjargal Sonomdorj.

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Chapter 1

Introduction

Social Security Disability Insurance (DI) provides financial and in-kind benefits to working-age persons who have mental and/or physical impairments that prevent them from engaging in a substantial gainful activity (SGA) for the next twelve months or longer. Over the last three decades, the surge in DI engagement has been remarkable, expanding nearly tenfold compared to the relatively modest growth of the labor force.[1] Simultaneously, overall health in the U.S. has experienced consistent improvement during this period, as documented in various health studies (Cutler et al., 1997; Houtenville, 2009; Burkhauser and Daly, 2011). Given these trends, the existing literature has largely attributed the increase in DI participation to non-health factors using reduced-form models.

However, three critical aspects warrant a closer look. Firstly, there is a scarcity of dynamic models that comprehensively describe how individual-level DI participation and labor market outcomes are influenced by non-health factors, such as the relative generosity of DI benefits and unemployment. Secondly, health factors, crucial to DI eligibility, have received relatively less attention compared to non-health factors. Even when considered, health is often evaluated through self-reported health status (SRHS), a subjective health measure, inconsistent across surveys due to its dependency on demographic and socio-economic conditions. Lastly, there is a notable concentration on aggregate-level data, overlooking the

[1]For this period, the U.S. labor force has experienced an increase of less thirty percent.

intricate dynamics playing out at the individual level. Therefore, this thesis seeks to address these gaps systematically.

The first chapter addresses the scarcity of dynamic models through a two-fold approach. Using the Panel Study of Income Dynamics (PSID), it conducts an in-depth empirical analysis revealing demographic differences among DI participants and the rest of the labor force. Importantly, future DI participants earn 17.2% less per hour than others.

Motivated by the wage gap, I develop a novel equilibrium search model incorporating heterogeneous skills and endogenous DI participation into the standard Diamond-Mortensen-Pissarides framework. For comparison, I introduce an equilibrium search model with exogenous DI participation (hereafter referred to as an exogenous model). The exogenous model fails to produce the wage gap, while the model with heterogeneous skills and endogenous participation shows a 16.9% wage gap, closely matching the observed 17.2%, without explicitly targeting this moment. This model flexibly describes how non-health factors influence individual DI participation and labor market outcomes.

Using this model, I conduct three numerical experiments related to aggregate productivity, health-related eligibility criteria for DI applicants, and average award rates for DI applications. The model provides the following three key insights: (*i*) During economic downturns, higher-skilled individuals are more likely to opt for disability benefits, increasing DI participation and narrowing the wage gap; (*ii*) Relaxed health-related eligibility criteria encourage relatively less skilled workers to participate in the DI program, widening the wage gap; (*iii*) While higher success rates for DI applications increase DI participation, their impact on the wage gap is less pronounced than that of relaxed health-related eligibility criteria.

The second chapter examines the underemphasized role of health factors by exploring the impact of objective health measures on DI participation and labor market outcomes. Using PSID data, the chapter observes that DI beneficiaries are more likely to be female, older, and less educated than non-beneficiaries. The frailty index, an objective health measure, is used to analyze how current health conditions affect the likelihood of becoming a DI participant within the next two years and current hourly wages. Empirical analysis suggests that better health conditions reduce the likelihood of future DI participation and increase current wage growth, especially among the more educated.

Expanding on these findings, this chapter introduces a novel equilibrium search model with *health-driven productivity* and *endogenous DI participation*. The model reproduces key U.S. data features, including health levels of employed individuals and DI beneficiaries, DI applicant and beneficiary rates, unemployment, and the wage gap between future DI beneficiaries and non-DI beneficiaries. It also mimics untargeted features such as the shares of DI beneficiaries through initial determination versus appeal, the probability of initiating an appeal, and the age distribution of health conditions among DI participants. Remarkably, the model captures the impact of health conditions on future DI participation and current wage growth without explicitly targeting these aspects.

Using the model, I evaluate the U.S. DI program with a focus on policy instruments like the length of the initial determination and appeal processes. For example, a shorter waiting period for initial determination increases unemployment, while a shorter waiting period for appeals reduces it. Importantly, the model's predictions highlight the importance of not only overall health levels but also the persistence and volatility of individual health conditions in understanding DI participation.

The third chapter explores the impact of non-health factors on individual DI participation using the Annual Social and Economic Supplement of the Current Population Survey (CPS-ASEC). It examines how DI and UI benefit replacement rates and unemployment duration affect DI participation. Empirical findings show that higher replacement rates and longer unemployment duration significantly increase DI participation, particularly among less educated and older individuals.

To gain further insights, I conduct two counterfactual experiments to shed light on the variations in the replacement rate of DI benefits and the contribution of the Great Recession.

The first experiment finds that if DI benefits had been proportional to wages since 2000, then the number of DI beneficiaries would have been lower by 19.3% (1.6 million), increasing the unemployment rate by up to 12.1% compared to what we had in 2020. The second experiment finds that the Great Recession induced around 600,000 working-age persons to engage in the DI program. The less educated account for 66.5% of these recession-induced DI beneficiaries. These findings contribute to the existing literature by bridging the gap in understanding the individual dynamics within the DI program.

In essence, this comprehensive investigation endeavors not only to bridge existing gaps in the literature but also to contribute empirical evidence and novel theoretical frameworks. The following chapters precisely discuss relevant literature, present stylized facts about the U.S. labor force and DI participation, describe the data and methodology, analyze empirical and theoretical results, conduct counterfactual experiments, and conclude by synthesizing key insights and discussing potential policy implications.

Chapter 2

Social Security Disability Insurance in an Equilibrium Search Model

2.1 Introduction

Over the past three decades, the number of Social Security Disability Insurance (DI) beneficiaries in the U.S. has tripled, despite significant improvements in the overall health of the labor force[1]. Numerous studies attribute this growth in DI engagement to non-health factors, especially shifts in the labor market using reduced-form models. Interestingly, in the literature, there is a scarcity of dynamic models that comprehensively describe how an individual's decision to engage in the DI program is related to non-health factors and labor market outcomes.

I aim to address this gap through a two-fold approach. Firstly, by leveraging data from the Panel Study of Income Dynamics (PSID), I compare the demographic compositions of DI beneficiaries and non-beneficiaries. The analysis reveals that individuals who are likely to become DI beneficiaries tend to be female, older, and less educated. After controlling for these demographic characteristics, it becomes evident that future DI participants earn 17.2% less per hour than those who will not join the program. This wage gap is more pronounced among the more educated and less pronounced among the less educated.

Secondly, motivated by these empirical findings, I introduce a novel equilibrium search model that integrates *heterogeneous skills* and *endogenous DI participation* into the standard Diamond-Mortensen-Pissarides framework. This model is calibrated using U.S. data and serves to explore how individuals' decisions to participate in the DI program are shaped by their skills, labor market outcomes, and policy variables. In contrast to a simpler model with *exogenous* DI participation (hereafter referred to as the exogenous model), which fails to adequately capture the wage gap dynamics, our model with heterogeneous skills and endogenous DI participation effectively mirrors the observed wage gap without direct targeting. This approach marks a significant advancement, as it offers a robust framework for assessing the current DI program, providing insights into how changes in economic conditions and

[1]See, for example, Cutler et al. (1997); Houtenville (2009); Burkhauser and Daly (2011).

policy settings influence DI participation and labor market outcomes.

To the best of my knowledge, the model presented in this chapter is the first equilibrium search model to integrate endogenous DI participation with heterogeneous skills. This model provides a robust framework for evaluating the current DI program. Using the model, I conduct three experiments: (*i*) analyzing the effects of aggregate productivity changes, (*ii*) examining the impact of varying health-related eligibility criteria for DI applicants, and (*iii*) evaluating the consequences of different average success rates for DI applications. The findings reveal that during economic downturns, relatively more skilled individuals are more likely to opt for DI benefits, which narrows the wage gap between future DI beneficiaries and non-DI beneficiaries. These results indicate countercyclical patterns in DI participation and the average skill level of DI participants. Furthermore, the analysis shows that less skilled workers are more inclined to participate in the DI program when health-related eligibility criteria are relaxed. Lastly, while higher success rates for DI applications lead to increased DI participation, their impact on the wage gap is less significant than the effect of relaxed health-related eligibility criteria. Notably, these policy instruments have only a marginal influence on overall labor market outcomes.

The remainder of this chapter is organized as follows: Section 2.2 provides a review of the relevant literature. Section 2.3 discusses empirical facts and presents the estimation results of the fixed-effects model, while Section 2.4 introduces the numerical model. Section 2.5 calibrates the model and presents its main predictions. Section 2.6 considers a set of counterfactual experiments. Finally, in Section 2.7, I conclude by synthesizing the key insights of this study.

2.2 Literature review

The growing strands of the literature center around two critical aspects: (*i*) the impact of labor market conditions on DI participation and (*ii*) the reciprocal impact of DI participation on labor force participation and unemployment. This chapter aligns itself with these two thematic strands.

In examining the influence of labor market conditions on DI participation, it becomes evident that economic downturns play a pivotal role in driving individuals with marginal impairments toward seeking disability benefits.[2] For example, research by Black et al. (2002) underscores this cyclical relationship, illustrating how fluctuations in unemployment rates affect DI enrollment trends. Recently, during the Great Recession of 2007-2009, there was a notable uptick in DI applications, as highlighted by studies such as Coe et al. (2013); O'Brien (2013); Maestas et al. (2015); Lindner et al. (2017); Meyer and Mok (2019); Maestas et al. (2021). These findings emphasize the sensitivity of DI enrollment to broader economic conditions, illustrating a critical interplay between labor market dynamics and disability benefit uptake.

The DI program significantly contributes to the non-labor force population in the U.S., consequently diminishing overall labor force participation. For instance, a pioneer work by Bound (1989, 1991) attributes one-third of the post-war decline in the U.S. labor force participation rate to DI participation, a finding corroborated by subsequent studies such as Chen and Van der Klaauw (2008); Von Wachter et al. (2011); French and Song (2014); Autor et al. (2016). Moreover, this program influences unemployment dynamics, often referred to as hidden unemployment. Notably, the 1984 liberalization of the DI program, examined by Autor and Duggan (2006), serves as a notable example, resulting in a decrease in the unemployment rate by 0.5 percentage points.[3] Other empirical studies, including de Mooij (1999); De Walque (2003); Koning and Van Vuuren (2010), have also supported these findings, highlighting the complex interaction between DI participation, labor force dynamics, and unemployment rates.

These insights from the literature underscore a counter-cyclical pattern in DI participa-

[2]Working-age persons with marginal impairments who face higher job destruction rates and lower arrival rates of job offers are more likely to apply for the DI program (Low and Pistaferri, 2020).

[3]Appendix A.1 discusses the main policy shifts concerning the DI program, including the 1984 liberalization.

tion in response to fluctuations in unemployment rates, alongside its role in reducing both unemployment and labor force participation. These findings suggest a mutual relationship between labor market dynamics, unemployment, and DI participation. Consequently, the prevalent use of reduced-form models in existing literature faces challenges related to potential endogeneity and causal inference. Therefore, this chapter introduces a structural model—an equilibrium search model integrating heterogeneous skills and endogenous DI participation—to provide a more robust framework for analyzing these interrelationships. This model aims to offer deeper insights into how policy changes and economic conditions influence DI participation and broader labor market outcomes.

2.3 Empirical analysis

2.3.1 Data and descriptive statistics

The main dataset is the PSID of 2005-2019. The sample consists of household heads and their spouses. I restrict the age range to 25-60 to minimize individuals' decisions related to schooling and retirement. I divide the main sample into two groups: DI beneficiaries and non-DI beneficiaries. Table 2.1 presents the corresponding descriptive statistics, offering a comprehensive overview of their demographic compositions.

Compared to the non-beneficiaries, the beneficiaries tend to be female, non-white, older, and less educated. For example, the proportions of non-white individuals are 39.8% and 54.5% among the non-beneficiaries and the beneficiaries, respectively. The average age of the beneficiaries is 47.7 years, approximately 7 years older than the non-beneficiaries. The beneficiaries have an average of 12.2 years of schooling, while the non-beneficiaries average 13.7 years. These comparisons suggest that the beneficiaries are distinct from the non-beneficiaries through demographic characteristics.

Table 2.1: Descriptive statistics

	all ($N_{obs} = 70,884$)	non-beneficiaries ($N_{obs} = 68,766$)	beneficiaries ($N_{obs} = 2,118$)
female	0.491	0.489	0.536
non-white	0.402	0.398	0.545
age	41.16	40.96	47.68
	(10.122)	(10.075)	(9.458)
years of schooling	13.65	13.70	12.17
	(2.489)	(2.484)	(2.205)

Notes: This table is based on the PSID of 2005-2019. The standard errors are in parentheses. When defining whether a survey participant is a DI beneficiary or not, I use two questions: (1) *Did you (HEAD or anyone else in the family) receive any income from Social Security, such as disability, retirement, or survivor's benefits?* and (2) *We would like to know about what you do - are you working now, looking for work, retired, keeping house, a student, or what?* If the survey participant answered the first question as 'SSDI benefits' and the second question as 'permanently disabled', he/she is counted as a DI beneficiary.

2.3.2 Wages of the future DI beneficiaries

Mishel et al. (2015) argue that for the past three decades, the average wage has stagnated among those with lower wages, even though it has been consistently increasing in the U.S. This wage stagnation, coupled with the progressive formula, used for calculating disability benefits, has led to a continuous increase in the relative generosity of disability benefits for those with lower wages, especially less educated workers (see Appendix C.4). Meanwhile, DI participation has been considerably increasing among the less educated compared to their more educated counterparts.

Motivated by these facts, I compare the average wage of future DI beneficiaries to that of future non-DI beneficiaries when both are employed. Specifically, I consider the following fixed-effect empirical model:

$$w_{i,t} = \Phi(a_i) + \beta s_{i,t} + \alpha_i + \alpha_t + \varepsilon_{i,t}, \tag{2.1}$$

where $w_{i,t}$ is the logarithm of the hourly wage of person i in year t, $\Phi(a_i)$ is a quartic polynomial of the person's yearly age a_i, $s_{i,t}$ is the person's schooling, α_i and α_t denote, respectively, the individual fixed-effects and year effects.

The fixed-effect model in equation 2.1 is estimated using the sample of white males in the PSID of 2005-2019.[4] The estimation results are detailed in Appendix A.3. Using the estimated coefficients, I predict error terms at the individual level. These predicted error terms represent the logarithm of hourly wages removing the impact of the age polynomial, years of schooling, individual fixed-effects, and year effects. Using those adjusted hourly wages, I define the NFP - FP wage gap by their difference. Specifically, the NFP - FP wage gap is defined as follows: NFP-FP wage gap $= E[\hat{\varepsilon}_{i,t}|b_i^f = 0] - E[\hat{\varepsilon}_{i,t}|b_i^f = 1]$, where "NFP" denotes future DI non-participants, while "FP" refers to future DI participants, and b_i^f is the dummy for the future beneficiaries.

Table 2.2: NFP - FP wage gaps measured by predicted error terms

	(1) both	(2) less educated	(3) more educated
NFP - FP wage gap	0.172	0.119	0.222
demographic characteristics	✓	✓	✓
individual fixed-effects	✓	✓	✓
year effects	✓	✓	✓
number of observations	8,700	4,715	3,985

Notes: This table is based on the PSID of 2005-2019. The label *both* represents the full sample. The labels *less educated* and *more educated* denote, respectively, less than or equal to 12 years of schooling and greater than or equal to 13 years of schooling.

The estimation results present that the future beneficiaries have a lower hourly wage than

[4] The empirical studies employing reduced-form models show significant diversity in DI participation across demographic groups. However, the calibration procedure in the current chapter is based on white males. This stems from two main reasons. Firstly, the analysis prioritizes studying the equilibrium impact of DI provisions. Secondly, data constraints come into play. With the limited sample size of the PSID and the low DI participation rate, establishing key differences between DI and non-DI participants within a small demographic group proves challenging. Consequently, for model calibration purposes, emphasis is placed on the largest demographic category within the PSID, namely white males.

their non-beneficiary counterparts, with an overall gap of 17.2%, when both are employed (see table 2.2). Interestingly, Low and Pistaferri (2015) find a moderate work limitation reduces the observed wage rate by 5.7%, whereas a severe limitation reduces the offered wage by 17.7%, comparable to the overall wage gap. Additionally, this wage gap narrows for the less educated (11.9%) and widens for the more educated (22.2%). Based on these findings, working-age persons with lower wages are more likely to engage in disability benefits in the future than their counterparts with higher wages.

2.4 Model

Motivated by these stylized facts and empirical findings, I introduce a novel equilibrium search model that extends the standard Diamond-Mortensen-Pissarides (DMP) framework by the following crucial features:[5]

Heterogeneous skills: Building on the approach of Ljungqvist and Sargent (1998, 2008), this model incorporates heterogeneous skills within the economy. Employed workers experience skill accumulation, while non-employed workers face skill deterioration, introducing a stochastic element to human capital dynamics.[6] The skill changes are governed by the functions $\Gamma^{(\mathrm{E})}(p' \mid p)$ for employed workers and $\Gamma^{(\mathrm{N})}(p' \mid p)$ for non-employed workers.[7]

Endogenous DI participation: Unemployed workers, eligible for the DI program, decide whether to apply for DI benefits or continue searching for jobs. Those who apply for DI benefits cease searching for a job and are counted as non-labor force participants. After one period, these applicants receive their determination decision. If favorable, they become DI beneficiaries; otherwise, they return to the labor force as unemployed.

[5]One could investigate the implications of DI using a lifecycle model without search frictions or by extending the islands model of Lucas Jr and Prescott (1974). However, my analysis diverges from such approaches. Instead, I build on the Diamond-Mortensen-Pissarides model, a standard textbook model in economic literature (Sargent and Ljungqvist, 2018). This approach provides a novel perspective on the impact of DI and unemployment insurance (UI) provisions. In particular, it allows us to delve into the equilibrium effects, especially regarding how job creation and vacancies respond to shifts in DI and UI provisions.

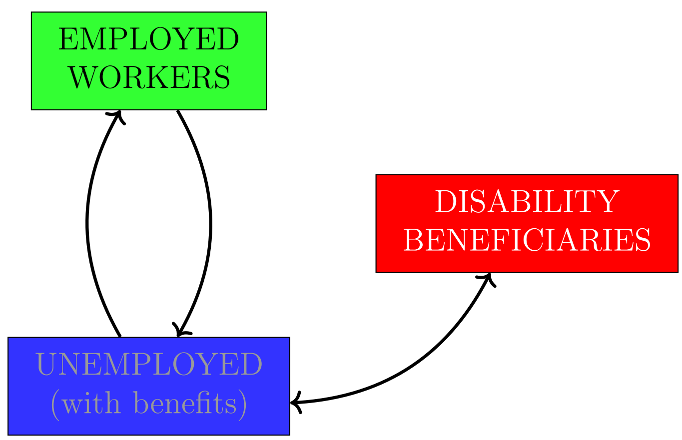
[6]See, for example, Rogerson et al. (2005).

[7]Introducing the accumulation and deterioration processes in p makes the individual's decision to enroll in the DI program not trivial, compared to keep looking for a job.

2.4.1 Environment

The economy consists of a continuum of risk-neutral workers and a continuum of firms, with time being discrete. Workers can be in one of three states: employed, unemployed, or DI beneficiaries. The employed are matched with firms, but these matches dissolve at an exogenous rate λ. Each period, unemployed workers may receive a DI eligibility shock, making them eligible to apply for the DI program. When eligible, they must decide whether to apply for DI benefits or continue job searching. Those not eligible simply continue their job search. DI beneficiaries are terminated at an exogenous rate ζ and then return to the labor force as unemployed. Figure 2.1 illustrates the transitions between the different states in the economy:

Figure 2.1: Flows and stocks in the model



Notes: Individuals can transition between three states: employed, unemployed, and DI beneficiaries. The arrows indicate the possible transitions between these states.

Firms create vacancies to search for workers. The flow cost of a vacancy is κ, and matches are randomly formed according to a matching technology that is non-negative, strictly increasing, concave, and homogeneous of degree one. The probability of finding a job or filling a vacancy depends on market tightness, denoted by θ_p, i.e., $\theta_p \equiv v(p)/u(p)$, where p is an idiosyncratic skill level, $v(p)$ is the number of vacant positions, $u(p)$ is the number of unemployed workers. Each period, a filled position produces output through a production function $y(p) = p$, where p is an idiosyncratic skill or productivity.

2.4.2 Timing

The dynamic events in each period are as follows (see figure 2.2):

1. In the first stage, some workers leave the economy as their working life is over, while newborn workers enter the economy as unemployed with the lowest skill level.
2. In the second stage, individuals observe their new skill levels, and the unemployed receive a DI eligibility shock that makes them eligible to apply for disability benefits.
3. In the third stage, eligible unemployed workers decide whether to apply for disability benefits or continue searching for a job. Those who apply for disability benefits must wait for a period to receive their determination decisions.[8] During this waiting period, they do not look for jobs and are counted as non-labor force participants. If the determination decision is favorable, they become DI beneficiaries. Otherwise, they return to the labor force as unemployed.
4. In the fourth stage, matching and exogenous job separation occurs in the economy. Before the end of the period, production takes place, and workers receive their wages and benefits.

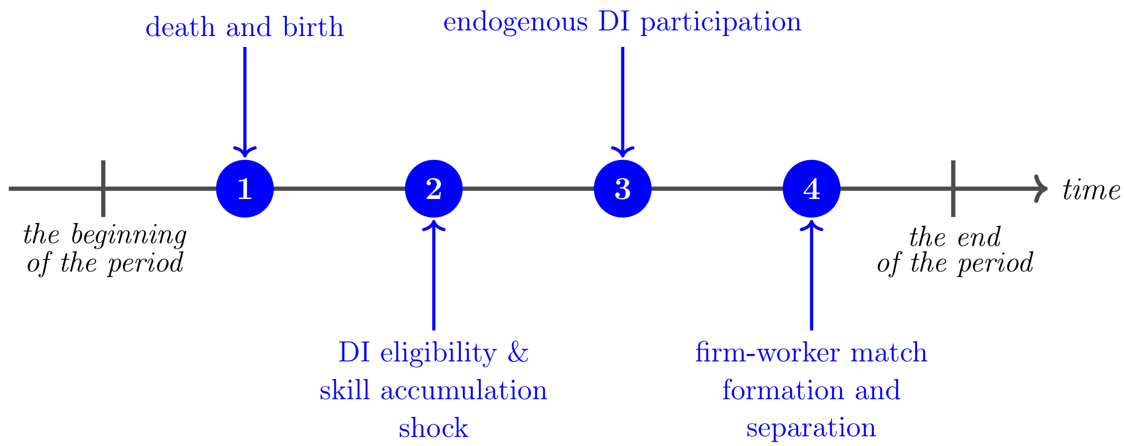
2.4.3 Matching technology

The matching technology governs the number of contracts formed between unemployed workers and vacant positions, given by the equation:

$$M = \mu u(p)^{\eta} v(p)^{1-\eta}, \tag{2.2}$$

[8] Individuals who applied for disability benefits in the previous period receive their determination decisions in the third stage of this period.

Figure 2.2: Timing of the events within a unit period



Notes. The figure shows the timing of the events taking place in each period.

where μ is the matching efficiency coefficient, η is the matching elasticity coefficient, p is a skill level, $u(p)$ and $v(p)$ denote the number of unemployed workers and vacant positions, respectively.

Let θ_p denote market tightness, defined as $\theta_p \equiv v(p)/u(p)$. Then, the job-finding rate for unemployed workers and the worker-finding rate for vacant positions are, respectively, determined by

$$f(\theta_p) = \frac{M}{u(p)} = \mu\theta_p^{1-\eta} \tag{2.3}$$

and

$$q(\theta_p) = \frac{M}{v(p)} = \mu\theta_p^{-\eta}. \tag{2.4}$$

2.4.4 Value functions

Consider the recursive representation where U, W, D, J, and V denote the values associated with unemployed workers, employed workers, DI beneficiaries, filled positions, and vacant positions, respectively.

In the economy, unemployed workers receive a DI eligibility shock each period with a probability of γ. Upon receiving this shock, unemployed workers decide whether to apply for disability benefits or continue their job search. If they do not receive the shock, they continue to search for a job without the option to apply for disability benefits. The value function for unemployed workers is specified as follows:

$$U(p) = b_U + \beta \left\{ \gamma \int \max\{A(p'), N(p')\} \, d\Gamma^{(\mathrm{N})}(p' \mid p) + (1-\gamma) \int N(p') \, d\Gamma^{(\mathrm{N})}(p' \mid p) \right\}, \quad (2.5)$$

where b_U represents the flow utility of unemployed workers, γ is the probability of receiving the DI eligibility shock, and $\Gamma^{(\mathrm{N})}(p' \mid p)$ represents the transition probabilities from skill level p to p' for unemployed workers in the next period. Here, $A(p) = \pi D(p) + (1-\pi)U(p)$, where π is the average success rate for DI applications, and $N(p) = f(\theta_p)W(p) + (1 - f(\theta_p))U(p)$, with $f(\theta_p)$ being the job-finding rate for unemployed workers with skill level p.

The value function of the employed is as follows:

$$W(p) = w(p) + \beta \left\{ \lambda \int U(p') d\Gamma^{(\mathrm{E})}(p' \mid p) + (1-\lambda) \int W(p') d\Gamma^{(\mathrm{E})}(p' \mid p) \right\}, \quad (2.6)$$

where $w(p)$ is the flow utility of employed workers, representing the Nash bargaining wage, λ is an exogenous job separation rate, and $\Gamma^{(\mathrm{E})}(p' \mid p)$ represents the transition probabilities from skill level p to p' for employed workers in the next period.

The value function of DI beneficiaries is as follows:

$$D(p) = b_D + \beta \left\{ \zeta \int U(p') d\Gamma^{(\mathrm{N})}(p' \mid p) + (1-\zeta) \int D(p') d\Gamma^{(\mathrm{N})}(p' \mid p) \right\}, \quad (2.7)$$

where b_D is the flow utility of DI beneficiaries, ζ is an exogenous DI termination rate, and $\Gamma^{(\mathrm{N})}(p' \mid p)$ represents the transition probabilities from skill level p to p' for DI beneficiaries in the next period.

A firm has either filled or vacant position. The value functions of filled and vacant positions are, respectively, given by

$$J(p) = y(p) - w(p) + \beta \left\{ \lambda \int V(p') d\Gamma^{(\mathrm{E})}(p' \mid p) + (1-\lambda) \int J(p') d\Gamma^{(\mathrm{E})}(p' \mid p) \right\} \tag{2.8}$$

and

$$V(p) = -\kappa + \beta \left\{ q(\theta_p) J(p) + (1 - q(\theta_p)) V(p) \right\}, \tag{2.9}$$

where $y(p)$ is the output, $w(p)$ is the Nash bargaining wage, and a vacant position incurs a job-creation cost κ and then finds a worker with a probability of $q(\theta_p)$.

2.4.5 Wage determination

Workers and firms engage in periodic negotiations based on new skill levels, bargaining power, and new matching surplus. The productivity-specific wage $w(p)$ is determined through the Nash bargaining rule:

$$w(p) \in \underset{w(p)}{\operatorname{argmax}} \left\{ \Big[W(p, w(p)) - U(p) \Big]^{\alpha} \Big[J(p, w(p)) - V(p) \Big]^{1-\alpha} \right\}, \ \forall p, \tag{2.10}$$

where α denotes the worker's bargaining power.

2.4.6 Evolution of measures

The measures of the unemployed, the employed, and DI beneficiaries are $\phi_u(p)$, $\phi_e(p)$, and $\phi_b(p)$, respectively. Since the value function of unemployed workers is strictly increasing with skill levels, there exists a value of R such that $N(p) > A(p)$ if and only if $p > R$. Let $\mathcal{P}$ denote sets of all possible realizations of skills. The law of motion for the measures are as follows:

$$
\begin{aligned}
\phi'_e(\mathcal{P}) =& (1-\lambda)\sum_{p'}\Gamma^e(p,p')\phi_e(p)+\gamma f(\theta_p)\sum_{R}^{p'}\Gamma^u(p,p')\phi_u(p)+ \\
&+(1-\gamma)f(\theta_p)\sum_{p'}\Gamma^u(p,p')\phi_u(p),
\end{aligned}
\tag{2.11}
$$

$$
\begin{aligned}
\phi'_u(\mathcal{P}) =& (1-\gamma)(1-f(\theta_p))\sum_{p'}\Gamma^u(p,p')\phi_u(p)+ \\
&+\gamma(1-\pi)\sum_{p'}^{R}\Gamma^u(p,p')\phi_u(p)+\gamma(1-f(\theta_p))\sum_{R}^{p'}\Gamma^u(p,p')\phi_u(p)+ \\
&+\lambda\sum_{p'}\Gamma^e(p,p')\phi_e(p)+\zeta\sum_{p'}\Gamma^u(p,p')\phi_b(p),
\end{aligned}
\tag{2.12}
$$

$$
\phi'_b(\mathcal{P}) = (1-\zeta)\sum_{p'}\Gamma^u(p,p')\phi_b(p)+\gamma\pi\sum_{p'}^{R}\Gamma^u(p,p')\phi_u(p). \tag{2.13}
$$

2.4.7 Definition of equilibrium

Decentralized equilibrium consists of a set of value functions, the Nash bargaining wage $w(p)$, the market tightness θ_p, and the law of motion $\mathcal{S}$ that satisfy the following conditions:

- given θ_p and $w(p)$, the value functions solve the optimization problems represented by equations (2.5) - (2.8);
- given the value function $J(p)$, market tightness θ_p satisfies the free-entry condition that a value of $V(p)$ in equation (2.9) is zero;
- given the value functions, the optimal wage $w(p)$ is determined through the Nash bargaining rule, which is set to maximize the outcome of equation (2.10), taking into account the worker's bargaining power (α), the matching surplus between workers and firms, and skill levels;
- given the transition functions and optimal decisions, the law of motion for distribution

$(\phi_e', \phi_u', \phi_b') = \mathcal{S}(\phi_e, \phi_u, \phi_b)$ is described in equations (2.11) - (2.13).

2.5 Numerical results

The model does not have an analytical solution. This section discusses numerical results.

2.5.1 Calibration

This subsection sets parameters in the model to U.S. data features. The model period is a month. The time discount factor is set to 0.994, implying an annual interest rate of 5% and a working life of 40 years.[9] The job separation rate mirrors that in Shimer (2005), normalized to a monthly frequency, implying an average job tenure of 2.5 years, i.e., $\lambda = 1/30$.

Table 2.3: Calibrated parameter values

Parameter	Value	Description
β	0.9939	time discount factor with mortality risk
λ	0.0333	job separation rate (= 1/30)
ω	0.2000	volatility of idiosyncratic skills
μ	0.5248	efficiency coefficient of matching technology
η	0.5000	parameter of matching technology
α	0.5000	worker's bargaining power
k	0.8134	vacancy creation cost (normalizing θ=1)
b_U	0.4000	flow utility of unemployed workers
b_D	1.0826	flow utility of DI beneficiaries
γ	0.0326	SRHS: poor health status
π	0.5240	the award rate of disability benefits
ζ	0.0006	the termination rate of disability benefits (Kitao, 2014)

There are 11 skill levels, evenly spaced between 0.80 and 1.20, i.e., $p \in [1-\omega, 1+\omega]$ and $\omega = 0.2$. Skill dynamics in the model follow insights from Ljungqvist and Sargent (1998, 2008), distinguishing between employed and non-employed workers (see Appendix A.4). Employed workers experience skill accumulation, advancing to higher skill levels with a probability of 0.1 each period (0.04 units of skills), or remaining at their current level with a

[9] $1/1.05^{1/12}(1-1/480) = 0.994$

probability of 0.9. Once an employed worker reaches the highest skill level, they retain it until job separation. If they become unemployed, their skill level remains unchanged from their last employment period. Non-employed workers, on the other hand, face skill depreciation with a probability of 0.2 each period, potentially lowering their skill level until re-entering employment. Newborn workers enter the economy with the lowest skill level.

The efficiency coefficient (μ) of the matching technology is set to 0.525 to target a 6.29% aggregate unemployment rate. The job creation cost (κ) is calibrated by targeting the aggregate market tightness of 1.[10] This yields 0.813 for κ. Parameters η and α adhere to the Hosios efficiency condition with values of 0.500. Following Shimer (2005), the flow utility of the unemployed is 0.4, i.e., $b_U = 0.400$. The flow utility of DI beneficiaries is calibrated to 1.083 to match a 5.44% beneficiary rate, i.e., $b_D = 1.083$. The probability of receiving the DI eligibility shock is 0.033 for the unemployed, representing a proportion of working-age persons with 'poor' health status in the Annual Social and Economic Supplement of the Current Population Survey (CPS-ASEC) and PSID for 2005-2019. The average success rate for qualifying for disability benefits (π) is 0.524, matching the official statistics of SSA.[11] The termination rate for disability benefits due to employment and health improvements occurs approximately every 135 years (Kitao, 2014).

2.5.2 Main predictions

For comparison purposes, I develop a simple model with heterogenous skills and exogenous DI participation (hereafter referred to as the exogenous model). Briefly, in the exogenous model, when being eligible for the DI program, unemployed workers apply for disability benefits with an exogenous probability of ψ. The value function of unemployed workers,

[10] The aggregate market tightness targeted is set at unity, following the approach outlined in Shimer (2005). In the standard search and matching framework, given the rest of the parameters, this tightness is influenced by two parameters: the vacancy creation cost (κ) and the efficiency of the matching function (μ). The specific choice of these parameters to achieve a desired market tightness level is inconsequential for the analysis, provided the job-finding rate remains the primary target, as is the case in this thesis (refer to Shimer (2005) for further discussion on this topic).

[11] Kitao (2014) used a value of 0.5 for the average success rate.

equation 2.5, is updated to as follows:

$$U(p) = b_U + \beta \left\{ \gamma\psi \int A(p')d\Gamma^{(\mathrm{N})}(p' \mid p) + \gamma(1-\psi) \int N(p')d\Gamma^{(\mathrm{N})}(p' \mid p) \right\} + \beta \left\{ (1-\gamma) \int N(p')\, d\Gamma^{(\mathrm{N})}(p' \mid p) \right\}, \tag{2.14}$$

where ψ is the probability of applying for the DI program when being eligible, its value is calibrated to achieve a 5.44% beneficiary rate.

Table 2.4: Model's main predictions

	data	model with endogenous DI participation	model with exogenous DI participation
Targeted moments			
market tightness	-	1.0000	1.0000
unemployment rate	0.0629	0.0629	0.0629
beneficiary rate	0.0544	0.0544	0.0544
Untargeted moment			
NFP - FP wage gap	0.1720	0.1688	-0.0012

Notes: In the exogenous model, when being eligible for the DI program, the unemployed apply for disability benefits with a probability of ψ. I calibrate, respectively, the efficiency coefficient of matching technology (μ), job-creation cost (κ), and exogenous probability (ψ) to match the unemployment rate, aggregate market tightness, and beneficiary rate when keeping $b_D = 1.0826$, i.e., $\mu = 0.5251$, $\kappa = 0.8290$, and $\psi = 0.0050$. "NFP" refers to future non-DI participants, while "FP" denotes the future participants.

Table 2.4 presents U.S. data features alongside their corresponding predicted moments from both models. Both models are capable of replicating the targeted three moments: (i) a unity aggregate market tightness, (ii) a 6.29% unemployment rate, and (iii) a 5.44% beneficiary rate. However, the exogenous model fails to reproduce the wage gap between the future beneficiaries and the future non-beneficiaries. On the other hand, the benchmark model mimics this wage gap, without explicitly targeting it, i.e., NFP - FP wage gap Specifically, it is 16.9% in the benchmark economy, while it stands at 17.2% in the PSID data (see table 2.2). These comparisons show that the benchmark model outperforms the exogenous model to replicate the targeted and untargeted moments. In the next section, using the benchmark model I conduct a set of counterfactual experiments.

2.6 Counterfactual experiments

In this section, I evaluate the impact of aggregate productivity and DI policy instruments, including health-related eligibility criteria for DI applicants and average success rates for DI applications, on labor market outcomes and DI participation.

2.6.1 Aggregate productivity

I employ an extended production function of $y = zp$, where z is aggregate productivity. Table 2.5 summarizes the model's predictions at different levels of aggregate productivity.

Table 2.5: Impact of aggregate productivity

	aggregate productivity, z				
	0.990	0.995	1.000 (benchmark)	1.005	1.010
per-worker wage	1.1001	1.1066	1.1123	1.1186	1.1245
market tightness	0.9770	0.9895	1.0000	1.0097	1.0189
unemployment	0.0639	0.0633	0.0629	0.0626	0.0623
beneficiary rate	0.0952	0.0616	0.0544	0.0420	0.0371
NFP - FP wage gap	0.0961	0.1585	0.1688	0.2109	0.2255

Notes: This table is based on the benchmark model's predictions. The level of aggregate productivity is 1.000 in the benchmark economy.

In the existing literature, the impact of aggregate productivity on labor market outcomes is sufficiently studied. Specifically, market tightness cyclically and unemployment countercyclically respond to aggregate productivity, consistent with the model's predictions.

Importantly, DI participation counter-cyclically responds to aggregate productivity in a steady state. For example, a 0.5% increase in aggregate productivity would reduce DI enrollments by 22.8%, narrowing the NFP - FP wage gap. These results suggest that (*i*) relatively skilled workers tend to seek disability benefits during economic downturns; (*ii*) the number of DI participants and their average skill level are in a counter-cyclical response to aggregate productivity.

2.6.2 Health-related eligibility criteria

This subsection examines how health-related eligibility criteria for disability benefits influence both DI participation and labor market outcomes. Table 2.6 summarizes predictions based on varying levels of these requirements.

Table 2.6: Impact of health-related eligibility criteria

	levels of eligibility requirements (γ)				
	0.0293	0.0310	0.0326 (benchmark)	0.0342	0.0359
per-worker wage	1.1123	1.1123	1.1123	1.1124	1.1124
market tightness	1.0021	1.0010	1.0000	0.9989	0.9977
unemployment	0.0628	0.0629	0.0629	0.0630	0.0630
beneficiary rate	0.0477	0.0509	0.0544	0.0566	0.0597
NFP-FP wage gap	0.1649	0.1669	0.1688	0.1694	0.1704

Notes: This table is based on the benchmark model's predictions. In the benchmark economy, the probability of being eligible for disability benefits among unemployed workers stands at 0.0326. The calculated elasticity of DI participation concerning the health-related eligibility criteria is approximately 1.079, indicating that DI participation depends on those requirements.

In the labor market, more relaxed health-related eligibility criteria decrease market tightness, elevate unemployment rates, and reduce job vacancies. This scenario suggests that unemployed individuals become more selective, prolonging their job search durations. Moreover, it anticipates an increase in per-worker wages, indicating that relatively less skilled workers are more likely to exit the labor force compared to their more qualified counterparts.

According to the benchmark model, a 10% reduction in the probability of being eligible for disability benefits (indicative of stricter health-related criteria) would decrease the beneficiary rate to 4.77%. Conversely, a 10% increase would raise it to 5.97%. Interestingly, widening the NFP - FP wage gap accompanies a higher probability of eligibility. These insights suggest that less skilled workers tend to opt for DI participation when health-related eligibility criteria are relaxed.

2.6.3 Average success rates

This subsection investigates the effects of alternative success rates for DI applications on labor market outcomes and DI participation. Table 2.7 summarizes the model's predictions across different success rates.

Table 2.7: Impact of alternative success rates

	levels of success rates (π)				
	0.4716	0.4978	0.5240 (benchmark)	0.5502	0.5764
per-worker wage	1.1124	1.1124	1.1123	1.1124	1.1124
market tightness	1.0026	1.0013	1.0000	0.9985	0.9971
unemployment	0.0628	0.0628	0.0629	0.0630	0.0630
beneficiary rate	0.0454	0.0499	0.0544	0.0585	0.0622
NFP-FP wage gap	0.1690	0.1700	0.1688	0.1687	0.1701

Notes: This table is based on the benchmark model's predictions with a probability of being awarded disability benefits at 0.5240. The calculated elasticity of DI participation concerning the average success rate for DI applications is approximately 1.563, indicating that DI participation is elastic to the average success rate.

In the labor market, a higher average success rate for DI applications reduces market tightness, leading to increased unemployment and fewer job vacancies. This phenomenon suggests that unemployed individuals become more selective, prolonging their unemployment durations.

According to the model's predictions, there is a positive relationship between the average success rate and DI participation. For example, a 10% increase in the average success rate raises the beneficiary rate to 6.22%, while a 10% decrease reduces it to 4.54%. However, there is no significant impact on the NFP-FP wage gap from varying success rates for DI applications. These results indicate that a higher average success rate attracts more individuals to the DI program but does not substantially alter the skill composition of DI beneficiaries.

2.7 Conclusion

In this chapter, I investigate how non-health factors such as aggregate productivity, health-related eligibility criteria for DI applicants, and average success rates for DI applications influence individuals' decisions to participate in DI, using an equilibrium search model. The novelty of the model lies in its integration of heterogeneous skills and endogenous DI participation within the standard Diamond-Mortensen-Pissarides framework. This study contributes significantly to the existing literature in two key ways: First, using data from the PSID, I quantify the NFP - FP wage gap when both are employed. Second, I develop a dynamic framework that flexibly examines how DI participation, labor market outcomes, and policy instruments of the DI program interact.

The model successfully replicates key features of U.S. data and notably reproduces the untargeted moment on NFP - FP wage gap. Furthermore, the model predicts that in response to worse labor market conditions, DI participation increases, narrowing the NFP - FP wage gap. These results suggest that (*i*) relatively skilled workers tend to seek disability benefits during economic downturns; (*ii*) the number of DI participants and their average skill level counter-cyclically respond to labor market conditions in a steady state.

Furthermore, the counterfactual experiments shed light on the impact of key policy instruments in the current DI program, such as health-related eligibility criteria and average success rates. For example, in the labor market, more relaxed health-related eligibility criteria would decrease market tightness, leading to increased unemployment and reduced vacancies. Furthermore, it would increase per-worker wage. Importantly, when health-related eligibility criteria are relaxed, relatively less skilled unemployed workers tend to apply for disability benefits, resulting in a higher beneficiary rate and a narrower NFP - FP wage gap. These predictions show that (*i*) health-related eligibility criteria are more important for the less skilled rather than their more skilled counterparts; (*ii*) relaxing these criteria makes unemployed workers more selective and, consequently, leads to longer unemployment duration.

Regarding the average success rate for DI applications, it positively impacts DI participation. For instance, a higher success rate increases the beneficiary rate, and conversely, a lower rate decreases it. Notably, these rates have minimal influence on the skill composition of DI beneficiaries. In the labor market, a higher average success rate decreases market tightness, resulting in higher unemployment rates and lower vacancy rates. Similarly to relaxed health-related eligibility criteria, a higher success rate for DI applications makes unemployed workers more selective, thereby prolonging periods of unemployment.

Through these experiments, I explore the complex relationship between policy instruments, DI participation dynamics, and labor market outcomes. Future research may focus on the effects of health-related factors on DI participation and labor market outcomes using a structural model.

Chapter 3

Health-Driven Productivity and Social Security Disability Insurance

3.1 Introduction

Over the past three decades, the number of working-age individuals receiving Social Security Disability Insurance (DI) benefits in the U.S. has grown nearly tenfold, far outpacing the growth rate of the labor force. For example, from 1990 to 2014, the number of DI beneficiaries tripled,[1] while the labor force expanded by less than 30%.[2] Meanwhile, there has been a substantial improvement in the overall health of the U.S. labor force.[3] In light of these trends, it is widely accepted in the literature that non-health factors are at the forefront of the growth in DI participation.

However, the existing literature highlights several gaps that warrant further investigation. Firstly, much of the research relies on aggregate data, overlooking individual-level dynamics. Secondly, studies exploring health factors in DI participation often rely on self-reported health status (SRHS) rather than objective health indexes. Thirdly, the scarcity of dynamic models that comprehensively integrate health and non-health factors to explain individual DI participation and labor market outcomes remains a significant gap.

This chapter aims to address these gaps by employing a novel approach. First, I develop an equilibrium search model with stochastic health shocks. This model innovatively incorporates *health-driven stochastic productivity* and *endogenous DI participation* within the Diamond-Mortensen-Pissarides framework. Second, leveraging data from the Panel Study of Income Dynamics (PSID), I compare future DI participants with those who will not enroll. Third, using the frailty index from PSID—a recognized objective health measure—I explore how current health conditions influence future DI participation and current wage levels. Using these empirical findings obtained from the PSID, I then calibrate the model to explore how an individual's DI participation decision depends on health, productivity, and labor market outcomes.

[1]The number of prime-age DI beneficiaries has more than doubled (SSA, 2021).
[2]Refer to official statistics from the Bureau of Labor Statistics.
[3]See, for instance, Cutler et al. (1997); Houtenville (2009); Burkhauser and Daly (2011).

In the data, I observe noticeable differences in demographic characteristics between individuals who enroll in the DI program and the rest of the labor force. Notably, DI participants tend to be female, older, and less educated. Accounting for these demographic factors is crucial for understanding the interplay between health, DI participation, and labor market outcomes. Upon controlling for demographics, key patterns emerge:

(*i*) individuals who will later become DI participants have a lower hourly wage than those who will not join the program,

(*ii*) better health conditions are associated with a reduced probability of future DI participation and increased current wage growth, and

(*iii*) these effects are more pronounced among the more educated.

The model closely mimics several important untargeted moments: (*i*) the relative shares of the DI beneficiaries who became DI participants through their initial determination versus an appeal process; (*ii*) the probability of initiating the appeal process among the applicants who were not approved for the DI program through the initial determination procedure of the Social Security Administration (SSA); (*iii*) the age-specific distribution of the health conditions of the DI participants. What is more remarkable is that the model can reproduce the impact of the current health conditions on the probability of engaging in the DI program within the next two years and the current hourly wages, without explicitly targeting those moments.

According to the model's predictions, the probability that relatively healthy and productive workers tend to seek disability benefits increases in response to adverse labor market conditions. This prediction is consistent with the observed counter-cyclicality of the number of new DI participants with relatively better health conditions and higher productivity during the Great Recession of 2007-2009. Furthermore, Maestas et al. (2015) and Lindner et al. (2017) find that the number of individuals who appeal the SSA's initial determination decision (hereafter referred to as *appellants*) are more responsive to the labor market conditions than the number of new DI applicants, consistent with the model's predictions.

To the best of my knowledge, the model presented in this chapter is the pioneering equilibrium search model that integrates health-driven productivity and endogenous DI participation. It offers a natural framework for examining the interplay between health, DI participation, labor market outcomes, and DI policies. I evaluate the current DI policies, including the waiting period for the initial determination procedure and the duration of the appeal process. These policy instruments have comparable impacts on DI participation but substantially different impacts on labor market outcomes. For example, a shorter waiting period for the initial determination raises unemployment, whereas a shorter waiting period for the appeal process reduces it.

One of the central findings of the experiments is that not only the aggregate health trends but also the persistence and volatility of individual health conditions are important for understanding the extent of DI participation. This underscores the importance of individual-level health dynamics in shaping both DI participation trends and effective policy formulation.

The remainder of this chapter is organized as follows: Section 3.2 provides the relevant literature, providing a foundation for this study. Section 3.3 discusses empirical facts, while Section 3.4 introduces the quantitative model. In Section 3.5, I calibrate the model and present its main predictions. In Section 3.6, I consider a set of counterfactual experiments. Finally, in Section 3.7, I present conclusions, highlighting the key insights of this study.

3.2 Literature review

The existing literature predominantly examines the effects of non-health factors on DI participation dynamics using reduced-form models. The most popular non-health factor is labor market conditions, followed by the relative generosity of disability benefits.

Regarding labor market conditions, Black et al. (2002) argue that DI participation counter-cyclically responds to shifts in the labor market, exemplified by the coal boom and bust. Charles et al. (2018) also find this counter-cyclical relationship in a sample of

U.S. oil-dependent states. Interest in this strand of literature heightened during the Great Recession of 2007-2009. For example, Lindner et al. (2017) explore characteristics of DI applicants over economic cycles and highlight that during economic downturns, applicants often possess higher work capacity, resulting in decreased award rates and increased rejection and appeal rates. Consequently, DI participation increases in response to adverse labor market conditions due to marginally impaired working-age persons (French and Song, 2014; Low and Pistaferri, 2015; Maestas et al., 2015; Mueller et al., 2016; Binder and Bound, 2019; Maestas et al., 2021).

The relative generosity of disability benefits is determined by the ratio of disability benefits to potential wages (hereafter referred to as *the replacement rate*). For example, Autor and Duggan (2003) documented the replacement rate of disability cash benefits reaching 0.74, which increased to 1.04 when accounting for in-kind Medicare benefits, depending on earnings percentiles. Although the average wage has been consistently increasing in the U.S., it has stagnated among less educated workers over the past three decades (Mishel et al., 2015; Binder and Bound, 2019). Because of wage stagnation and the progressive formula used for disability benefits calculation (see Appendix C.4), the DI program has been becoming more generous among less educated workers.

An influential study by Low and Pistaferri (2015) employs a lifecycle framework, highlighting high rejection rates of truly disabled applicants and the acceptance of some non-disabled applicants. They suggest that to improve DI targeting, means-tested programs should be more generous. Similarly, Kitao (2014) examines the effects of cash and in-kind benefits for DI beneficiaries, finding that eliminating the Medicare component would reduce DI participation by over one-third, while a 20% reduction in cash benefits could yield a similar outcome. Kim and Rhee (2022) evaluate the effects of removing the DI program on labor market dynamics, suggesting it would increase the relative labor supply of older and disabled workers, reducing wages. However, these studies overlook several critical elements in the DI system:

(i) the five-month waiting period for the initial determination,

(ii) the appeal process,

(iii) the fact that applicants and appellants are out of the labor force, and

(iv) vacancies.

When applying for disability benefits, applicants must be unable to engage in substantial gainful activity (SGA) due to their mental and/or physical impairments (SSA, 2021). Surprisingly, the existing literature does not consider the health eligibility criteria as important as the non-health factors. Few studies explore the impact of health-related factors on DI participation using self-reported health status (SRHS) (Rutledge et al., 2014; Cutler et al., 2017). However, SRHS is inconsistent across different surveys due to its dependence on demographic characteristics and socio-economic conditions.[4] Due to these disadvantages, I construct a *frailty index* using the PSID, known as an objective and continuous health measure in health economics and gerontology (Mitnitski et al., 2002, 2005; Hosseini et al., 2022).

To the best of my knowledge, this chapter presents a pioneering contribution by incorporating *health-driven productivity* and *endogenous DI participation* within the standard Diamond-Mortensen-Pissarides framework. Distinguishing itself from prior studies, this research precisely captures disability and health dynamics using an objective and continuous health measure.

3.3 Empirical facts

3.3.1 Data and descriptive statistics

The primary dataset utilized in this study is the PSID of 2005-2019. The primary sample comprises household heads and their spouses. To minimize an individual's decision related

[4]See, for example, Chirikos and Nestel (1984); Kreider (1999); Kreider and Pepper (2007); Black et al. (2017).

to schooling and retirement, the age range is restricted from 25 to 60. Table 3.1 presents descriptive statistics by DI beneficiary status.

Table 3.1: Descriptive statistics

	all ($N_{obs} = 70,884$)	non-beneficiaries ($N_{obs} = 68,766$)	beneficiaries ($N_{obs} = 2,118$)
female	0.491	0.489	0.536
non-white	0.402	0.398	0.545
age	41.16	40.96	47.68
	(10.122)	(10.075)	(9.458)
years of schooling	13.65	13.70	12.17
	(2.489)	(2.484)	(2.205)

Notes: This table is based on the PSID of 2005-2019. The standard errors are in parentheses. When defining whether a survey participant is a DI beneficiary or not, I use two questions: (1) *Did you (HEAD or anyone else in the family) receive any income from Social Security, such as disability, retirement, or survivor's benefits?* and (2) *We would like to know about what you do - are you working now, looking for work, retired, keeping house, a student, or what?* If the survey participant answered the first question as 'SSDI benefits' and the second question as 'permanently disabled', he/she is counted as a DI beneficiary.

Table 3.1 shows that the beneficiaries are more likely to be female, non-white, older, and less educated, compared to the non-beneficiaries. For instance, the proportions of the females are 53.6% and 48.9% among the beneficiaries and the non-beneficiaries, respectively. The non-whites constitute 54.5% of the beneficiaries, while it is 39.8% of the non-beneficiaries. The average age of the beneficiaries is 47.7 years, whereas it is 41.0 years for the non-beneficiaries. The average years of schooling for the beneficiaries is 12.2, while it is 13.7 years for the non-beneficiaries. These descriptive statistics show that the beneficiaries are different from the non-beneficiaries through their demographic characteristics.

3.3.2 Frailty and health indices

The frailty index measures the accumulation of deficits across various health dimensions (Mitnitski et al., 2002, 2005). Starting in 2005, the PSID began collecting health-related information from household heads and their spouses. Following Searle et al. (2008), I construct this index using 24 impairments that reflect physical and cognitive functions, as well as chronic diseases.[5] Each impairment is coded as 1 if present, and 0 otherwise. The frailty index is then defined as the fraction of impairments present: a value closer to zero signifies better health, while a value closer to one indicates worse health.

$$H_{it} = 1 - frailty_{it}, \tag{3.1}$$

where H_{it} represents the health index of individual i in year t, and $frailty_{it}$ is the person's frailty index. In the sample, the frailty index has a mean of 0.085 and a standard deviation of 0.0857, while the health index has a mean of 0.919 and a standard deviation of 0.0775.[6]

Compared to the overall sample, the health index is higher for male, white, and young non-beneficiaries. Interestingly, the average health index of less educated individuals is lower for the non-beneficiaries and higher for the beneficiaries. This suggests that less educated workers are more likely to engage in disability benefits due to non-health factors compared to other demographic subgroups. These findings indicate observable health differentials between the beneficiaries and the non-beneficiaries.

These comparisons of health indices may be questionable if DI beneficiaries and non-beneficiaries differ significantly in observable and unobservable characteristics. As shown in Table 3.1, these groups differ demographically. To account for these differences, I re-measure the health index difference between the beneficiaries and the non-beneficiaries using the following empirical model:

$$H_{i,j,t} = \gamma b_{i,j,t} + X'_{i,j,t}\beta + \alpha_i + \alpha_s + \alpha_t + \epsilon_{i,j,t}, \tag{3.2}$$

[5]The list of impairments is in Table B.2.

[6]Figure B.3 displays the distributions of the two indices. Most survey participants have a lower frailty index and a higher health index. Additionally, 5,166 out of 70,884 individuals in the PSID have a health index of one.

Table 3.2: Health index, by beneficiary status and demographic characteristics

	all	non-beneficiaries	beneficiaries	difference
overall	0.918	0.924	0.735	0.188***
	(0.0811)	(0.0698)	(0.1667)	(0.0016)
female	0.912	0.918	0.711	0.208***
	(0.0891)	(0.0760)	(0.1744)	(0.0024)
white	0.921	0.925	0.718	0.208***
	(0.0776)	(0.0670)	(0.1730)	(0.0023)
old	0.899	0.909	0.706	0.203***
	(0.0980)	(0.0824)	(0.1656)	(0.0023)
less educated	0.909	0.918	0.748	0.218***
	(0.0924)	(0.0789)	(0.1587)	0.0025

Notes: This table is based on the PSID of 2005-2019. The standard errors are in parentheses. The label *old* denotes working-age persons aged 43-60. The label *less educated* refers to working-age persons with less than or equal to 12 years of schooling.

where $H_{i,j,t}$ is the health index of person i in state j in year t, $b_{i,j,t}$ is a dummy for the beneficiaries, X represents demographic factors such as sex, race, age, age squared, and years of schooling, α_i is the individual fixed-effects, α_s and α_t, respectively, represent state and year effects.

I estimate this empirical model by three methods: (i) fixed-effects for the panel dataset, (ii)random-effects for the panel dataset, and (iii) ordinary least squares (OLS) for the pooled cross-sectional dataset. Table 3.3 presents the estimation results. The estimated coefficients are consistent across methods. For instance, females have a lower health index than males. Black individuals have a lower health index compared to white individuals, while Asians and others have a higher health index. Importantly, the beneficiary dummy variable negatively affects the health index by 0.057 to 0.172 points.

To measure the difference in the health index between the beneficiaries and the non-beneficiaries, I predict the health indices for the non-beneficiaries using different estimation methods and calculate their average ($E[H_{i,j,t}|b_{i,j,t} = 0] = 0.9234$). Using this average and the average estimated coefficients for the beneficiary dummy variable, I calculate the average health index for the beneficiaries. This approach estimates the average health index of the beneficiaries when the beneficiaries were comparable to the non-beneficiaries through their observable and unobservable characteristics. The results indicate that the average health index for the beneficiaries would be 0.8167, which is 0.1067 points lower than for the non-beneficiaries. These findings are incorporated into a quantitative model.

3.3.3 Empirical analysis

In this subsection, I focus on a specific subsample comprising of white and male household heads and spouses. Using the subsample, I measure a wage gap between the future beneficiaries and the future non-beneficiaries. Additionally, I examine the effects of the health index on the probability of engaging in disability benefits within the next two years and the current hourly wages.

3.3.3.1 Wage gaps between the future beneficiaries and non-beneficiaries

The primary question is whether the future beneficiaries have comparable hourly wages to the future non-beneficiaries when both are employed. In micro surveys, wages are observable for the employed but unobservable for non-employed workers, leading to a self-selection bias. To address this, I employ Heckman's selection model. First, I estimate the following probit model on the probability of being employed and then define the inverse Mill's ratio:

$$\Pr(E_{i,j,t} = 1|Z) = \Phi(Z'\beta), \tag{3.3}$$

where $E_{i,j,t}$ is a dummy variable indicating whether individual i in state j in year t is employed. The vector Z includes the individual's covariates, such as self-reported health status (SRHS), a quartic polynomial of age, years of schooling, and state and year effects.

Next, I estimate a random-effects model incorporating the inverse Mill's ratio from equa-

Table 3.3: Estimation results of health index

	fixed-effects	random-effects	OLS model
beneficiary ($b_{i,j,t}$)	-0.0556***	-0.0924***	-0.1720***
	(0.0018)	(0.0016)	(0.0036)
female		-0.0123***	-0.0122***
		(0.0010)	(0.0006)
black		-0.0066***	-0.0040***
		(0.0012)	(0.0007)
american indian		-0.0135**	-0.0158***
		(0.0056)	(0.0049)
asian		0.0117***	0.0065***
		(0.0035)	(0.0020)
others		0.0056**	0.0059***
		(0.0024)	(0.0016)
age	0.00313***	0.0016***	0.0015***
	(0.0007)	(0.0002)	(0.0003)
age squared	-4.82e-05***	-4.23e-05***	-3.68e-05***
	(3.04e-06)	(2.72e-06)	(3.13e-06)
years of schooling	-0.0011***	0.0014***	0.0017***
	(0.0002)	(0.0002)	(0.0001)
individual fixed-effects	✓		
state effects		✓	✓
year effects	✓	✓	✓
number of observations	68,958	68,373	68,373
R^2	0.1438	0.1930	0.2164

Notes: This table is based on the PSID of 2005-2019. The standard errors are in parentheses.

tion 3.3:

$$w_{i,j,t} = \gamma b_i^f + A(a_i) + \beta s_{i,j,t} + \hat{\lambda}_{i,j,t} + \alpha_i + \alpha_j + \alpha_t + \varepsilon_{i,j,t}, \tag{3.4}$$

where $w_{i,j,t}$ is the logarithm of the hourly wage of individual i in state j in year t. The variable b_i^f is a dummy indicating whether the individual is a future beneficiary, and it is time-invariant. The function $A(a_i)$ is a quartic polynomial of the individual's age. The variable $s_{i,j,t}$ represents the individual's years of schooling, and $\hat{\lambda} i, j, t$ is the inverse Mill's ratio. The terms α_i, α_j, and α_t represent individual, state, and year random effects, respectively, and $\varepsilon i, j, t$ is the error term.

Table 3.4: Wage gaps between future DI beneficiaries and non-beneficiaries

	(1) all	(2) less educated	(3) more educated
future beneficiary	-0.188***	-0.135***	-0.281***
	(0.0498)	(0.0477)	(0.102)
inverse Mill's ratio	-0.107***	-0.106***	-0.147*
	(0.0350)	(0.0344)	(0.0799)
demographic effects	✓	✓	✓
state and year effects	✓	✓	✓
number of observations	8,532	4,579	3,921
R^2	0.185	0.198	0.174

Notes: This table is based on data from the PSID (2005-2019). Standard errors are shown in parentheses. The variable *future beneficiary* represents a dummy variable for future DI beneficiaries, denoted as b_i^f in equation (3.4). I estimate this empirical model using the random-effects method because the main independent variable, b_i^f, is time-invariant. When not controlling for self-selection bias, the estimated coefficients are comparable (see Appendix B.2). The label *all* represents the full sample. The labels *less educated* and *more educated* denote individuals with less than or equal to 12 years of schooling and more than 12 years of schooling, respectively.

Table 3.4 displays the estimation results. For comparison purposes, I rerun the empirical model for *less educated* and *more educated* subsamples. The main independent variable is the dummy for the future beneficiaries, which negatively affects hourly wages. For example, in the overall sample, the future beneficiaries have lower hourly wages than their corresponding non-beneficiaries by 18.8%. This finding is consistent with the results of Low and Pistaferri (2015), who found that moderate work limitations reduce the wage rates by 5.7%, whereas severe limitations reduce them by 17.7%.

It is noteworthy to mention that the wage gap widens with education levels. For the less educated, the wage gap is 13.5%, while for the more educated, it si 28.1%. These results suggest that working-age persons with lower wages are more likely to engage in disability benefits in the future than those with higher wages.[7]

3.3.3.2 Current health index and future DI participation

Table 3.2 shows that beneficiaries have a lower health index, indicating worse health conditions compared to non-beneficiaries. Estimating the effects of the health index on current DI participation status leads to biased coefficients due to causal and endogeneity issues. To address this, I examine the effects of the current health index on future DI participation using the following linear probability model with individual fixed effects:

$$D_{i,t+2} = \gamma H_{i,t} + A(a_i) + \beta s_{i,t} + \alpha_i + \alpha_t + \varepsilon_{i,t+2}, \tag{3.5}$$

where $D_{i,t+2}$ is a dummy variable for individual i who is not a DI beneficiary in year t but becomes one by year $t+2$. $H_{i,t}$ represents the health index, $A(a_i)$ is a quartic polynomial of the individual's age, $s_{i,t}$ is the years of schooling, and α_i and α_t represent individual fixed-effects and year effects, respectively.

Table 3.5 presents the estimation results. For comparison, I also run the linear probability model on subsamples of the less educated and the more educated. The results show that the health index negatively impacts the probability of becoming a DI beneficiary within the next two years. Specifically, a 0.1-point increase in the health index reduces this probability by 0.020 points for the overall sample. For less educated and more educated workers, this

[7] I also measure the wage gap using the fixed-effects model. The wage gaps are comparable regardless of estimation methods (see Appendix A.3).

Table 3.5: Effects of the health index on future DI participation

	(1) all	(2) less educated	(3) more educated
health index	-0.203***	-0.157***	-0.258***
	(0.0206)	(0.0192)	(0.0420)
demographic factors	✓	✓	✓
individual fixed effects	✓	✓	✓
year effects	✓	✓	✓
number of observations	16,781	10,415	6,366
R^2	0.010	0.010	0.014

Notes: This table is based on the PSID of 2005-2019. The standard errors are in parentheses. The label *health index* represents the health index denoted as $H_{i,t}$ in equation (3.5). I use the fixed-effects and random-effects methods to estimate the empirical model. Next, I run the Hausman test to determine an appropriate model specification. The label *all* represents the full sample. The labels *less educated* and *more educated* denote, respectively, less than or equal to 12 years of schooling and greater than or equal to 13 years of schooling.

reduction is 0.016 and 0.026 points, respectively.

These results indicate that (i) current health conditions can predict future DI participation, and (ii) health conditions are more significant predictors for more educated workers compared to less educated ones.

3.3.3.3 Current health index and current hourly wage

In the previous subsections, it was observed that the beneficiaries have lower hourly wages and worse health conditions than the non-beneficiaries (see tables 3.4 and 3.5). This suggests that worse health conditions may lead to lower hourly wages. To investigate this relationship, I employ the following regression model:

$$w_{i,j,t} = \gamma H_{i,j,t} + \theta b_i^f + A(a_i) + \beta s_{i,j,t} + \hat{\lambda}_{i,j,t} + \alpha_t + \alpha_j + \varepsilon_{i,j,t}, \tag{3.6}$$

where $w_{i,j,t}$ is the logarithm of hourly wage of person i in state j in year t, $H_{i,j,t}$ is the person's health index, b_i^f is a dummy for a future beneficiary and time-invariant, $A(a_i)$ is a quartic polynomial of the person's yearly age, $s_{i,j,t}$ is the person's years of schooling, $\hat{\lambda}_{i,j,t}$ is the person's inverse Mill's ratio, and α_t and α_j denote, respectively, the year and state effects.

Table 3.6: Effects of the health index on the current hourly wage

	(1) all	(2) less educated	(3) more educated
health index	0.342***	0.227*	0.385**
	(0.1061)	(0.1330)	(0.1630)
demographic factors	✓	✓	✓
self-selection bias controlled	✓	✓	✓
state and year effects	✓	✓	✓
number of observations	8,532	4,579	3,921
R^2	0.192	0.208	0.179

Notes: This table is based on the PSID of 2005-2019. The standard errors are in parentheses. The label *health index* represents the health index denoted as $H_{i,j,t}$ in equation (3.6). To be consistent with the previous wage estimation, I choose the random-effects method/technique. The label *all* represents the full sample. The labels *less educated* and *more educated* denote, respectively, less than or equal to 12 years of schooling and greater than or equal to 13 years of schooling.

Table 3.6 presents the estimated coefficients. For comparison, I also run the regression for *less educated* and *more educated* subsamples. The results indicate that health conditions positively affect hourly wages. Specifically, a 0.1-point increase in the health index results in a 3.42% increase in hourly wages. This increase is 2.27% for the less educated and 3.85% for the more educated.

These empirical findings suggest two key points: (i) the future beneficiaries may have lower hourly wages than their corresponding non-beneficiaries due to worse health conditions; (ii) the future beneficiaries are more likely to engage in disability benefits because of their poor health rather than their lower wages Building on these findings, I develop an equilibrium search model with health-driven productivity in the next section.

3.4 Quantitative model

The model extends the standard Diamond-Mortensen-Pissarides framework by the following features:

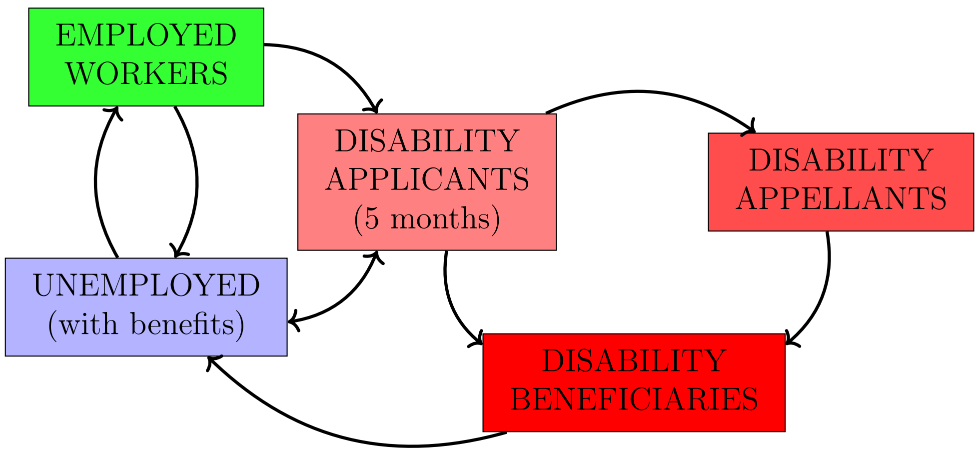
1. *Stochastic health-driven productivity*: Idiosyncratic health is the fundamental determinant of a worker's productivity.
2. *Endogenous job separation*: The employed voluntarily quit their jobs based on health and labor market conditions.
3. *Endogenous DI participation*: By modeling DI participation as an endogenous outcome, the framework captures the interplay between health, labor market dynamics, and social insurance programs.

3.4.1 Environment

The economy is populated by a continuum of risk-neutral workers and a continuum of risk-neutral firms. Individuals can be employed, unemployed, DI applicants, DI appellants, or DI beneficiaries. The employed are matched with firms. In each period, the employed endogenously decide whether to apply for the DI program. Additionally, the unemployed decide whether to search for a job or to apply for disability benefits. Once applying for disability benefits, they become DI applicants who wait for 5 months to receive their initial determination decision. When their initial determination is favorable, DI applicants become DI beneficiaries. Otherwise, DI applicants decide whether to initiate the appeal process (DI appellants) or rejoin the labor force as unemployed. DI appellants are exogenously awarded disability benefits with probability $\tilde{\pi}$. DI beneficiaries are exogenously terminated with probability ζ. Figure 3.1 illustrates these transitions between the different states in the economy.

Each period, firms search for workers by creating vacancies. The flow cost of a vacancy is κ. Free entry drives the expected present value of an open vacancy to zero. Vacant jobs and

Figure 3.1: Flows and stocks in the model



Notes: In the model, an individual can be in one of the five states depicted in the figure. The arrows show the transitions between the states.

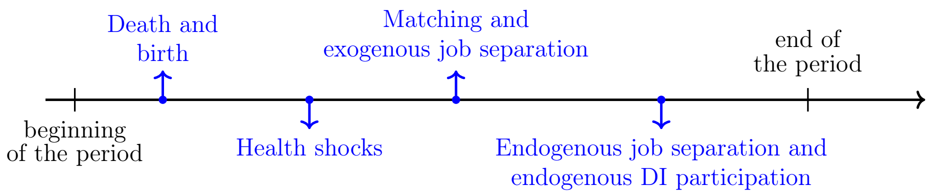
unemployed workers are matched according to a matching technology that is non-negative, strictly increasing, concave, and homogeneous of degree one. The probability of finding a job or filling a vacancy depends on market tightness, denoted by θ_h, i.e., $\theta_h \equiv v(h)/u(h)$, where h denotes the idiosyncratic health condition (hereafter referred to as *idiosyncratic health*), $v(h)$ is the number of vacancies, and $u(h)$ is the number of the unemployed. Without loss of generality, I assume that each firm employs at most one worker. All matches are dissolved exogenously with a probability of λ. Each period, a filled position produces output through a production function $y(h) = \exp(h)$.

3.4.2 Timing

The model operates in discrete periods, and each period consists of four stages. In the first stage, newborn workers enter the economy as unemployed and draw their idiosyncratic health from an initial health distribution. Some workers exit the economy as their working life is over. In the second stage, employed and unemployed workers receive a health shock. Following the health shock, they draw new idiosyncratic health from a general health distribution

$G(h)$. In the third stage, matching and exogenous job separation occur in the economy.

Figure 3.2: Sequence of the events within a unit period



In the fourth stage, employed workers endogenously decide whether to quit their current jobs to apply for disability benefits. Unemployed workers who have found a job decide whether to accept a job offer, remain unemployed, or apply for disability benefits. Unemployed workers who have not found a job decide whether to remain unemployed or apply for disability benefits. The applicants who have waited for five months receive the initial determination decision. If the decision is favorable, the applicants become the beneficiaries. Otherwise, denied applicants decide whether to start the appeal process or rejoin the labor force as unemployed. The appellants also receive their decision. If the decision is favorable, the appellants become the beneficiaries. Otherwise, they stay in the appeal state/pool for a period. The beneficiaries are exogenously terminated and then rejoin the labor force as unemployed. Before the end of the period, production takes place, and workers receive their wages and benefits. This four-stage sequence repeats in each period.

3.4.3 Stochastic health processes

To increase the model tractability, the following specification of the transition functions is adopted from Andolfatto and Gomme (1996):

$$Q_j(h' \mid h) = \begin{cases} \gamma_j G(h') & \text{if } h' < h, \\ (1-\gamma_j)+\gamma_j G(h') & \text{otherwise,} \end{cases} \tag{3.7}$$

where $j \in \{e, u\}$, G represents the cumulative distribution function (CDF) of uniform distribution on the interval of $[-\omega, \omega]$, and ω is the volatility of idiosyncratic health.[8]

This specification implies that current idiosyncratic health h remains unchanged with a probability of $(1-\gamma_j)$, whereas it becomes h' with a probability of γ_j in the next period, depending on their employment status. These transition functions are captured by three parameters γ_e, γ_u, and ω.

3.4.4 Matching technology

Let u_h and v_h denote the number of unemployed workers and vacancies at the health level h, respectively. The number of matches formed between these workers and vacancies is determined according to the following matching technology:[9]

$$M = \mu u_h^{\eta} v_h^{1-\eta}. \tag{3.8}$$

Let θ_h denote market tightness, a ratio of vacancies to unemployment, i.e., $\theta_h \equiv v_h/u_h$. Using market tightness, the job-finding and worker-finding rates are, respectively, given by

$$f(\theta_h) = \frac{M}{u_h} = \mu\theta_h^{1-\eta} \tag{3.9}$$

and

$$q(\theta_h) = \frac{M}{v_h} = \mu\theta_h^{-\eta}. \tag{3.10}$$

[8]This health process replaces the human capital accumulation and deterioration process in the Chapter 1.

[9]The model assumes that the matching technology is specific to the health status h, meaning that there are submarkets by health status. These submarkets naturally arise in competitive search models, where wages are determined through wage posting (Moen, 1997). Additionally, a competitive search model coincides with a search and matching model with Nash bargaining when fulfilling Hosios condition, where the matching function's elasticity w.r.t. unemployment $(1-\kappa)$ equals the worker's bargaining power (α), as argued by Rogerson et al. (2005). Given that Hosios condition holds in my analysis, the model can be recast as a competitive search model with health-specific submarkets, rendering the initial assumption innocuous.

3.4.5 Value functions

Consider a recursive representation where the lifetime utilities of unemployed and employed workers are $U(h)$ and $W(h)$, respectively. Given the probability that an unemployed worker with idiosyncratic health h finds a job is $f(\theta_h)$, the lifetime utility of unemployed workers is given by

$$U(h) = b_U + \beta \left[f(\theta_h) \int_{h'} F(h') Q_u(dh' \mid h) + (1 - f(\theta_h)) \int_{h'} N(h') Q_u(dh' \mid h) \right], \tag{3.11}$$

where b_U is the flow utility of unemployed workers, $f(\theta_h)$ is the job-finding rate, unemployed workers draw their new idiosyncratic health from the general distribution $G(h)$, governed by the transition function of $Q_u(h' \mid h)$, which will be discussed later. Here, $F(h) = \max\{W(h), U(h), A_0(h)\}$ and $N(h) = \max\{U(h), A_0(h)\}$, where the term $A_0(h)$ is the lifetime utility of the applicants when applying for disability benefits, $W(h)$ is the lifetime utility of employed workers.

If a worker of idiosyncratic health h is employed at wage $w(h)$, the lifetime utility is given by

$$W(h) = w(h) + \beta \left[\lambda \int_{h'} N(h') Q_e(dh' \mid h) + (1 - \lambda) \int_{h'} F(h') Q_e(dh' \mid h) \right], \tag{3.12}$$

where $w(h)$ is the flow utility of employed workers, representing the Nash bargaining wage, λ is an exogenous job separation rate, employed workers draw their new idiosyncratic health from the general distribution $G(h)$, governed by the transition function of $Q_e(h' \mid h)$, which I will discuss below. Here, $N(h) = \max\{U(h), A_0(h)\}$ and $F(h) = \max\{W(h), U(h), A_0(h)\}$.

The lifetime utility of the applicants who have waited for τ months is given by

$$A_\tau(h) = b_A + \beta A_{\tau+1}(h), \tag{3.13}$$

where b_A is the flow utility of the applicants.

After waiting for five months, the applicants are awarded disability benefits with a probability of π and rejected with a probability of $(1-\pi)$. The lifetime utility of the applicants who have waited for five months is determined by

$$A_T(h) = b_A + \beta\Big\{\pi D(h) + (1-\pi)S(h)\Big\}, \tag{3.14}$$

where $D(h)$ is the lifetime utility of DI beneficiaries, $S(h) = \max\{\tilde{A}(h), U(h)\}$, where the term $\tilde{A}(h)$ is the lifetime utility of the appellants.

By recursively substituting out the lifetime utilities of DI applicants, when applying for the DI program, i.e., $\tau = 0$, the lifetime utility $A_0(h)$ can be expressed as follows:

$$A_0(h) = \frac{(1-\beta^6)}{1-\beta} b_A + \beta^6\Big\{\pi D(h) + (1-\pi)S(h)\Big\}, \tag{3.15}$$

The appellants become the beneficiaries with a probability of $\tilde{\pi}$ and remain in the appeal state/pool with a probability of $(1-\tilde{\pi})$. The lifetime utility of the appellants is defined as follows:

$$\tilde{A}(h) = b_{AP} + \beta\Big\{\tilde{\pi} D(h) + (1-\tilde{\pi})\tilde{A}(h)\Big\}, \tag{3.16}$$

where b_{AP} is the flow utility of the appellants.

The beneficiaries are terminated with a probability of ζ and remain as the beneficiaries with a probability of $(1-\zeta)$. The lifetime utility of the beneficiaries is given by

$$D(h) = b_D + \beta\Big\{\zeta U(h) + (1-\zeta)D(h)\Big\}, \tag{3.17}$$

where b_D is the flow utility of the beneficiaries.

A firm has either a filled or vacant position. The value of a firm with a filled position is determined as follows:

$$J(h) = y(h) - w(h) + \beta \left\{ \lambda \int_{h'} V(h') Q_e(dh' \mid h) + (1-\lambda) \int_{h'} K(h') Q_e(dh' \mid h) \right\}, \qquad (3.18)$$

where $y(h)$ is the output, λ is an exogenous job-separation rate, $V(h)$ is the value of a vacant position, $K(h) = \max\{J(h), V(h)\}$ represents endogenous job-separation.

The value of a firm with a vacant position is given by

$$V(h) = -\kappa + \beta \Big\{ q(\theta_h) J(h) + (1 - q(\theta_h)) V(h) \Big\}, \qquad (3.19)$$

where κ is a job-creation cost and $q(\theta_h)$ is a worker-finding rate.

3.4.6 Wage bargaining

Each period, workers and firms renegotiate the wage level depending on new idiosyncratic health, bargaining power, and new matching surplus. The optimal wage is determined using the Nash bargaining rule, which maximizes the weighted product of the worker's surplus and the firm's surplus. The Nash bargaining rule is given by:

$$w(h) \in \underset{w(h)}{\operatorname{argmax}} \left\{ \Big[W(h) - U(h) \Big]^{\xi} \Big[J(h) - V(h) \Big]^{1-\xi} \right\}, \ \forall h, \qquad (3.20)$$

where ξ is the worker's bargaining power, i.e., $0 \leq \xi \leq 1$.

3.4.7 Evolution of measures

Consider a recursive representation where $\phi_e(h)$, $\phi_u(h)$, $\phi_a(h, \tau)$, $\phi_{\tilde{a}}(h)$, and $\phi_b(h)$ denote, respectively, the measures of the employed, unemployed, applicants, appellants, and beneficiaries with idiosyncratic health h. For the applicants, τ represents how many months they have waited for their initial determination decision.

Since $W(h)$ is strictly increasing in idiosyncratic health, there exists a value of r_e such that $W(h) \geq A_0(h)$ if and only if $h \geq r_e$. Also, $U(h)$ is strictly increasing in the idiosyncratic health, there exists a value of r_u such that $U(h) \geq A_0(h)$ if and only if $h \geq r_u$, and a value of $\tilde{r}_u$ such that $U(h) \geq \tilde{A}(h)$ if and only if $h \geq \tilde{r}_u$. Let $\mathcal{H}$ denote sets of all possible realizations of idiosyncratic health. The evolution of the measures are as follows:

$$\phi_e'(\mathcal{H}) = (1-\lambda)\int_{r_e}^{\omega} \phi_e(h)dQ_e(h' \mid h)dh' + f(\theta_h)\int_{r_e}^{\omega} \phi_u(h)dQ_u(h' \mid h)dh', \tag{3.21}$$

$$\begin{aligned}\phi_u'(\mathcal{H}) =&(1-f(\theta_h))\int_{r_u}^{\omega} \phi_u(h)dQ_u(h' \mid h)dh' + \\ &+\lambda\int_{r_u}^{\omega} \phi_e(h)dQ_e(h' \mid h)dh' + \zeta\int_h \phi_b(h)dh,\end{aligned} \tag{3.22}$$

$$\begin{aligned}\phi_a'(\mathcal{H}) =&\sum_{\tau=1}^{4}\int_h \phi_a(h,\tau)dh + (1-\lambda)\int_{-\omega}^{r_e} \phi_e(h)dQ_e(h' \mid h)dh' + \\ &+\lambda\int_{-\omega}^{r_u} \phi_e(h)dQ_e(h' \mid h)dh' + f(\theta_h)\int_{-\omega}^{r_e} \phi_u(h)dQ_u(h' \mid h)dh' + \\ &+(1-f(\theta_h))\int_{-\omega}^{r_u} \phi_u(h)dQ_u(h' \mid h)dh',\end{aligned} \tag{3.23}$$

$$\phi_{\tilde{a}}'(\mathcal{H}) = (1-\tilde{\pi})\int_h \phi_{\tilde{a}}(h)dh + (1-\pi)\int_{-\omega}^{\tilde{r}_u} \phi_a(h,\tau=5)dh, \tag{3.24}$$

$$\phi_b'(\mathcal{H}) = (1-\zeta)\int_h \phi_b(h)dh + \pi\int_h \phi_a(h,\tau=5)dh + \tilde{\pi}\int_h \phi_{\tilde{a}}(h)dh. \tag{3.25}$$

These measures are subject to various transitions and flows, reflecting the complex interplay between health and productivity at the individual level, as well as the dynamics of labor force and DI participation.

3.4.8 Equilibrium

Decentralized equilibrium in the model is characterized by a set of conditions involving value functions, the Nash bargaining wage $w(h)$, market tightness θ_h, and the law of motion $\mathcal{P}$

that satisfy the following conditions:

(i) given θ_h and $w(h)$, the value functions solve the optimization problems represented by equations (3.11) - (3.18);

(ii) given the value function $J(h)$, market tightness θ_h satisfies the free-entry condition that $V(h)$ in equation (3.19) is equal to zero;

(iii) given the value functions, the optimal wage $w(h)$ is determined through the Nash bargaining rule, taking into account the bargaining power of workers (ξ), the matching surplus, and idiosyncratic health;

(iv) given the transition functions and optimal decisions, the law of motion for the distribution $(\phi'_e, \phi'_u, \phi'_a, \phi'_{\tilde{a}}, \phi'_b) = \mathcal{P}(\phi_e, \phi_u, \phi_a, \phi_{\tilde{a}}, \phi_b)$ is described in equations (3.21) - (3.25).

3.5 Quantitative analysis

This section calibrates the model and presents its main quantitative predictions.

3.5.1 Calibration

This subsection sets parameters in the model to U.S. data features. The model period is a month. The time discount factor with a mortality risk is denoted by β, set to 0.994, implying an annual rate of 5% and a working-life of 40 years.[10] The exogenous job separation rate is set to the one measured by Shimer (2005); normalizing it to a monthly frequency, i.e., $\lambda = 1/30$. In the matching technology, the efficiency coefficient μ is 0.5320, chosen by targeting the unemployment rate of 6.29%. The vacancy creation cost κ is 0.6364, targeting the aggregate unity market tightness. Following Shimer (2005), I choose $\eta = 0.5$ and $\xi = 0.5$, satisfying the Hosios efficiency condition.

[10] $1/1.05^{1/12}(1-1/480) = 0.994$.

Table 3.7: Benchmark parameterization

Pre-specified parameters		
β	0.994	time discount factor with a mortality risk
λ	$1/30$	job separation rate
η	0.500	parameter of the matching technology
ξ	0.500	worker's bargaining power
Calibrated parameters		
μ	0.5320	efficiency coefficient of the matching technology
κ	0.6364	job-creation cost
$Beta(\alpha_1, \alpha_2)$	$(22.68, 1.43)$	initial health distribution
γ_e	6.524e-04	persistence of the health shock among the employed
γ_u	0.0030	persistence of the health shock among the unemployed
ω	0.1327	volatility of the idiosyncratic health shock
b_U	0.4000	flow utility of the unemployed
b_A	0.4000	flow utility of the applicants
b_{AP}	0.4351	flow utility of the appellants
b_D	0.9551	flow utility of the beneficiaries
π	0.3562	success rate of the initial determination
$\tilde{\pi}$	$1/20$	success rate of the appeal process
ζ	0.0057	disability benefits termination rate

When entering the economy, newborn workers draw their idiosyncratic health from the initial health distribution. It proxies the empirical health index distribution of household heads and spouses aged 25-26 in the PSID. Following the health economics literature, I approximate this empirical distribution by a Beta distribution, $Beta(\alpha_1, \alpha_2)$, where α_1 and α_2 represent the shape parameters. I choose values of α_1 and α_2 to match the mean (0.941) and standard deviation (0.047) of the health index, resulting in $\alpha_1 = 22.683$ and $\alpha_2 = 1.432$.

Employed and unemployed workers receive health shocks with probabilities of γ_e and γ_u, respectively. Following the health shocks, both employed and unemployed workers draw their new idiosyncratic health from the general uniform distribution, $G(h)$, where h is on the interval of $[-\omega, \omega]$. The value of γ_e is a ratio of fatal and non-fatal cases involving days away from work to the number of employed workers in the U.S. for 2003-2019 (see `https://data.bls.gov/PDQWeb/cs`). The value of γ_u is chosen to provide that the individual health persistence at an annual frequency is 0.991, as measured by Hosseini et al. (2022).[11] The value of ω, the volatility of the idiosyncratic health, is set to 0.133, targeting that the average wage of the future beneficiaries is lower by 18.8% than the future non-beneficiaries as found in my empirical analysis (see table 3.4).

Following Shimer (2005), the flow utility of the unemployed is 0.4, and I simplify that it is the same for the applicants, i.e., $b_A = b_U$.[12] The flow utility of the appellants is 0.435, targeting the applicant rate of 0.41%,[13] while it is 0.955 for the beneficiaries, calibrated to the beneficiary rate of 5.43%. After waiting for five months, the applicants qualify for disability benefits with a probability of 0.356.[14] The denied applicants endogenously decide

[11] The monthly persistence coefficient of the health index has to satisfy the following equation: $[1-(\gamma_e\bar{e}+\gamma_u\bar{u})]^{12} = 0.991$. Given $\lambda = 1/30$, $\gamma_e = 6.524e-04$, and the targeted employment and unemployment rates, it dictates that $\gamma_u = 0.0030$.

[12] Although the applicants do not receive disability benefits when waiting for their initial determination decisions, they can collect Supplemental Security Income (SSI) from SSA.

[13] Depending on how many months the appellants have waited for their appeal decision, they can receive retroactive disability benefits up to 12 months.

[14] The literature frequently uses a ratio of the total number of new beneficiaries, who are awarded in the initial and appeal stages, to the initial total applicants, not including technical denials. For example, Kitao (2014) uses a value of 0.5 for the average success rate, i.e., $\pi = 0.5$. In this chapter, I calculate the award rate by a ratio of the number of new beneficiaries who are only awarded in the initial stage to the initial total applications, excluding technical denials.

whether to initiate the appeal process. The appellants are awarded disability benefits with a probability of $\tilde{\pi}$, which corresponds to a waiting period of 605 days (see `https://www.gao.gov/products/gao-18-501`). DI beneficiaries are terminated with a probability of ζ, set to 0.006, measured from the official statistics of SSA.

Moreover, I assume that idiosyncratic health in the model economy is mapped to the health index by the following function:

$$H_{i,t} = \upsilon_0 + \upsilon_1 h_{i,t}, \tag{3.26}$$

where $H_{i,t} \in [0, 1]$ and $h_{i,t} \in [-\omega, \omega]$. I choose values of υ_0 and υ_1 by targeting the average health index of the employed and the beneficiaries, i.e., $\upsilon_0 = 0.7980$ and $\upsilon_1 = 0.1445$.

3.5.2 Main predictions

The benchmark model's predictions are summarized in Table **??**. It successfully matches key targeted moments, including a market tightness of 1.000, an unemployment rate of 6.29%, and a wage gap between non-future beneficiaries and future beneficiaries (NFP-FP) of 0.188%. It also replicates specific rates such as a DI applicant rate of 0.41% and a DI beneficiary rate of 5.43%. Regarding health indices, the model predicts values of 0.923 for the employed and 0.815 for beneficiaries.

The benchmark model also reasonably predicts untargeted moments. For instance, the average health index of the population is 0.917 in the model economy, comparable to the observed value of 0.919 in the PSID. The probability of starting the appeal process among denied applicants is 26.6% in the model economy, closely aligned with the 25.7% found by Autor and Duggan (2010) in 2005. Similarly, the proportion of appellants among new beneficiaries is 32.4% in the model economy, consistent with the range of 27.8% to 39.6% reported for 2000-2020 by SSA (2021).

Furthermore, the model's predictions suggest that the average health index of appellants

Table 3.8: Benchmark model's predictions

	data	model
Targeted moments		
market tightness	-	1.000
unemployment rate	6.292	6.292
NFP - FP wage gap	0.188	0.188
DI applicant rate	0.406	0.406
DI beneficiary rate	5.428	5.428
health index		
employed	0.923	0.923
beneficiaries	0.815	0.815
Untargeted moments		
per-worker output	-	1.103
per-worker wage	-	1.057
job-finding rate	0.475	0.532
unemployment duration	1.936	1.880
health index		
population	0.919	0.917
applicants	-	0.814
appellants	-	0.802
beneficiaries	-	0.815
DI appellant rate	-	0.003
DI application duration (months)	-	11.802
the probability of initiating the appeal process	25.724	26.552
the appellants among new beneficiaries	[27.82, 39.65]	32.433

Notes: I present the averages of job-finding rates and unemployment durations documented in the literature. Specifically, the job-finding rate is on the interval of $[0.32, 0.63]$, while unemployment duration is on the interval of $[1.29, 2.58]$. The probability of initiating the appeal process is 0.26, as found in Autor and Duggan (2010), while the proportion of the appellants among new DI beneficiaries is from 0.28 to 0.40 for 2000-2020 (SSA, 2021).

is lower than those of applicants and beneficiaries. This observation indicates potential instances of false rejection and acceptance within the DI system, a phenomenon consistent with findings by Low and Pistaferri (2015). While the literature often overlooks appellant rates due to data limitations, the benchmark model estimates the ratio of appellants to the labor force at 0.28%. Regarding the appeal process, the model predicts an average duration of approximately one year to reach a favorable decision.

Tables 3.4 to 3.6 summarize three key empirical findings: (*i*) the wage gap between the future beneficiaries and non-beneficiaries, (*ii*) the impact of the current health index on the probability of engaging in disability benefits within the next two years, and (*iii*) the impact of the health index on the current hourly wages. Specifically, the benchmark model accurately produces a wage gap of 18.8% as a targeted moment. Additionally, using simulated data, I estimate other two coefficients from the following regressions:

$$D_{i,t+2} = \alpha H_{i,t} + \epsilon_{i,t+2}, \tag{3.27}$$

$$w_{i,t} = \beta H_{i,t} + \varepsilon_{i,t}, \tag{3.28}$$

where $D_{i,t+2}$ is a dummy for a person i who transitions from the non-beneficiary to the beneficiary between years t and $t+2$, $w_{i,t}$ is the person's wage, and $H_{i,t}$ is the person's health index.

Table 3.9 shows the estimation results along with corresponding coefficients and confidence intervals from the PSID. Notably, in the benchmark model, the impact of the health index on the probability of engaging in disability benefits within the next two years stands at -0.211, compared to -0.203 observed in the PSID. This finding indicates that a 0.1-point increase in the health index would decrease the likelihood of non-beneficiaries engaging in the DI program by 0.021 points over the next two years in the model economy. Similarly, the health index's effect on current hourly wages is estimated at 0.302, slightly lower than the 0.342 observed in empirical data. A 0.1-point increase in the health index corresponds to a 3.0% rise in current hourly wages in the model economy. Notably, these estimated coefficients fall within the 95% confidence intervals defined by the PSID, confirming the benchmark model's ability to replicate these empirical moments.

Table 3.9: Observed and simulated empirical moments

	PSID	95% confidence interval	benchmark model
α	-0.203*** (0.0206)	$[-0.2434, -0.1626]$	-0.211*** (0.0037)
β	0.342*** (0.1058)	$[0.1345, 0.5494]$	0.302*** (0.0016)

Notes: The estimated coefficients in the PSID are in tables 3.5 and 3.6. Using the simulated data, I run the two regressions and then present their estimated coefficients in the 'benchmark model.'

These results underscore the benchmark model's capacity to replicate key empirical moments derived from the PSID without explicit targeting. In the next section, I will leverage the model to conduct counterfactual experiments, exploring policy impacts and alternative scenarios.

3.6 Counterfactual experiments

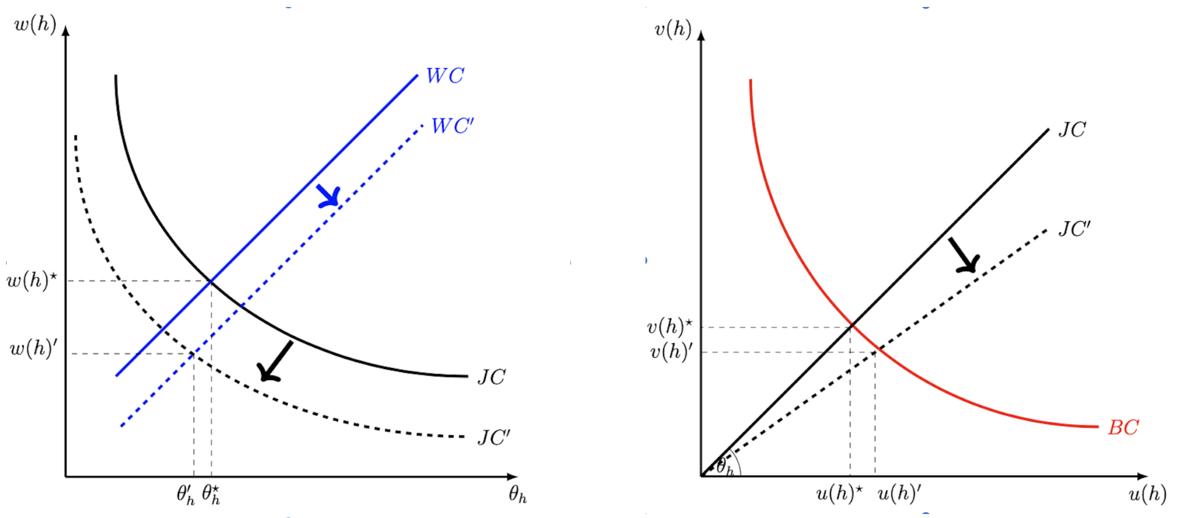
In this section, I conduct counterfactual experiments regarding aggregate productivity, alternative waiting periods for the initial determination procedure, alternative durations of the appeal process, and mean-preserving spread and contraction in idiosyncratic health.

3.6.1 Aggregate productivity

The first experiment is about how aggregate productivity affects labor market outcomes and DI participation. Given the standard equilibrium search framework, a decrease in aggregate productivity shifts the job creation curve to the left and pushes the wage curve downward in the tightness-wage space (see panel (a) of figure 3.3). These shifts lead to simultaneous decreases in wages and market tightness in the steady state due to the worker's bargaining power (ξ) being less than unity. In the vacancy-unemployment space, this lower market tightness results in a clockwise rotation of the job creation line, reducing vacancies and increasing unemployment (see panel (b) of figure 3.3). As a result, the unemployment rate exhibits a countercyclical response to aggregate productivity, while the vacancy rate shows a cyclical response.

Figure 3.3: Lower aggregate productivity in the steady state

(a) market tightness and wages (b) vacancies and unemployment



Notes: In a steady state, lower aggregate productivity reduces the total surplus, resulting in a lower wage and lower market tightness that indicates fewer vacancies and higher unemployment.

In the labor economics literature, the impact of aggregate productivity on labor market outcomes has been sufficiently studied. I numerically examine this relationship using the benchmark model with an extended production function, i.e., $y(h) = z\,exp(h)$, where z is aggregate productivity. For example, the model predicts that lower aggregate productivity would reduce wage and market tightness in a steady state. It would increase the average output because workers with worse health and lower productivity leave the labor force for disability benefits. Additionally, lower market tightness implies higher unemployment and fewer vacancies, as shown in figure 3.3.

In the DI literature, empirical studies find that DI participation counter-cyclically responds to broader economic conditions. In the benchmark economy, the DI participation rate stands at 6.12%, including the applicants, the appellants, and the beneficiaries (see table 3.10). The model predicts that a 1% increase in aggregate productivity would decrease the DI participation rate to 4.82%, whereas a 1% decrease would raise it to 7.34%. These predictions show that DI participation counter-cyclically responds to aggregate productivity in a steady state, consistent with empirical studies.

Table 3.10: Impact of aggregate productivity

	levels of aggregate productivity, z				
	0.990	0.995	1.000	1.005	1.010
Labor market					
market tightness	0.9860	0.9931	1.0000	1.0063	1.0128
unemployment	0.0633	0.0631	0.0629	0.0627	0.0626
per-worker wage	1.0476	1.0522	1.0566	1.0609	1.0653
per-worker output	1.1045	1.1037	1.1027	1.1016	1.1006
Average health index					
employed	0.9242	0.9238	0.9233	0.9228	0.9223
unemployed	0.9239	0.9234	0.9228	0.9221	0.9215
applicants	0.8225	0.8207	0.8187	0.8164	0.8143
appellants	0.8099	0.8078	0.8064	0.8047	0.8031
beneficiary	0.8176	0.8164	0.8148	0.8132	0.8117
Disability insurance					
applicant rate	0.0045	0.0044	0.0041	0.0037	0.0036
appellant rate	0.0039	0.0032	0.0028	0.0023	0.0018
beneficiary rate	0.0650	0.0605	0.0543	0.0483	0.0428
application duration (months)	12.6952	12.2705	11.7970	11.1211	10.2050
the share of appellants among new beneficiaries	0.3763	0.3394	0.3243	0.2980	0.2575
the probability of initiating the appeal process	0.3337	0.2842	0.2655	0.2349	0.1919

Notes: This table is based on the model's predictions with respect to alternative levels of aggregate productivity. In the benchmark economy, aggregate productivity z is 1.000.

Importantly, the applicants, the appellants, and the beneficiaries differently respond to changes in aggregate productivity. For example, when aggregate productivity decreases by

1%, the beneficiary and applicant rates would increase by 19.9% and 11.9%, respectively. The appellant rate would increase by 40.6%, two or three times more responsive than DI beneficiaries and applicants. Moreover, the probability of initiating the appeal process among the applicants rejected in the initial determination stage would increase by 25.7%, increasing the share of appellants among new beneficiaries by 16.0%. The average health index would, respectively, increase by 1.09%, 1.07%, and 0.8% among the applicants, the appellants, and the beneficiaries.

These results indicate that (*i*) workers misuse the DI program as a form of insurance against worse broader economic conditions; (*ii*) relatively healthy and productive workers tend to seek disability benefits during economic downturns; (*iii*) those marginally impaired workers are more likely to qualify for disability benefits through the appeal process. These findings are supported by previous empirical studies.[15]

3.6.2 Initial determination procedure

The second experiment is about the length of the waiting period for the initial determination procedure. Even though the waiting period for initial applicants is one of the important features in the DI system, the existing literature often ignores it. I extend the standard Diamond-Mortensen-Pissarides framework by the waiting period for the initial determination procedure for the first time in the literature. Using this model, I numerically examine the effects of shorter and longer waiting periods for the initial determination procedure on DI participation and labor market outcomes. The model predictions are summarized in table 3.11.

In the benchmark economy, the DI participation rate, including the applicants, the appellants, and the beneficiaries, is 6.12%. When the waiting period is extended to seven months, the participation rate would decline to 4.54%. On the other hand, when the waiting period is shortened to three months, the participation rate would increase to 9.47%. It is noteworthy

[15] See, for example, Autor and Duggan (2003, 2006); Maestas et al. (2015); Lindner et al. (2017), and Maestas et al. (2021).

Table 3.11: Impact of alternative waiting periods for the initial applicants

	alternative waiting periods (months)				
	3	4	5	6	7
Labor market					
market tightness	0.9957	0.9972	1.0000	0.9989	0.9967
unemployment	0.0633	0.0631	0.0629	0.0629	0.0630
per-worker wage	1.0610	1.0583	1.0566	1.0555	1.0543
per-worker output	1.1075	1.1045	1.1027	1.1015	1.1001
Average health index					
employed	0.9257	0.9242	0.9232	0.9227	0.9221
unemployed	0.9244	0.9234	0.9228	0.9221	0.9214
applicants	0.8239	0.8201	0.8187	0.8120	0.8101
appellants	-	-	0.8064	0.8117	0.8101
beneficiary	0.8238	0.8199	0.8148	0.8122	0.8101
Disability insurance					
applicant rate	0.0060	0.0062	0.0041	0.0023	0.0023
appellant rate	-	-	0.0028	0.0045	0.0038
beneficiary rate	0.0887	0.0680	0.0543	0.0466	0.0393
application duration (months)	3.0000	4.0000	11.7970	18.2131	18.6793
the share of appellants among new beneficiaries	-	-	0.3243	0.5754	0.5344
the probability of initiating the appeal process	-	-	0.2655	0.7498	0.6350

Notes: This table is based on the model's predictions with respect to alternative waiting periods for the initial determination procedure. In the benchmark economy, the waiting period is 5 months. Here, hyphens (-) represent zero values.

to mention that DI components differently respond to the length of the waiting period. For example, when the waiting period is three months, the applicant and beneficiary rates would be 0.60% and 8.87%, respectively. None of the denied applicants would initiate the appeal process. It implies that the denied applicants would reapply for disability benefits instead of initiating the appeal process, doubling the monthly applicant rate from 0.08% to 0.20%. This finding suggests that the appeal process is not as crucial as the initial determination procedure, contradicting the main empirical findings of French and Song (2014).

Additionally, the 3-month waiting period would improve the overall health across the states in the economy. For instance, compared to the benchmark economy, the average health index would be, respectively, higher for the beneficiaries and the applicants by 1.45% and 2.62%. It suggests that relatively healthy and more productive workers would engage in disability benefits due to a shorter waiting period for the initial determination procedure. In the labor market, it would increase the average output and the average wage but reduce the aggregate market tightness. This lower market tightness implies fewer vacancies and higher unemployment in a steady state.

These predictions indicate that (*i*) the waiting period for the initial determination procedure influences the decisions of marginally impaired workers on DI participation and (*ii*) the shorter waiting period encourages unemployed workers to wait for a higher wage offer, extending their unemployment duration.

3.6.3 Appeal process

The third experiment is about the length of the waiting period for the appeal process. Although the appeal process is a critical element of the DI program, the literature does not study as much as the initial determination procedure due to data limitations. I extend the standard Diamond-Mortensen-Pissarides framework by the endogenous appeal option for the first time in the literature. Using the benchmark model, I quantitatively explore the effects of alternative waiting periods in the appeal stage on DI participation and labor market outcomes. The model predictions are summarized in table 3.12.

Table 3.12: Impact of alternative waiting periods in the appeal process

	alternative waiting periods (months)				
	18	19	20	21	22
Labor market					
market tightness	1.0027	1.0016	1.0000	0.9965	0.9961
unemployment	0.0628	0.0629	0.0629	0.0630	0.0631
per-worker wage	1.0568	1.0571	1.0566	1.0560	1.0560
per-worker output	1.1040	1.1033	1.1027	1.1020	1.1019
Average health index					
employed	0.9240	0.9236	0.9233	0.9230	0.9229
unemployed	0.9236	0.9232	0.9228	0.9222	0.9221
applicants	0.8158	0.8177	0.8187	0.8156	0.8152
appellants	0.8159	0.8127	0.8064	0.7987	-
beneficiary	0.8161	0.8150	0.8148	0.8152	0.8152
Disability insurance					
applicant rate	0.0025	0.0029	0.0041	0.0055	0.0057
appellant rate	0.0055	0.0047	0.0028	0.0003	-
beneficiary rate	0.0618	0.0570	0.0543	0.0513	0.0512
application duration (months)	16.1186	15.2093	11.7970	5.7229	5.0000
the share of appellants among new beneficiaries	0.6289	0.5448	0.3243	0.0346	-
the probability of initiating the appeal process	0.9375	0.6621	0.2655	0.0199	-

Notes: This table is based on the model's predictions with respect to alternative waiting periods in the appeal process. In the benchmark economy, the average waiting period is 20 months. Here, hyphens (-) represent zero values.

I consider four scenarios for the average waiting period in the appeal process, ranging from 18 to 22 months.[16] For example, a shorter waiting period in the appeal stage (18 months) would lower the applicant rate by 39.0%, while it would increase the appellant rate by 96.4%, resulting in a 13.8% increase in the beneficiary rate. The share of appellants among new beneficiaries would increase by 93.92%. Additionally, the average health index

[16]The waiting period and success rate in the appeal stage are inverse to each other. For example, as in the benchmark economy, the average success rate in the appeal stage is 0.05, i.e., $\tilde{\pi} = 0.05$, implying the average waiting period of 20 months ($= 1/0.05$).

would be lower for the applicants but higher for the other four states - the employed, the unemployed, the appellants, and the beneficiaries. These findings show that the shorter waiting period encourages the applicants denied in the initial determination procedure to initiate the appeal process, resulting in a higher beneficiary rate.

In the labor market, the shorter waiting period in the appeal process would increase average output, wages, and market tightness. Higher market tightness would imply more vacancies and lower unemployment in a steady state. These predictions indicate that the shorter waiting period in the appeal process would positively affect labor market outcomes such as a lower unemployment rate.

3.6.4 Mean-preserving spread and contraction

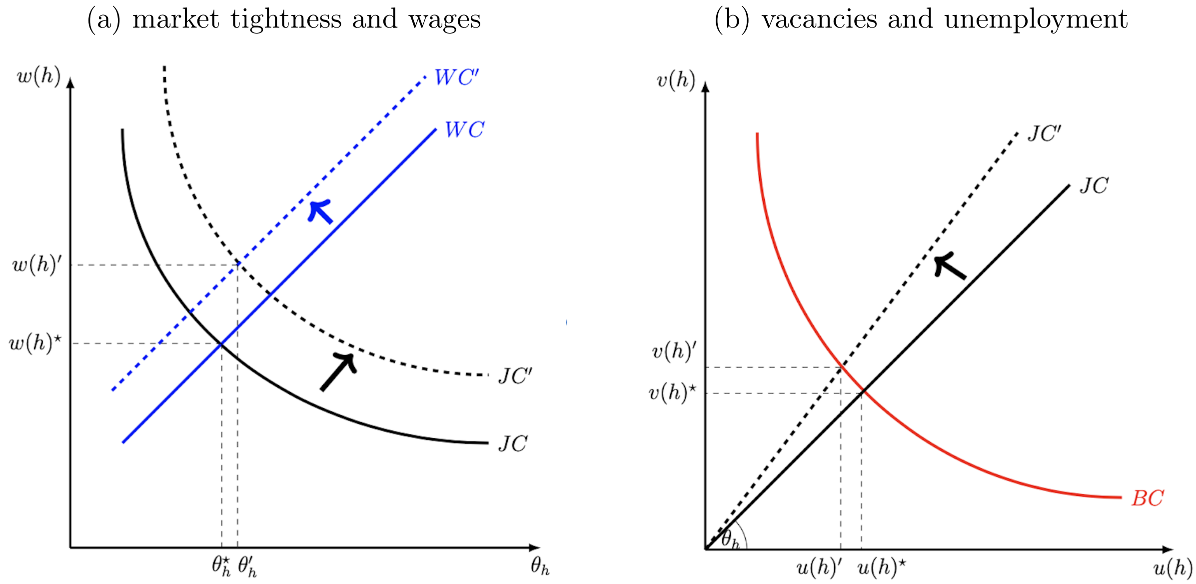
The fourth experiment is about how labor market outcomes and DI participation respond to changes in the volatilities of idiosyncratic health and stochastic productivity. This experiment is motivated by empirical findings suggesting that the overall health index has improved alongside widening volatilities in the PSID from 2005 to 2019.

Given the equilibrium search framework, the mean-preserving spread shifts the job creation curve to the right and pushes the wage curve upward in the tightness-wage space (see panel (a) of figure 3.4). These shifts simultaneously increase wage and market tightness in the steady state due to the worker's bargaining power (ξ) being less than unity. Increased market tightness results in a counterclockwise rotation of the job creation line in the vacancy-unemployment space (see panel (b) of figure 3.4). As a result, the vacancy rate increases, while the unemployment rate decreases, with respect to the mean-preserving spread.

The quantitative model replicates these relationships accurately. For example, mean-preserving spread increases average output, wages, and market tightness, which correlates with more vacancies and lower unemployment in the steady state.

The model predicts that DI participation decreases with mean-preserving contraction but increases with mean-preserving spread (see table 3.13). For instance, when the volatility

Figure 3.4: Mean-preserving spread in the steady state



Notes: In a steady state, the mean-preserving spread increases the total surplus, resulting in a higher wage and higher market tightness that indicates more vacancies and lower unemployment.

of idiosyncratic health contracts to 0.100, the DI participation rate (including applicants, appellants, and beneficiaries) decreases to 3.55%. However, with volatility widening to 0.165, the participation rate rises to 7.87%. These results suggest that DI participation positively depends on the volatility of idiosyncratic health.

Moreover, DI applicants, appellants, and beneficiaries respond differently to mean-preserving spread and contraction. For instance, at a volatility of 0.165, the beneficiary rate is 6.95%, with applicant and appellant rates of 0.44% and 0.48%, respectively. Compared to the benchmark economy, these rates are higher by 28.12%, 8.81%, and 75.02%, respectively. The probability of initiating the appeal process among applicants rejected in the initial determination stage increases by 60.16%, leading to a 60.76% increase in the share of appellants among new beneficiaries. Additionally, the average health index increases by 0.38%, 0.53%, and 0.67% among beneficiaries, applicants, and appellants, respectively. These predictions highlight that appellants are more responsive to volatility in idiosyncratic health than applicants and beneficiaries.

Table 3.13: Impact of mean-preserving contraction and spread

	volatilities of idiosyncratic health, ω				
	0.1000	0.1164	0.1327	0.1490	0.1654
Labor market					
market tightness	0.9460	0.9729	1.0000	1.0271	1.0541
unemployment	0.0646	0.0638	0.0629	0.0621	0.0615
per-worker wage	1.0281	1.0423	1.0566	1.0713	1.0863
per-worker output	1.0732	1.0879	1.1027	1.1178	1.1333
Average health index					
employed	0.9211	0.9224	0.9233	0.9241	0.9248
unemployed	0.9206	0.9218	0.9228	0.9235	0.9240
applicants	0.8091	0.8147	0.8187	0.8212	0.8230
appellants	-	0.8028	0.8064	0.8095	0.8118
beneficiary	0.8091	0.8124	0.8148	0.8167	0.8179
Disability insurance					
applicant rate	0.0035	0.0038	0.0041	0.0042	0.0044
appellant rate	-	0.0017	0.0028	0.0038	0.0048
beneficiary rate	0.0320	0.0447	0.0543	0.0627	0.0695
application duration (months)	5.0000	9.5096	11.7970	12.9477	13.6368
the share of apellants among new beneficiaries	-	0.2359	0.3243	0.3881	0.4356
the probability of initiating the appeal process	-	0.1708	0.2655	0.3508	0.4269

Notes: This table is based on the model's predictions with respect to volatilites of idiosyncratic health. In the benchmark, its volatility is 0.2, i.e., $\omega = 0.2$. Here, hyphens (-) represent zero values.

These results show that (i) unemployment and DI participation differently respond to the volatility of idiosyncratic health and productivity; (ii) not only the overall health level of the labor force (population) but also the persistence and volatility of the individual-level health conditions are important for understanding the extent of DI participation; (iii) the appellants are more responsive than the applicants and beneficiaries.

3.7 Conclusion

In this chapter, I explored how an individual's decision on DI participation is influenced by health and non-health factors. The chapter makes two important contributions to the existing literature. First, using the PSID, I establish key dynamic relationships between DI participation, health, employment, and wages at the individual level. Second, I construct a flexible and dynamic framework to examine the interplay between DI participation and labor market outcomes.

The novelty of the model is incorporating health-driven stochastic productivity and endogenous DI participation into the standard Diamond-Mortensen-Pissarides framework. I calibrate the model by linking DI participation, health, wages, and labor market outcomes in the PSID data at the individual level. I show that the model can replicate key features of the U.S. data. What is more remarkable is that the model can reproduce these empirical findings about the impact of the health conditions on the probability of engaging in the DI program within the next two years and the current hourly wages, without explicitly targeting those moments. In addition, the model performs remarkably well along several dimensions that are not targeted in the calibration process:

(i) the relative shares of the DI beneficiaries who became DI participants through their initial determination versus the appeal process;

(ii) the probability of initiating the appeal process among the applicants who were not approved for the DI program by the initial determination process of the SSA;

(iii) the age distribution of the health conditions of the DI participants.

To the best of my knowledge, the model developed in the chapter is the first equilibrium search model with health-driven productivity and endogenous DI participation. As such, the model offers a natural framework to address various policy issues concerning the impact of health and non-health factors.

According to the model predictions, the probability that relatively healthy and productive workers tend to seek disability benefits increases in response to adverse labor market conditions. This aligns with the observed surge in new DI participants during economic downturns, especially the Great Recession of 2007-2009. Furthermore, the model predicts that the number of individuals who appeal the initial eligibility determination is more responsive to the labor market conditions than the number of new DI applicants. This prediction is consistent with the existing empirical literature such as Maestas et al. (2015) and Lindner et al. (2017).

Using the model, I evaluated the current DI program in the U.S. while focusing on policy instruments such as the lengths of the waiting periods for the initial determination procedure and the duration of the appeal process. Specifically, I find that a shorter waiting period for the initial determination increases the unemployment rate, whereas a shorter waiting period for the appeal process reduces it. These policy instruments differently affect the decisions related to DI participants and labor market outcomes.

Last but most importantly, the model's predictions show that not only the overall health level of the labor force but also the persistence and volatility of the individual-level health conditions are important for understanding the extent of DI participation.

For future research, it might be of interest to consider aggregate fluctuations in the model and use the extended version to explore the impact of unemployment benefits on DI participation.

Chapter 4

On the Interplay between Social Security Disability Insurance Participation and Labor Market Outcomes

4.1 Introduction

Social Security Disability Insurance (DI) provides financial and in-kind benefits to working-age persons who have mental and/or physical impairments that prevent them from engaging in a substantial gainful activity (SGA) for the next twelve months or longer. Over the last decades, the number of DI beneficiaries has risen substantially. In the existing literature, numerous studies emphasized that non-health factors are important for understanding the evolution of DI participation.[1] However, many of those studies evaluate the effects of non-health factors using aggregate-level data.

This chapter examines the impact of non-health factors, such as the replacement rates of DI and UI (unemployment insurance) benefits and unemployment duration, on DI participation using microdata, namely the Annual Social and Economic Supplement of the Current Population Survey (CPS-ASEC).

The estimation results show that the replacement rate of DI benefits and unemployment duration have a strong positive impact on DI participation at the individual level. Their effects are stronger among the less educated and/or older workers. Regarding the state replacement rate of UI benefits, it positively affects DI participation at the individual level, except for more educated workers. These empirical findings provide microdata-based support for the view of Autor and Duggan (2006) that workers misuse the DI program as a form of financial option.

Using the empirical findings, I consider counterfactual experiments to address the following two questions:

(i) What might the labor force participation rate be had there not been an increase in the replacement rate of DI benefits?

(ii) How did the Great Recession of 2007-2009 contribute to the number of DI beneficiaries?

[1] See, for example, Bound (1989, 1991); Gruber and Kubik (1997); Autor and Duggan (2003, 2006); Duggan and Imberman (2009); Von Wachter et al. (2011); Coe et al. (2013); French and Song (2014); Low and Pistaferri (2015).

The counterfactual experiments find that the increase in the replacement rate of DI benefits and the Great Recession of 2007-2009 significantly influenced DI participation and even labor force participation. For example, if DI benefits had been proportional to wages since 2000, DI participation would be lower by 19.5% (1.6 million persons), increasing up to 12.1% in the unemployment rate compared to what we had in 2020. Additionally, the Great Recession induces 600,000 new beneficiaries for 2008-2012; the less educated account for around 66.4%. Based on these two findings, the increase in the replacement rate of DI benefits attracts more working-age persons to this social security program than the Great Recession of 2007-2009.

The remainder of this chapter is organized as follows: Section 4.2 provides an overview of the relevant literature on DI participation and the role of non-health factors. Section 4.3 presents stylized facts about the U.S. labor force participation rate and DI participation. Section 4.4 describes the data and methodology. Section 4.5 presents the empirical results regarding the effects of non-health factors on DI participation and examines their robustness. Section 4.6 discusses the counterfactual experiments and their potential policy implications. Section 4.7 concludes the chapter.

4.2 Literature review

The existing literature mainly accounts for DI participation dynamics using non-health factors, such as shifts in the labor market, and the replacement rates of DI and UI benefits.

The most popular non-health factor in the literature is labor market conditions. An influential study of Black et al. (2002) found that DI participation is in a counter-cyclical response to changes in labor market conditions using the coal boom and bust. This strand of the literature considerably grew during the Great Recession of 2007-2009. For example, Maestas et al. (2015) estimated that the number of DI applications increased by 6.7% due to the Great Recession, with the majority of them being awarded DI benefits through the appeal process. Lindner et al. (2017) highlighted that DI applicants who applied during economic downturns often have a higher work capacity than those who applied during economic upturns. These empirical findings suggest that DI participation counter-cyclically responds to labor market conditions due to those marginally impaired workers (Autor et al., 2013; Coe et al., 2013; O'Brien, 2013; Charles et al., 2018; Anderson et al., 2019; Meyer and Mok, 2019; Maestas et al., 2021).

The next non-health factor is the replacement rate of DI benefits, a ratio of DI benefits to potential wages. In recent decades, the average wage has been increasing in the U.S., while it has stagnated for those with lower wages (Mishel et al., 2015; Binder and Bound, 2019). This wage stagnation, coupled with a progressive formula (see Appendix C.4). the Social Security Administration (SSA) uses to calculate the amount of DI benefits, increased the replacement rate of DI benefits for those with lower wages. The more generous DI benefits become, the more working-age persons apply for and engage in the DI program (Autor and Duggan, 2003, 2006; Von Wachter et al., 2011; Marie and Castello, 2012).

The third non-health factor is the replacement rate of UI benefits. In recent years, the literature has been arguing on whether UI benefits affect DI participation. For example, using the Survey of Income and Program Participation (SIPP) and aggregate official statistics, Rutledge (2011) found that extended UI benefits discourage working-age persons from applying for DI benefits. Nevertheless, Mueller et al. (2016) did not find this relationship but did not rule out the possibility of such a relationship. In light of the conflicting perspectives within the literature, the conclusive stance remains elusive.

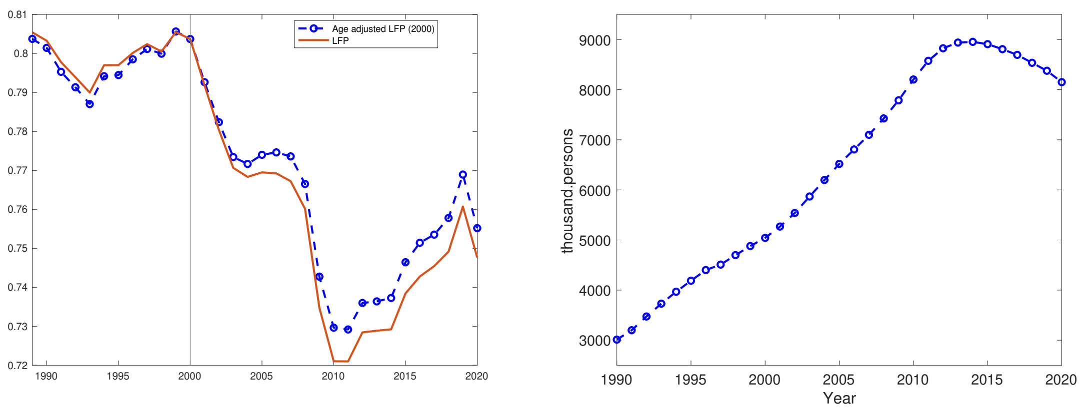
Unlike the existing literature that primarily relies on aggregate-level data, this chapter examines the effects of those popular non-health factors on DI participation at the individual level. Furthermore, this chapter offers microdata-based evidence to the argument of the effects of UI benefits on DI participation. By utilizing the CPS-ASEC, this study explores their effects on a broader representation of the U.S. labor force and in different demographic subgroups.

4.3 Stylized facts

In this section, I present empirical facts related to the U.S. labor force participation rate and DI participation. Panel (a) of figure 4.1 displays the observed and adjusted U.S. labor force participation rates for 1990-2020. Both rates show a comparable trend. This fact implies that the aging in the U.S. labor force, particularly the baby boom generation, cannot account for the fluctuations in labor force participation.

Figure 4.1: U.S. labor force participation and DI beneficiaries

(a) labor force participation **(b)** DI beneficiaries



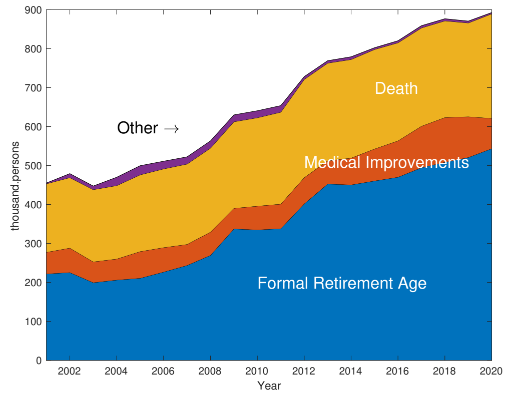
Notes: These figures are based on the CPS-ASEC of 2001-2021 and SSA's official statistics. I define the actual labor force participation rate using the survey participants aged 25-61 and then run the regression with age polynomials and year dummies to construct the age-adjusted labor force participation rate.

Panel (b) of figure 4.1 displays the number of DI beneficiaries for 1990-2020. It rapidly increased from 3 million to around 9 million from 1990 to 2014, before gradually declining. These observations regarding labor force participation and DI engagement highlight a documented inverse relationship in the U.S., as discussed in Bound (1989, 1991) and Autor and Duggan (2006).

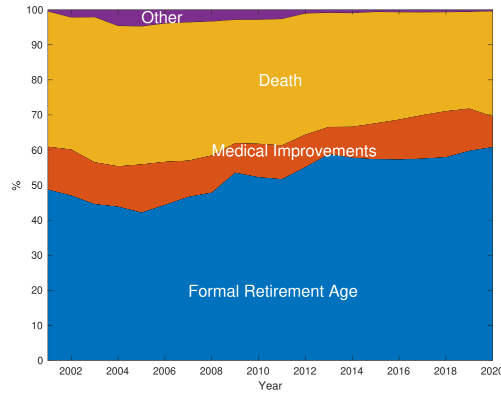
Shifting focus, figure 4.2 presents the primary causes of DI benefits termination, illustrating both the number of persons affected and their proportional distribution for 2000-2020. There are four main causes - formal retirement age, medical improvements, death, and oth-

Figure 4.2: Main causes of DI termination, by year

(a) number of persons



(b) proportions



Notes: These figures are based on the official statistics reported by SSA.

ers. The most frequent cause is the formal retirement age (around 58.2%), followed by death (around 28.3%). Importantly, medical improvements account for approximately 12.7% of the total DI termination.[2] While the expectation is that medically improved beneficiaries rejoin the labor force, French and Song (2014) discovered that a majority initiate the appeal process and then eventually reenter the program. These facts show that working-age persons do not return to the labor force after entering the DI program. Therefore, this program can be harmful to the labor force participation rate, labor market, and economic development in the long term.

[2]SSA runs a continuing eligibility review on each recipient to examine whether he is still eligible for DI benefits. After being approved for DI benefits, each application is placed into one of three different categories, including Medical Improvement Expected (MIE), Medical Improvement Possible (MIP), or Medical Improvement Not Expected (MINE). If an applicant is labeled as MIE, he will receive a continuing eligibility review within 6 to 18 months. If his condition worsens, the status of his case may change from MIE to MIP or MINE. However, he will still receive continuing eligibility reviews from SSA, but the length between the reviews will increase. For example, if his case changes from MIE to MIP, a continuing eligibility review will be conducted every three years. If his case changes from MIE to MINE, his continuing eligibility reviews will likely be conducted every seven years.

4.4 Who are the disabled?

The main dataset is the CPS-ASEC of 2001-2021, covering the calendar years of 2000-2020. I restrict the sample to individuals aged 25-60, to minimize the individual's decision related to schooling and retirement. I divide survey participants into two groups - DI beneficiaries and non-DI beneficiaries. Table 4.1 presents their descriptive statistics.

Table 4.1: Descriptive statistics

	overall	DI beneficiary	non-DI beneficiary
observations	1,636,793	71,131	1,565,662
male (%)	48.2	48.8	48.2
black (%)	11.8	20.4	11.6
married (%)	65.9	45.5	66.6
age	39.3	49.6	39.3
	(13.7)	(11.5)	(13.6)
years of schooling	13.4	12.1	13.4
	(2.93)	(2.68)	(2.93)

Notes: The table is based on the CPS-ASEC of 2001-2021. The standard errors are in parentheses. If a survey participant received DI benefits from SSA, he/she is a DI beneficiary; a non-DI beneficiary otherwise. The label *overall* represents the full sample.

Table 4.1 shows that DI beneficiaries tend to be black, unmarried, older, and less educated than non-DI beneficiaries. For example, black individuals constitute 20.4% of the beneficiaries, while it is lower at 11.6% for the non-beneficiaries. Married individuals account for 45.5% and 66.6% of the beneficiaries and the non-beneficiaries, respectively. The average age of the beneficiaries is 49.6 years, whereas it is 39.3 years for the non-beneficiaries. The average years of schooling is 12.1 for the beneficiaries, while it is 13.4 years for the non-beneficiaries. Notably, in the previous chapters, the PSID argues that DI beneficiaries tend to be female, which is not observed in the CPS-ASEC. That may be because of their samples.

These descriptive statistics show that DI beneficiaries and non-DI beneficiaries are different from each other through these demographic characteristics.

The main objective of this chapter is to explore the impact of non-health factors on DI participation, rather than demographic factors. Therefore, I restrict the main sample to a subsample of white and male working-age persons who are not retired, armed force members, self-employed, and unpaid workers.

4.5 Non-health factors

This section discusses the identifications of non-health factors, the estimation results, and their robustness.

4.5.1 Labor market conditions

While the existing literature often utilizes the unemployment rate as a proxy for labor market conditions at the aggregate level, it falls short of capturing the nuanced impact of these conditions at the individual level. Recognizing this limitation, I use unemployment duration in this chapter, a metric that better reflects the heterogeneous effects experienced by individuals. Unlike the unemployment rate, which offers a broad perspective, unemployment duration provides a granular understanding by measuring the number of weeks individuals remain unemployed, as observed in the CPS-ASEC.

Using observed unemployment durations, I calculate the average number of unemployed weeks by year and then compare it with the unemployment rate. Importantly, the average number of unemployed weeks exhibits a similar pattern to the unemployment rate at the aggregate level (see figure 4.7). This fact suggests that observed unemployment durations proxy labor market conditions at the aggregate level as well as at the individual level.

In the CPS-ASEC, unemployment duration is unobservable for non-unemployed workers. To characterize the labor market conditions facing these non-unemployed workers, I use the unemployment duration of otherwise similar, unemployed workers. Specifically, I ask the following question: If these non-unemployed workers were unemployed or looking for a job, what would be their unemployment duration? To address the question, I estimate the potential unemployment duration for non-unemployed workers, I employ the following empirical procedure:

(*i*) Run a probit model on the probability of being unemployed.

(*ii*) Using the estimated coefficients, calculate the inverse Mill's ratio for the unemployed.

(*iii*) Estimate an empirical unemployment duration model in the subsample of unemployed workers, incorporating the inverse Mill's ratio to remove a self-selection bias (Heckman, 1979).

(*iv*) Using the empirical unemployment duration model, predict the potential unemployment duration for non-unemployed workers.

This procedure a more comprehensive assessment of labor market conditions, both at the aggregate and individual levels.

The probit model is specified as follows:

$$\Pr(U = 1|X) = \Phi(X'\gamma), \tag{4.1}$$

where U is a dummy for unemployed workers, Φ is the cumulative distribution function (CDF) of the standard normal distribution, and X represents the covariates, including age, age squared, years of schooling, marital status, self-reported health status (SRHS), and year and state effects.

The empirical model is as follows:

$$\log(UD_{i,s,t}) = A(a_{i,s,t}) + \beta s_{i,s,t} + \theta m_{i,s,t} + \hat{\lambda}^{U}_{i,s,t} + \alpha_s + \alpha_t + \epsilon_{i,s,t}, \tag{4.2}$$

where $\log(UD_{i,s,t})$ is the logarithm of unemployment duration of individual i in state s in year t, $A(a_{i,s,t})$ is a quartic polynomial of the person's yearly age, $s_{i,s,t}$ is the person's years of schooling, $m_{i,s,t}$ is a dummy for married persons, $\hat{\lambda}^{U}_{i,s,t}$ is the inverse Mill's ratio defined from equation (4.1), and the terms α_s and α_t, respectively, represent state and year effects.

The estimation results show that unemployment duration increases with age but decreases with age squared. Also, it decreases with years of schooling, implying that more educated workers tend to have shorter unemployment duration than their corresponding less educated ones. Additionally, married working-age persons have an 11.9% shorter unemployment duration than non-married ones (see table C.1). Using the estimated coefficients, I predict the potential unemployment duration for non-unemployed workers.

4.5.2 DI generosity

The relative generosity of the DI program is measured by a ratio of DI benefits to potential wages, known as the replacement rate of DI benefits. When measuring the replacement rate of DI benefits using micro public surveys, the main challenge is how to define potential wages for non-employed workers and potential DI benefits for the non-beneficiaries. In this chapter, I adhere to the following steps: (*i*) I run a probit model on the probability of being a full-time and full-year[3] (FTFY) worker; (*ii*) using the estimated coefficients of the probit model, I define the inverse Mill's ratio; (*iii*) I estimate an empirical wage model in the subsample of FTFY workers, incorporating the inverse Mill's ratio, removing a self-selection bias (Heckman, 1979); (*iv*) using the empirical wage model I predict potential wages for non-FTFY workers; (*v*) I calculate the potential DI benefits for the non-beneficiaries using the SSA's progressive formula; (*vi*) the replacement rate of DI benefits is defined by the ratio of DI benefits to wages.

The probit model is specified as follows:

$$\Pr(E_{FTFY} = 1|X) = \Phi(X'\gamma), \tag{4.3}$$

[3]Following Autor et al. (2008), full-time and full-year workers are those who usually worked 35-plus hours per week and worked forty-plus weeks in the previous year.

where E_{FTFY} is a dummy for FTFY employed workers, Φ is the standard normal CDF, and X represents the covariates, including age, age squared, years of schooling, marital status, SRHS, and year and state effects.

The empirical wage model with the inverse Mill's ratio is as follows:

$$\log(w_{i,s,t}) = A(a_{i,s,t}) + \beta s_{i,s,t} + \theta m_{i,s,t} + \hat{\lambda}^{E}_{i,s,t} + \alpha_s + \alpha_t + \varepsilon_{i,s,t}, \tag{4.4}$$

where $\log(w_{i,s,t})$ is the logarithm of the annual wage of FTFY worker i in state s in year t, $A(a_{i,s,t})$ is a quartic polynomial of the person's yearly age, $s_{i,s,t}$ is the person's years of schooling, $m_{i,s,t}$ is a dummy for married persons, $\hat{\lambda}^{E}_{i,s,t}$ is the inverse Mill's ration, and the terms α_s and α_t, respectively, represent state and year effects.

The estimation results show that the annual wage positively depends on years of schooling and marital status. Specifically, a one-year increase in years of schooling would raise the annual wage level by 7.4%, whereas married individuals tend to have an 11.4% higher annual wage than non-married ones (see table C.1). Using these estimated coefficients I predict the potential wages for non-FTFY survey participants.

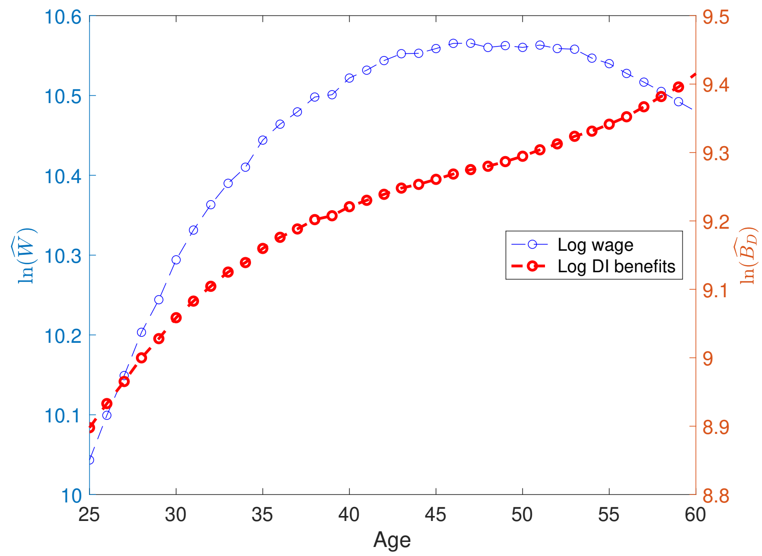
When calculating the amount of DI benefits, SSA uses Average Indexed Monthly Earnings (AIME) and the bend points (see Appendix C.4). In this chapter, I calculate it using the bend points and annual wages due to data limitations. Therefore, the potential DI benefits for the non-beneficiaries are calculated as follows:

$$\begin{cases} 0.9 \times w, & \text{if } w \in [0, b_1] \\ 0.9 \times b_1 + 0.32 \times (w - b_1), & \text{if } w \in (b_1, b_2] \\ 0.9 \times b_1 + 0.32 \times (b_2 - b_1) + 0.15 \times (w - b_2), & \text{if } w > b_2 \end{cases}, \tag{4.5}$$

where w is the observed or potential monthly wage, b_1 and b_2 are the monthly bend points. For example, as of 2024, $b_1 = \$996$ and $b_2 = \$6,002$.

Using the actual and potential annual wages and DI benefits, figure 4.3 presents their dynamics over the lifecycle. The DI benefits consistently increase with age, while the annual wage increases until the age of 48 and then decreases. These lifecycle patterns show that the replacement rate of DI benefits tends to be higher for older working-age persons who account for a significant fraction of DI beneficiaries.

Figure 4.3: Logarithms of annual wage and DI benefits over the lifecycle



Notes: This figure is based on the CPS-ASEC of 2001-2021. $ln(\hat{W})$ and $ln(\hat{B}_D)$, respectively, represent the annual wage and DI benefits.

Moreover, I compare the distributions of the replacement rate of DI benefits among the beneficiaries and the non-beneficiaries (see figure C.1). Specifically, the average replacement rate of DI benefits is 0.465 among the beneficiaries, 9.8% higher than the non-beneficiaries. These facts suggest that (i) working-age persons with a higher replacement rate of DI benefits are more likely to engage in the DI program than those with a lower replacement rate; (ii) older individuals may tend to engage in the DI program due to a relatively higher replacement rate of DI benefits.

4.5.3 UI generosity

The relative generosity of UI benefits is measured by the proportions of a worker's previous earnings that are replaced by UI benefits when they become unemployed. It can affect individuals' incentives to enroll in the DI program through two channels: (*i*) a higher replacement rate may reduce the likelihood of being a DI beneficiary by providing a stronger safety net during unemployment; (*ii*) a higher replacement rate may make unemployed workers more selective, and eventually increase the likelihood of engaging in the DI program. In this empirical analysis, I use a series of UI state replacement rates reported by the U.S. Department of Labor.

4.5.4 Evidence from the CPS-ASEC

I employ a logistic regression model to explore the effects of these non-health factors on DI participation at the individual level. The logistic regression model is specified as follows:

$$\Pr(D=1|Z) = \Lambda\left(\beta_0 + \beta_1 \log(\widehat{RDI}) + \beta_2 \log(\widehat{UD}) + \beta_3 \log(RUI_s)\right), \tag{4.6}$$

where D is the dummy for DI beneficiaries, and Z denotes the covariates, including the log replacement rate of DI benefits ($\log(\widehat{RDI})$), the log unemployment duration ($\log(\widehat{UD})$), and the log state replacement rate of UI benefits ($\log(RUI_s)$).

Table 4.2 presents a correlation matrix of dependent and independent variables. Specifically, the likelihood of being the beneficiary increases with the replacement rates of DI and UI benefits and unemployment duration. The replacement rate of DI benefits is found to be higher for individuals with longer unemployment duration and for those living in states with higher UI replacement rates. Interestingly, unemployment duration decreases with the state replacement rate of UI benefits.

Table 4.3 contains the estimated coefficients of the logistic regression model. The first column presents the marginal effects of non-health factors on the likelihood of being a DI beneficiary for the overall sample. Notably, a 1% increase in the replacement rate of DI benefits increases the probability by 0.096 percentage points, while a 1% increase in unemployment duration results in an increase of 0.025 percentage points. Additionally, a 1%

Table 4.2: Correlation matrix

	D	$\log(\widehat{RDI})$	$\log(\widehat{UD})$	$\log(RUI_s)$
D	1.0000			
$\log(\widehat{RDI})$	0.0965***	1.0000		
$\log(\widehat{UD})$	0.0502***	0.0965***	1.0000	
$\log(RUI_s)$	0.0065***	0.0277***	-0.0108***	1.0000

Notes: This table is based on the CPS-ASEC of 2001-2021. The correlation coefficients are statistically significant at 1% (***), 5% (**), and 10% (*), respectively.

increase in the state replacement rate of UI benefits raises the probability by 0.007 percentage points. These findings show that (*i*) the non-health factors positively affect the probability of engaging in DI benefits at the individual level; (*ii*) the most influential non-health factor is the replacement rate of DI benefits, followed by unemployment duration and the state replacement rate of UI benefits.

4.5.5 Heterogeneity

This subsection examines the effects of non-health factors on DI participation in four demographic subgroups: less educated, more educated, young (25-42), and old (43-60).

4.5.5.1 Less and more educated workers

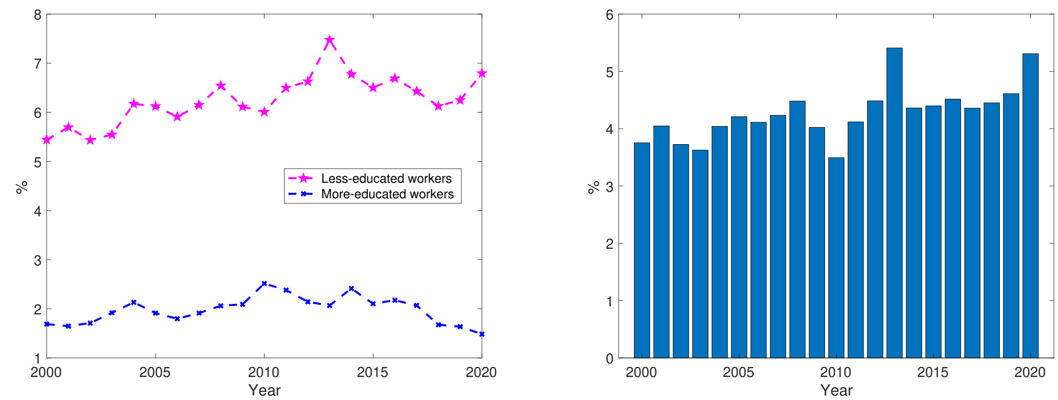
Less educated workers have less than or equal to 12 years of schooling, while more educated workers have greater than or equal to 13 years of schooling. Panel (a) of figure 4.4 compares DI participation rates in less educated and more educated subgroups, while panel (b) shows their differences. These figures display that the less educated have higher DI participation than their more educated counterparts, and their differences tend to increase further.

To gain deeper insights into this discrepancy, I rerun the logistic regression model in each subgroup. The estimated marginal effects for the subsamples of less educated and more

Figure 4.4: DI participation rate and differences, by education level

(a) DI participation rate

(b) difference



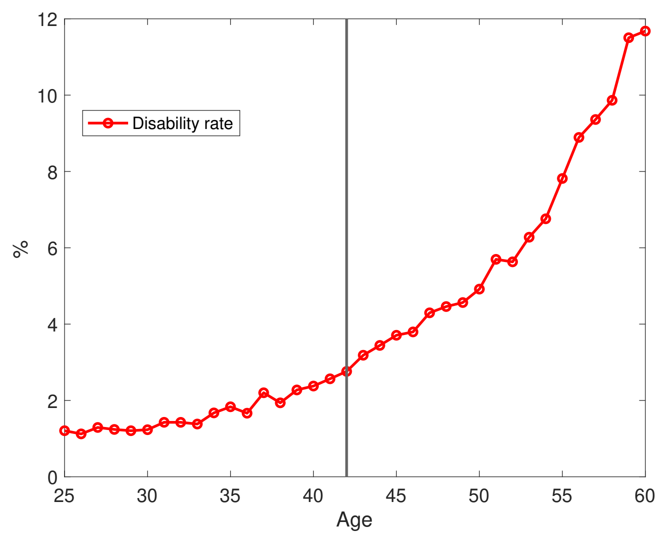
Notes: These figures are based on the CPS-ASEC of 2001-2021.

educated workers are in the second and third columns of table 4.3, respectively. For example, a 1% increase in the replacement rate of DI benefits raises DI participation for less educated workers by 0.111 percentage points and for more educated workers by 0.054 percentage points. Also, a 1% increase in unemployment duration results in increases of 0.027 and 0.018 percentage points in DI participation for less and more educated workers, respectively. Interestingly, the state replacement rate of UI benefits affects positively the probability of being a beneficiary for less educated workers, but negatively for more educated workers. These findings show that (*i*) the non-health factors significantly affect DI participation at the individual level regardless of their education level; (*ii*) less educated workers are more responsive to the non-health factors than their more educated counterparts; (*iii*) a higher state replacement rate of UI benefits discourages more educated workers from engaging in the DI program.

4.5.5.2 The young and the old

Figure 4.5 presents the DI participation rate over the lifecycle. Specifically, it is less than 2% for individuals aged 25-35 but higher than 8% for those aged 55-60. This fact suggests that the DI program is less important for younger (25-42) workers but more important for older (43-60) workers. To gain deeper insights, I rerun the logistic regression model in each subsample.

Figure 4.5: DI participation rate, by age



Notes: This figure is based on the CPS-ASEC of 2001-2021.

The estimated marginal effects for younger and older subsamples are in the fourth and fifth columns of table 4.3, respectively. For example, a 1% increase in the replacement rate of DI benefits, respectively, results in increases of 0.051 and 0.177 percentage points in DI participation for younger and older workers. Also, a 1% increase in unemployment duration corresponds to a 0.007 percentage point increase in the probability for younger workers and a 0.024 percentage point increase for older workers. The impact of the state replacement rate of UI benefits on DI participation is positive, but negligible for both subsamples. These findings show that (i) the non-health factors positively affect DI participation at the individual level regardless of their age groups; (ii) older workers are over three times more responsive to the replacement rate of DI benefits and unemployment duration than their younger counterparts.

Table 4.3: Logit marginal effects on DI participation, by demographic subgroup

	overall	heterogeneity			
		less educated	more educated	younger (25-42)	older (43-60)
$\log(\widehat{RDI})$	0.0962***	0.111***	0.0539***	0.0509***	0.177***
	(3.06e-05)	(7.97e-05)	(3.05e-05)	(3.13e-05)	(5.33e-05)
$\log(\widehat{UD})$	0.0248***	0.0274***	0.0181***	0.00729***	0.0236***
	(1.96e-05)	(3.50e-05)	(2.08e-05)	(1.83e-05)	(3.74e-05)
$\log(RUI_s)$	0.00659***	0.0171***	-0.00102***	0.00657***	0.00422***
	(4.10e-05)	(7.88e-05)	(4.08e-05)	(3.96e-05)	(7.33e-05)
constant	0.0586***	0.0826***	0.0216***	0.0459***	0.153***
	(7.04e-05)	(0.000136)	(7.24e-05)	(6.68e-05)	(0.000133)
Number of observations	650,506	277,148	373,358	348,215	302,291

Notes: This table is based on the CPS-ASEC of 2001-2021. The standard errors are in parentheses. The main sample consists of white and male working-age persons aged 25-60, who are not retired, armed force members, self-employed, and unpaid workers. I examine how those estimated coefficients respond to alternative specifications of the empirical model. Specifically, I consider three specifications of the logistic regression model: (1) the original model presented in this table; (2) the restricted model without the log state replacement rate of UI benefits (see table C.2); and (3) the original model with demographic characteristics (see table C.3). Regardless of the alternative specifications of the logistic regression model, the estimated coefficients are comparable with each other. These findings show that the model specification is robust.

4.6 Numerical experiments

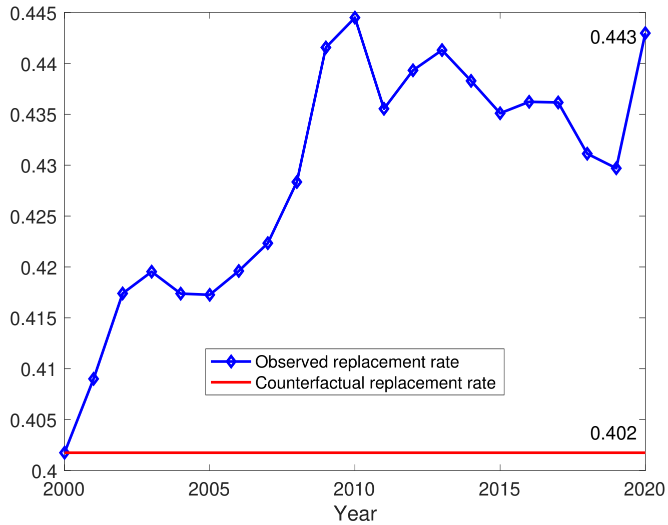
In the previous section, the logistic regression results showed that the non-health factors positively affect the probability of being a DI beneficiary at the individual level. Given the estimated coefficients, the most influential non-health factor is the replacement rate of DI benefits, followed by unemployment duration. Inspired by these empirical findings, I conduct two counterfactual experiments focused on the following questions: (*i*) What might the labor force participation rate be had there not been an increase in the replacement rate of DI benefits? (*ii*) How did the Great Recession of 2007-2009 contribute to the number of DI beneficiaries? The first experiment is related to the replacement rate of DI benefits, whereas the second is associated with unemployment duration.

4.6.1 DI generosity

The average wage has been consistently increasing in the U.S. for the past three decades, while it has stagnated for those with lower wages. This wage stagnation and SSA's progressive formula have been making DI benefits more generous for those workers. Driven by this empirical fact, I calculate the average replacement rate of DI benefits among DI beneficiaries for 2000-2020 using the CPS-ASEC (see figure 4.6). According to my calculation, the average replacement rate of DI benefits was 40.2% in 2000, whereas it reached 44.3% in 2020, increased by 10.2%.

In the former section, the logistic regression model found that a 1% increase in the replacement rate of DI benefits corresponds to an increase of 0.096 percentage points in the probability of being a DI beneficiary at the individual level for the overall sample. Using this empirical finding a 10.2% lower replacement rate would decrease the DI participation rate from 5.29% to 4.09% by 0.98 percentage points. As a result, the number of DI beneficiaries would have been 19.3% fewer (around 1.6 million working-age persons), and the number of unemployed individuals would have increased by up to 12.1% compared to what we had in

Figure 4.6: Average replacement rate of DI benefits, 2000-2020



Notes: This figure is based on the CPS-ASEC of 2001-2021.

2020.

4.6.2 Great recession

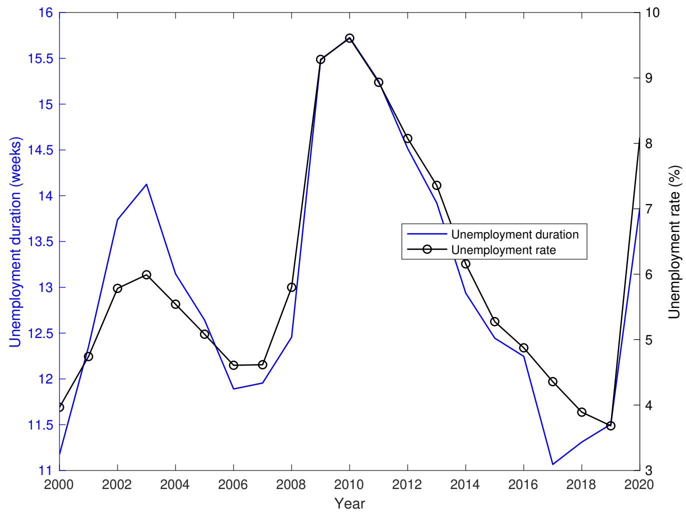
During the Great Recession of 2007–2009, the unemployment rate more than doubled.[4] Figure 4.7 compares the unemployment rate and the average number of unemployed weeks for 2000-2020.[5] The recent considerable jumps in both occurred during the Great Recession. Specifically, they started increasing in 2008, then reached their peak in 2010, and then remained relatively high until 2012. These comparable fluctuations show that unemployment duration can serve as a reliable indicator, capturing economic and labor market conditions both at the aggregate level, similar to the unemployment rate, and at the individual level. Based on those dynamics, I choose the period of 2008-2012 as the recession period.

Figure 4.8 displays the annual growth rates in unemployment duration and the number

[4] The unemployment rate increased by 5.3 percentage points since November 2007, peaking at 10.0% in October 2009, when more than 15 million people were unemployed.

[5] I calculate the average number of unemployed weeks using the CPS-ASEC, while the seasonally adjusted unemployment rate is reported by the U.S. Bureau of Labor Statistics. It is noteworthy to mention that these measures have remained comparable throughout the sample period.

Figure 4.7: Unemployment duration (weeks) and unemployment rate, by year



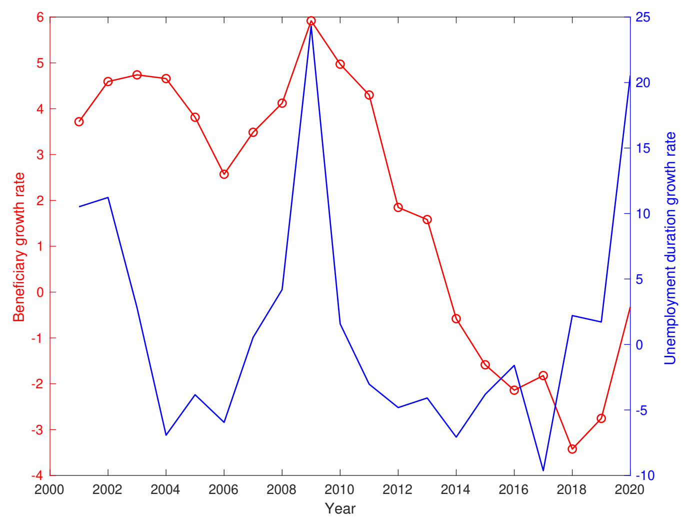
Notes: This figure is based on the overall unemployment duration defined in the subsection of *Labor market conditions* and the seasonally adjusted unemployment rate reported by the U.S. Bureau of Labor Statistics.

of DI beneficiaries. Surprisingly, their annual growth rates exhibit similar fluctuations to each other: individuals are more likely to engage in the DI program when the unemployment duration is longer, and vice versa.

The average number of unemployed weeks is 12.91 for the non-recession period, whereas it is 15.24 for the recession period, longer by 15.3%. According to the logistic regression model, a 1% increase in unemployment duration results in an increase of 0.025 percentage points in the probability of being a DI beneficiary for the overall sample. If the average number of unemployed weeks had been 12.91 for the recession period, then the average beneficiary rate would be lower at 4.91% (7.57 million) instead of 5.29% (8.16 million). These calculations show that the Great Recession induced around 600,000 working-age persons to engage in DI benefits for the period of 2008-2012.

Additionally, for the subsamples of less educated and more educated workers, a 1% decrease in unemployment duration leads to decreases of 0.0274 and 0.0181 percentage points in the probability of being a DI beneficiary, respectively. If unemployment duration had been

Figure 4.8: Annual growth rates in DI beneficiaries and unemployment duration



Notes: This figure is based on the overall unemployment duration defined in the subsection of *Labor market conditions* and the number of DI beneficiaries reported by SSA.

the same for those working-age persons regardless of their education levels, less educated workers would account for 60.2% (around 361,000); more educated workers, 39.8% (around 239,000) of the total recession-induced beneficiaries.

However, as found in the CPS-ASEC, unemployment duration is longer for less educated workers compared to more educated ones. Specifically, for less educated workers, the average number of unemployed weeks is 15.84 and 13.06 for the periods of recession and non-recession, respectively. For more educated workers, it is 14.79 weeks for the recession period, whereas it is 12.81 weeks for the non-recession period. Therefore, the Great Recession, respectively, increased the average number of unemployed weeks for the subsamples of less educated and more educated workers by 17.6% and 13.4%. Using these findings the less educated account for 66.5% (around 400,000) of the total recession-induced beneficiaries. The less educated were two times more responsive to the Great Recession of 2007-2009 than their more educated counterparts.

4.7 Conclusion

In this chapter, I examined the effects of three popular non-health factors, including the replacement rates of DI and UI benefits and unemployment duration, on DI participation at the individual level using the CPS-ASEC. The estimation results show that the non-health factors significantly affect the probability of being a DI beneficiary. These findings offer the first microdata-based support for the view of Autor and Duggan (2006) that workers misuse the DI program as a form of financial option.

According to the estimation results, the replacement rate of DI benefits is the most influential non-health factor, followed by unemployment duration and the state replacement rate of UI benefits. For example, for the overall sample, a 1% increase in the replacement rate of DI benefits raises the likelihood of engaging in DI benefits by 0.096 percentage points, whereas a 1% increase in unemployment duration increases the probability by 0.025 percentage points. Compared to the overall sample, their impacts are stronger in the subsamples of less educated and older workers. More specifically, a 1% increase in the replacement rate of DI benefits increases the likelihood by 0.111 and 0.177 percentage points for the less educated and older subsamples, respectively. A 1% increase in unemployment duration increases the probability by 0.028 percentage points for less educated workers and 0.024 percentage points for older workers. Interestingly, the state replacement rate of UI benefits positively affects DI participation, except for the subsample of more educated workers. These estimation results show that

(*i*) the individual's decision to engage in the DI program statistically depends on the non-health factors;

(*ii*) less educated and/or older workers are more responsive to the replacement rate of DI benefits and unemployment duration;

(*iii*) a higher state replacement rate of UI benefits discourages more educated workers from engaging in the DI program.

To gain further insights, I conducted counterfactual experiments related to the replacement rate of DI benefits and the Great Recession of 2007-2009. The first experiment found that if DI benefits had been proportional to wages since 2000, then the number of DI beneficiaries would have been lower by 19.3% (1.6 million), increasing the unemployment rate by up to 12.1% compared to what we had in 2020. The second experiment found that the Great Recession induced around 600,000 working-age persons to engage in the DI program; less educated workers account for 66.5%.

Thesis Conclusion

This thesis deeply explores the complex dynamics surrounding DI participation, utilizing micro-public surveys and employing a combination of empirical and theoretical dynamic models across three chapters.

Chapter 1: This chapter advances our understanding through a two-fold approach. Firstly, leveraging the PSID, I compare current DI beneficiaries with the rest of the labor force in terms of demographic compositions. After controlling for demographic characteristics, individual fixed-effects, and year effects, it is identified that future DI beneficiaries had a 17.2% lower hourly wage than those who would not engage in the DI program in the future when both were employed. Importantly, this wage gap widens for more educated workers, while it narrows for less educated workers.

Secondly, an equilibrium search model is introduced, integrating *heterogenous skills* and *endogenous DI participation* within the standard Diamond-Mortensen-Pissarides framework. This theoretical model reproduces the wage gap between future DI beneficiaries and non-beneficiaries, without explicitly targeting it. Additionally, the model predicts that individuals with relatively higher skill levels tend to opt for disability benefits during economic downturns, resulting in a countercyclical pattern in DI participation and the average skill level of DI beneficiaries. In terms of the policy experiments, relatively less skilled workers tend to participate in the DI program when faced with more relaxed health-related eligibility criteria. The average success rates for DI applications exhibit an increase in DI participation, but their impact on the wage gap between future DI beneficiaries and non-beneficiaries is not as pronounced as the impact of the health-related eligibility criteria.

Chapter 2: In this chapter, I examine how an individual's decision regarding DI participation is associated with health factors, labor market outcomes, and policy instruments. First, using the PSID, I establish key dynamic relationships between health, DI participation, and wages at the individual level. Second, a flexible and dynamic numerical model, built on the standard Diamond-Mortensen-Pissarides framework, is employed to examine the interplay between DI participation and labor market outcomes, incorporating *health-driven stochastic productivity* and *endogenous DI participation*. The model reproduces the empirical findings about the impact of the current health condition on the probability of engaging in the DI program within the next two years and the current hourly wages, without explicitly targeting those moments. It also performs well along the following dimensions not targeted in the calibration process:

(*i*) the relative shares of the DI beneficiaries who became DI participants through their initial determination versus the appeal process;

(*ii*) the probability of initiating the appeal process among the applicants who were not approved for the DI program by the initial determination process;

(*iii*) the age distribution of the health conditions of DI participants.

The collective findings underscore the diverse aspects of DI participation, urging policymakers and scholars to consider the interplay between health and non-health factors in developing effective policies. Moreover, the counterfactual experiments conducted in this chapter yield valuable insights into potential policy reforms, revealing the potential impact on both DI participation and labor market outcomes. For example, a shorter waiting period for the initial determination of the DI application increases the unemployment rate, whereas a shorter waiting period for the appeal process reduces it. Importantly, the model's predictions show that not only the overall health level of the labor force but also the persistence and volatility of the individual-level health conditions are important for understanding the extent of DI participation.

Chapter 3: This chapter conducts a thorough examination of non-health factors, including the replacement rates of DI and UI benefits and unemployment duration, utilizing the CPS-ASEC data. The analysis not only enhances existing literature with individual-level empirical findings but also aligns with Autor and Duggan (2006)'s argument about the potential misuse of the DI program among working-age persons. Notably, individuals with lower education levels or those who are older are more likely to engage in disability benefits due to these non-health factors compared to other demographic subgroups.

Limitations: While the analyses presented here significantly contribute to the ongoing discourse on the DI program, it is important to point out the following two key limitations of the analyses in Chapters 1 and 3. First, in Chapter 1, I assume that there is no discernible relationship between an individual's skill level and health conditions. However, the health economics literature widely recognizes that the two variables are not uncorrelated. Nevertheless, this inconsistency is adequately addressed in Chapter 2. The second main limitation is that the empirical analysis in Chapter 3 omits individuals' health conditions. This is inherently due to the data limitation: in the CPS-ASEC, there is no objective and reliable measure of the respondents' health conditions. This omission may lead to overestimated effects of non-health factors on DI participation, which should be taken into account when interpreting certain estimation results in Chapter 3.

Implications for future research: Future research could explore various areas, expanding our understanding of DI participation. It might be of interest to investigate the impact of demographic trends, geographic variations, or evolving workplace dynamics on DI participation. Additionally, possible theoretical research avenues include considering aggregate fluctuations in the model and using the extended version to examine the impact of unemployment benefits on DI participation.

In essence, this thesis establishes a robust foundation for future quantitative and policy analyses of the DI program. By exploring the intersection of health and non-health factors using empirical evidence and theoretical dynamic models, it offers a compelling framework to address current challenges and guide the future trajectory of disability insurance research and policy.

Chapter 5

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Appendix A

Appendix for Chapter 1

A.1 Liberalization of the DI program

This appendix describes the main policy shifts concerning the DI program.

1. According to the 1984 liberalization, SSA was required to

   (a) relax its strict screening of mental illness by placing less weight on diagnostic and medical factors and relatively more on functional factors, such as ability to function in a work or worklike setting;

   (b) consider source evidence provided by the applicant's own health care provider prior to the results of SSA consultative examination;

   (c) give additional weight to pain and related factors;

   (d) consider multiple nonsevere impairments as constituting a disability during the initial determination (whereas prior to 1984, applicants were automatically denied awards during the initial determination if all impairments were judged to be nonsevere);

   (e) desist from terminating benefits for any individual for whom SSA could not demonstrate substantial evidence of medical improvement;

   (f) provide benefits for those former recipients whose terminations were under appeal;

(g) suspend Continuing Disability Reviews (CDRs) for mental impairments and pain until appropriate guidelines could be developed. In the post-1984 period, two additional administrative factors affected applications and terminations.

2. In 1991, due to successful court challenges to SSA's treatment of source evidence, regulations were adopted placing further weight on the information provided by an SSI or DI applicant's medical provider.

3. Finally, agency downsizing during the 1980s and increased claims workload in the 1990s resulted in a substantial decrease in the frequency of CDRs during 1989 – 1993 (Stapleton et al., 1998).

A.2 Overview of the PSID

The Panel Study of Income Dynamics (PSID) is a seminal longitudinal survey in the field of social science research, notably within economics and sociology. Initiated in 1968 by the University of Michigan, the PSID serves as a pivotal instrument for comprehending the economic and social trajectories of U.S. families over an extended timeframe. This appendix provides an in-depth overview of the key features, significance, and contributions of the PSID to research:

- *Longitudinal design:* The PSID adopts a longitudinal approach, tracking the same families and individuals over an extended period. This design facilitates the observation of changes in economic status, employment patterns, and family structures.
- *Representative sample:* The study commenced with a nationally representative sample of U.S. households in 1968. The PSID maintains its commitment to representativeness, ensuring a diverse cross-section of the population.
- *Generational perspective:* An exceptional feature of the PSID is its inclusion of information on multiple generations within the same families, enabling exploration of intergenerational mobility and socio-economic factors.
- *Comprehensive data:* The PSID gathers a wealth data encompassing income, employment, education, health, and other demographic and economic variables, making it an invaluable resource for researchers.
- *Dynamic panel structure:* The PSID's dynamic panel structure captures the evolving life course of individuals and families, providing insights into the lasting impacts of events and decisions.
- *Public accessibility:* The PSID data is publicly accessible, fostering a collaborative research environment and enabling scholars from diverse disciplines to utilize the dataset

for various studies and analyses.

Additionally, over the decades, the PSID has significantly contributed to advancing our understanding of economic and social dynamics in the U.S. Many researchers have utilized the data from PSID to explore critical topics such as income inequality, intergenerational mobility, labor market dynamics, health disparities, and the impact of social policies such as Social Security Disability Insurance.

A.3 Alternative specification for wage gaps

Following the labor economics literature, I run the following fixed-effects model:

$$w_{i,t} = A(a_i) + s_{i,t} + \alpha_i + \alpha_t + \varepsilon_{i,t}, \tag{A.1}$$

where $w_{i,t}$ is the logarithm of the hourly wage of person i in year t, $A(a_i)$ is a quartic polynomial of the person's yearly age, $s_{i,t}$ is the person's schooling, α_i and α_t denote, respectively, the individual fixed-effects and year effects.

Table A.1: Estimation results with the individual fixed-effects, by education level

	(1) both	(2) less educated	(3) more educated
age	0.338***	0.0102	0.635***
	(0.127)	(0.151)	(0.218)
$\text{age}^2/100$	-1.041**	0.0437	-2.006**
	(0.470)	(0.556)	(0.809)
$\text{age}^3/1{,}000$	0.142*	-0.0209	0.283**
	(0.0759)	(0.0893)	(0.131)
$\text{age}^4/10{,}000$	-0.00731	0.00166	-0.0150*
	(0.00448)	(0.00526)	(0.00780)
years of schooling	0.0252***	0.0314***	0.0136
	(0.00456)	(0.00590)	(0.0128)
individual fixed-effects	✓	✓	✓
year effects	✓	✓	✓
number of observations	8,700	4,715	3,985
R^2	0.2163	0.2219	0.2287

Notes: This table is based on white males in the 2005-2019 PSID. The standard errors are clustered at the individual level. The label *both* represents the full sample. The labels *less educated* and *more educated* denote, respectively, less than or equal to 12 years of schooling and greater than or equal to 13 years of schooling.

Using those estimated coefficients, I predict the error terms, removing the effects of demographic factors, individual fixed-effects, and year effects from the logarithm of hourly wages. Next, the FP-NFP wage gap between the future DI beneficiaries and non-beneficiaries is defined by the following formula:

$$FP - NFP\, wage\, gap = E[\hat{\varepsilon}_{i,t}|b_i^f = 0] - E[\hat{\varepsilon}_{i,t}|b_i^f = 1], \tag{A.2}$$

where b_i^f is the dummy for the future beneficiaries and time-invariant.

Table A.2: Predicted error terms ($\hat{\varepsilon}_{i,t}$), by education level

	(1) both	(2) less educated	(3) more educated
$E[\hat{\varepsilon}_{i,t}\|b^f = 0]$	-0.1703	-0.1577	-0.2446
$E[\hat{\varepsilon}_{i,t}\|b^f = 1]$	-0.3425	-0.2769	-0.4663
FP-NFP wage gap	0.1722	0.1192	0.2217

Notes: This table is based on the PSID of 2005-2019. $\hat{\varepsilon}$ is the predicted error terms in equation (A.1), while b^f is the dummy for the future beneficiaries. "FP" refers to future DI beneficiaries, while "NFP" denotes future non-participants. The label *both* represents the full sample. The labels *less educated* and *more educated* denote, respectively, less than or equal to 12 years of schooling and greater than or equal to 13 years of schooling.

The following table separately presents the wage gaps between future DI beneficiaries and non-beneficiaries for the overall sample and the subsamples of less educated and more educated workers (see table A.3. For example, the future beneficiaries had a 17.2% lower hourly wage than their corresponding non-beneficiaries when both were employed. Compared to the overall sample, this gap narrows for the less educated subsample (11.9%), while it widens for the more educated subsample (22.6%).

Table A.3: Wage gaps with the individual fixed-effects

	(1) both	(2) less educated	(3) more educated
FP-NFP wage gap	0.172	0.119	0.226
demographic effects	✓	✓	✓
individual fixed-effects	✓	✓	✓
year effects	✓	✓	✓
observations	8,700	4,715	3,985

Notes: This table is based on the PSID of 2005-2019. The standard errors are clustered at the individual level. After running the individual fixed-effcts model, I predict the error terms by removing the effects of demographic factors, individual fixed-effects, and year effects. Next, I measure the FP-NFP wage gap by a difference in the average error terms between the future beneficiaries and non-beneficiaries. The label *both* represents the full sample. The labels *less educated* and *more educated* denote, respectively, less than or equal to 12 years of schooling and greater than or equal to 13 years of schooling.

A.4 Skill accumulation and deterioration processes

The skill evolution processes in the model in Section 2.4 are adopted from Ljungqvist and Sargent (1998, 2008), and summarized as follows:

$$\Gamma^{(\mathrm{E})}(p' \mid p) = \begin{bmatrix} 1-\phi^{(\mathrm{E})} & \phi^{(\mathrm{E})} & 0.0 & \dots & 0.0 \\ 0.0 & 1-\phi^{(\mathrm{E})} & \phi^{(\mathrm{E})} & \dots & 0.0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0.0 & 0.0 & 0.0 & 1-\phi^{(\mathrm{E})} & \phi^{(\mathrm{E})} \\ 0.0 & 0.0 & 0.0 & 0.0 & 1.0 \end{bmatrix}, \tag{A.3}$$

$$\Gamma^{(\mathrm{N})}(p' \mid p) = \begin{bmatrix} 1.0 & 0.0 & 0.0 & \dots & 0.0 \\ \phi^{(\mathrm{N})} & 1-\phi^{(\mathrm{N})} & 0.0 & \dots & 0.0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0.0 & 0.0 & \phi^{(\mathrm{N})} & 1-\phi^{(\mathrm{N})} & 0.0 \\ 0.0 & 0.0 & 0.0 & \phi^{(\mathrm{N})} & 1-\phi^{(\mathrm{N})} \end{bmatrix}, \tag{A.4}$$

where $\phi^{(\mathrm{E})} = 0.1$ and $\phi^{(\mathrm{N})} = 0.2$, i.e., $\phi^{(\mathrm{N})} > \phi^{(\mathrm{E})}$.

Appendix B

Appendix for Chapter 2

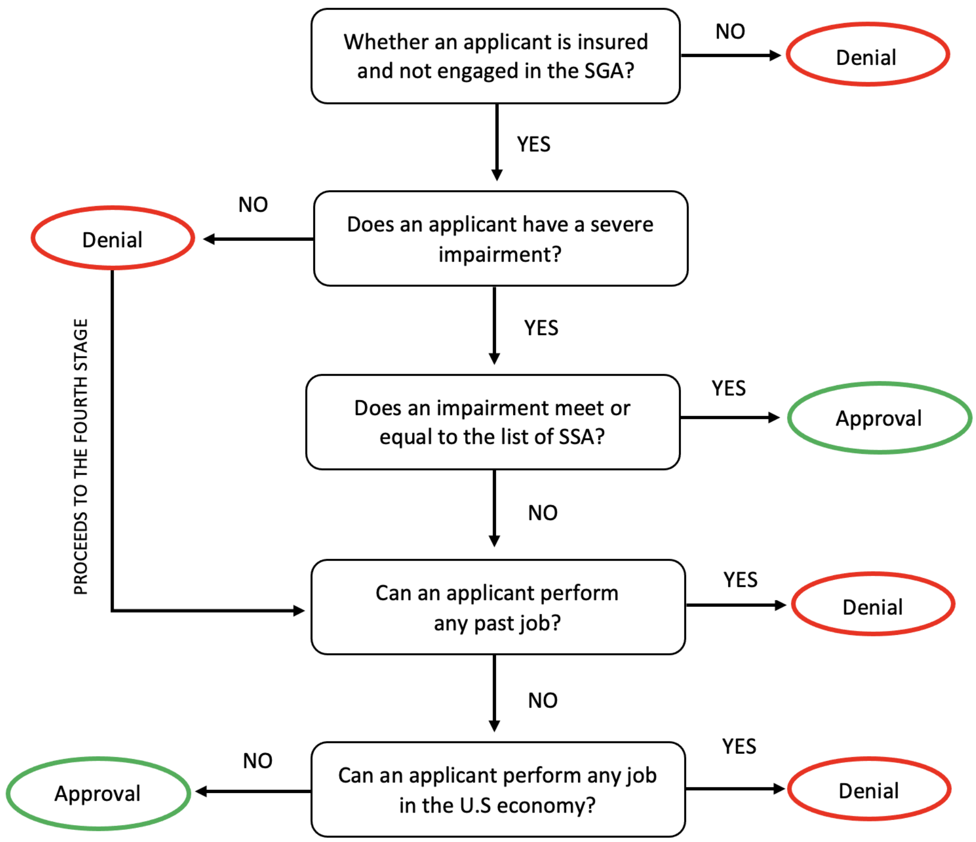
B.1 DI application procedure

The DI program provides financial and in-kind support to working-age persons who are unable to engage in an SGA for the next 12 months or longer due to their physical and/or mental impairment.

The initial determination process involves several stages, as depicted in figure B.1. It begins at local SSA field offices, where disability applications are received and eligibility criteria are verified. If an applicant does not meet the eligibility requirements, the process is stopped through *technical denials*. If the applicant satisfies the eligibility requirements, the application is forwarded to *State-run Disability Determination Service* (DDS) offices for further review.

The DDS offices handle the second through fifth stages of the initial determination process. In the second stage, a disability examiner evaluates whether the applicant has severe and permanent impairments expected to continue for 12 months or longer (or to result in death). If the impairments are non-severe or temporary, the application is denied but proceeds to the fourth stage. Otherwise, it proceeds to the third stage, where the examiner assesses whether the applicant has a medical impairment listed by the SSA. If the impair-

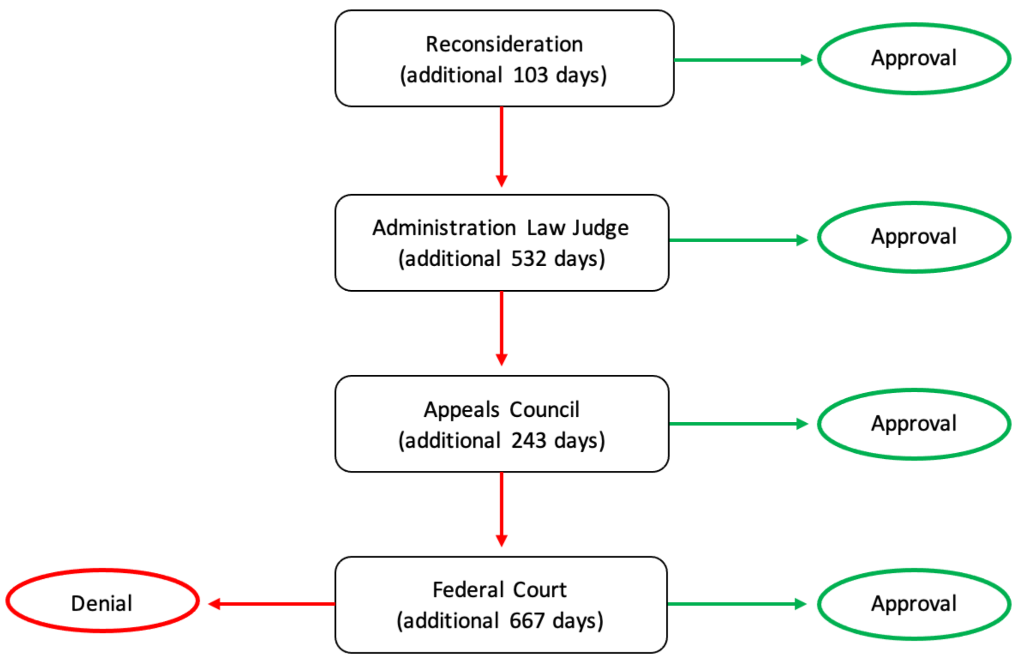
Figure B.1: DI determination procedure



Notes: This flowchart summarizes the key stages involved in determining whether a DI claimant is disabled. For further details of the determination procedure, see SSA (2023).

ment matches a listed impairment or is equivalent in severity, the application is approved based on *medical criteria* alone. Otherwise, the application proceeds to the fourth stage. In this stage, the examiner examines the applicant's ability to perform past jobs. If the applicant is found capable, the application is denied. Otherwise, it proceeds to the fifth stage, where the examiner examines the applicant's ability to perform any job in the U.S. economy. If the applicant is found capable, the application is denied; otherwise, disability benefits are awarded based on a combination of *medical* and *vocational criteria*.

Figure B.2: DI appeal process



Notes: This flowchart shows four main steps involved in the appeal process. Here, green arrows represent the favorable decision, while red arrows denote the unfavorable decision. For further details of the determination procedure, see O'Carroll (2008).

During the initial determination process, the applicant waits for five months to receive the decision. If the decision is unfavorable, the applicant can initiate the appeal process within 60 days. The appeal process varies between non-prototype and prototype states.[1]

[1]The 10 prototype states are: Alabama, Alaska, California (only Los Angeles North and Los Angeles West Branches), Colorado, Louisiana, Michigan, Missouri, New Hampshire, New York, and Pennsylvania.

In non-prototype states, the first stage of the appeal process is *reconsideration*, where the application is reviewed by another DDS examiner without the submission of additional evidence. In prototype states, the appeal process begins directly with a hearing conducted by an *Administrative Law Judge* (ALJ).

Figure B.2 presents the sequential flow of the appeal process. In the ALJ stage, a judge reviews the application following the five stages outlined in figure B.1. The applicant can present additional evidence at this stage. If the ALJ's decision is still unfavorable, the applicant can further appeal to the Appeal Council (AC) and, if necessary, to a Federal court. The progression to the AC and Federal court stages, however, is relatively rare.

Importantly, the waiting period is extended depending on which stage of the appeal process the claim reaches. According to O'Carroll (2008), it is an additional 103 days (over three months) and an additional 532 days (over one year) for reconsideration and ALJ, respectively. If the appeal process reaches the AC or Federal court, the waiting period is extended by an additional 243 days and an additional 667 days, respectively. When waiting for their decisions on the initial determination and appeal processes, the applicants are more likely to be out of the labor force due to the SGA requirements.

B.2 Alternative wage specification with random-effects

In this subsection, I estimate the following random-effects wage empirical model:

$$w_{i,t} = A(a_i) + \beta s_{i,t} + \varphi FP_i + \alpha_s + \alpha_t + \varepsilon_{i,t}, \tag{B.1}$$

where $w_{i,t}$ is the logarithm of the hourly wage of person i in year t, $A(a_i)$ is a quartic polynomial of the person's yearly age, $s_{i,t}$ is the person's schooling, FP_i is the dummy for future DI beneficiaries, α_s and α_t denote, respectively, the state and year effects.

Table B.1: FP - NFP wage gaps without controlling for self-selection

	(1) both	(2) less educated	(3) more educated
FP - NFP wage gap	-0.208*** (0.0494)	-0.137*** (0.0487)	-0.319*** (0.0979)
demographic characteristics	✓	✓	✓
health index	✓	✓	✓
state and year effects	✓	✓	✓
number of observations	8,700	4,715	3,985

Notes: This table is based on the PSID of 2005-2019. The label *both* represents the full sample. The labels *less educated* and *more educated* denote, respectively, less than or equal to 12 years of schooling and greater than or equal to 13 years of schooling.

The main reason for estimating this model using the random-effects method is that the main independent variable FP_i is time-invariant. The table presents the estimation results. For example, for the overall sample, the FP - NFP wage gap is -0.21, implying that future DI beneficiaries have a 20.8% lower hourly wage than future non-DI beneficiaries. This gap narrows to 13.7% for the less educated and widens to 31.9% for the more educated. These estimated coefficients are comparable to those estimated from the Heckman selection model and those estimated from the fixed-effects panel analysis.

B.3 Tables

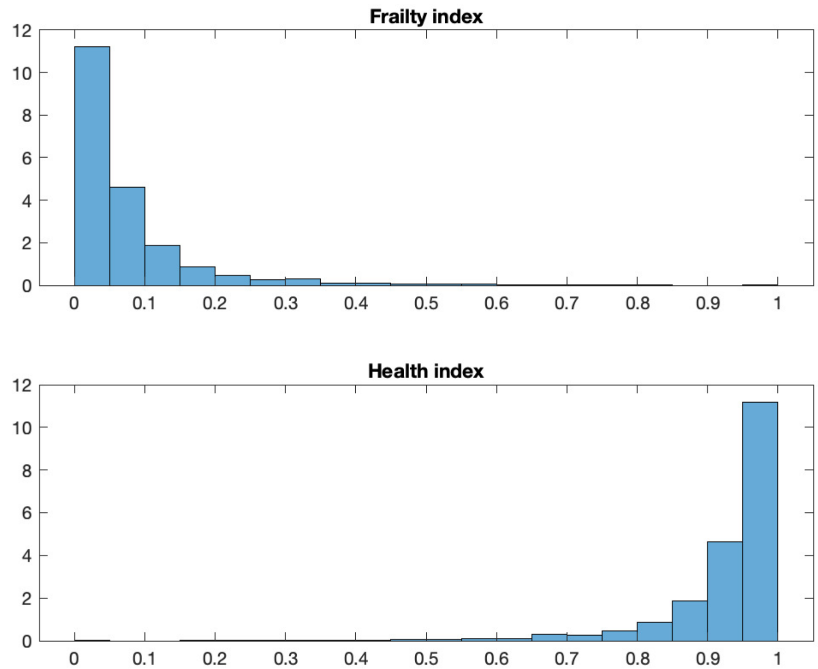
Table B.2: List of health deficits recorded in the PSID

Difficulty with performing each of the following activities of daily living (ADL):		
• Bathing	• In/out of bed/chair	• Getting outside
• Eating	• Walking	• Using toilet
Difficulty with performing each of the following instrumental activities of daily living:		
• Preparing meals	• Managing money	• Light housework
• Shopping	• Heavy housework	
Past experience of the following diseases:		
• Stroke	• Asthma	• Memory loss
• Heart attack	• Lung disease	• Cancer
• Heart disease	• Diabetes	• Chronical conditions
• Hypertension	• Arthritis	• BMI ≥ 30

Notes: The responses to these questions are dichotomous (*i.e.*, "Yes/No").

B.4 Figures

Figure B.3: Distributions of the frailty and health indices



Notes: These figures are based on frailty and health indices constructed from the data of PSID of 2005-2019. A higher value implies worse health for the frailty index, but better health for the health index.

Appendix C

Appendix for Chapter 3

C.1 Overview of the CPS

The Current Population Survey (CPS) is the source of the official Government statistics on employment and unemployment, which has been conducted monthly for over 60 years. Currently, it interviews about 54,000 households monthly, statistically selected based on the area of residence to represent the nation as a whole, individual states, and other specified areas. Each household is interviewed once a month for four consecutive months one year, and again for the corresponding period a year later. This technique enables one to obtain month-to-month and year-to-year comparisons at a reasonable cost while minimizing the inconvenience to any household. The CPS is the only source of monthly estimates of (1) total employment (both farm and non-farm); (2) non-farm self-employed persons, domestics, and unpaid workers in non-farm family enterprises; (3) wage and salary employees; (4) total unemployment.

Regarding the sample, the CPS sample is based on the civilian non-institutional population of the U.S. The sample is located in approximately 826 sample areas comprising 1,328 counties and independent cities with coverage in every State and the District of Columbia. In the CPS, some 70,000 housing units or other living quarters are assigned for interview each month; about 50,000 of them containing approximately 100,000 persons 15 years old and over are interviewed.

C.2 Sampling design of the CPS

The CPS utilizes a rotating panel design to collect data on labor force characteristics. Here's an explanation of how the rotation works:

- *Incoming rotation group (Group A):* The cycle begins with an incoming rotation group, which is newly selected for interviews.

- *Interviewed for four consecutive months:* Group A is interviewed in the first four months of the year (January, February, March, April), during which detailed information about labor force characteristics is collected from households in Group A.

- *Outgoing rotation group:* After completing their four months of interviews, Group A becomes the outgoing rotation group. They will not be interviewed for the next eight months (May to December), allowing other rotation groups to be interviewed during this period.

- *Successive rotation groups:* While Group A is in its outgoing phase, the incoming rotation group (Group B) starts its interviews in the next four months (May, June, July, August). This process continues with additional rotation groups (C and D) in subsequent months.

- *Continuous cycle:* The cycle repeats throughout the year. Each month, one-fourth of the sample is in its first month of the interview (incoming rotation group), one-fourth is in its second month, and so on. This ensures a continuous and representative sample for analysis.

The rotation system allows researchers and policymakers to analyze changes in labor force characteristics over time. It provides a more complete and accurate picture of the U.S. labor market by capturing seasonal variations and long-term trends. The rotating panel design also enables the examination of individual and household dynamics.

C.3 Overview of the CPS-ASEC

The CPS is designed to provide a large amount of detailed and supplementary data. For example, the Annual Social and Economic (ASEC) Supplement contains the basic monthly demographic and labor force data described above, plus additional data on work experience, income, non-cash benefits, health insurance coverage, and migration.

Whether living on or off post, male and female members of the armed forces are included in the CPS-ASEC as long as at least one civilian adult lives in the same household. The armed forces members, however, are not asked the monthly labor force questions. In addition, the CPS-ASEC is supplemented with a sample of Hispanic households identified in the previous November. This results in the addition of about 6,000 households (approximately 4,500 interviewed). The inclusion of the additional sample of Hispanic households began in 1976.

In 2002, the CPS-ASEC incorporated a significant sample expansion. The sample was expanded primarily to improve state estimates of children's health insurance coverage. This sample expansion, known as the Child Health Insurance Program (CHIP) sample, has three components: 1) asking the ASEC Supplement questions of one-quarter of the February and April CPS samples, that is, of the households not also included in the March sample; 2) interviewing selected sample households from the preceding August through November CPS sample during the February - April period using the ASEC Supplement; and 3) increasing the monthly CPS sample in states with high sampling errors for uninsured children. This sample increase results in the addition of about 19,000 households to the CPS-ASEC. Adding together the regular sample (70,000), plus the Hispanic sample (6,000), plus the CHIP sample (19,000), it arrives at the total sample size for the CPS-ASEC of about 95,000 households.

C.4 Disability benefits calculation

This appendix outlines the key factors involved in determining the amount of disability benefits for eligible individuals.

Work credits: To qualify for disability benefits, individuals must accumulate a sufficient number of work credits based on their annual income. For example, as of 2024, one work credit is earned for each $1,470 of earnings, up to a maximum of four credits per year. The number of work credits required for DI eligibility depends on an individual's age at the time of disability onset.

Determination process: Eligibility for the DI program is contingent on having a severe impairment that prevents the individual from engaging in an SGA. The SSA assesses the severity and duration of the disability through a detailed evaluation process (see figure B.1 and B.2).

Average Indexed Monthly Earnings (AIME): The SSA calculates the Average Indexed Monthly Earnings (AIME) by using the individual's highest-earning years adjusted by the Consumer Price Index (CPI). Specifically, the SSA considers the 35 years with the highest earnings (or fewer if the person has not worked for 35 years).

Bend points: The SSA uses the following formula with the AIME and 'bend points' to calculate the Primary Insurance Amount (PIA):

$$\begin{cases} 0.9 \times AIME, & \text{if } AIME \in [0, b_1] \\ 0.9 \times b_1 + 0.32 \times (AIME - b_1), & \text{if } AIME \in (b_1, b_2] \\ 0.9 \times b_1 + 0.32 \times (b_2 - b_1) + 0.15 \times (AIME - b_2), & \text{if } AIME > b_2 \end{cases}, \tag{C.1}$$

where b_1 and b_2 are the monthly bend points annually adjusted by the overall wage growth. For example, as of 2024, $b_1 = \$996$ and $b_2 = \$6,002$.

Family benefits: Family members, such as spouses and dependent children, may be eligible for auxiliary benefits based on the disabled individual's work record. Family benefits are typically up to 50% of the disabled individual's PIA, subject to family maximum limits.

Reduction for other income: DI benefits may be reduced if the individual is also receiving other sources of income, such as workers' compensation, public disability benefits, or pensions from work not covered by Social Security. This reduction is known as the Windfall Elimination Provision (WEP) or the Government Pension Offset (GPO).

Additionally, the SSA conducts Continuing Disability Reviews (CDRs) periodically to reassess the medical condition of individuals receiving DI benefits, ensuring ongoing eligibility. Following a CDR, there are several possible outcomes:

- if the SSA determines that the individual's medical condition has not improved, and they continue to meet the disability criteria, disability benefits will typically continue;
- if there is evidence of medical improvement and the individual is no longer considered disabled, disability benefits may be terminated;
- in some cases, the SSA may find that the individual's condition has improved, but they still meet the disability criteria, leading to a continuation of benefits.

Individuals have the right to appeal the outcome of a CDR if their benefits are terminated. The appeal process allows individuals to present additional evidence supporting their continued eligibility for disability benefits.

Note: The information provided here is a general overview.

C.5 Tables

Table C.1: Estimation results of wage and unemployment duration

	$\log(UD)$	$\log(w)$
age	0.0932	0.0154
	(0.144)	(0.0321)
$\text{age}^2/100$	-0.389	0.0759
	(0.538)	(0.119)
$\text{age}^3/1000$	0.0716	-0.0221
	(0.0874)	(0.0192)
$\text{age}^4/10000$	-0.0047	0.0015
	(0.0052)	(0.0011)
years of schooling	-0.00810***	0.0741***
	(0.00139)	(0.000328)
marital status	-0.119***	0.114***
	(0.00826)	(0.00224)
constant	1.687	8.681***
	(1.402)	(0.316)
state and year effects	✓	✓
observations	48,484	288,304
R-squared	0.358	0.026

Notes: This table is based on the CPS-ASEC of 2001-2021. The main sample consists of white and male working-age persons who are not retired, armed force members, self-employed, and unpaid workers. The standard errors of the estimated coefficients are in parentheses.

Table C.2: Logit marginal effects without the state UI replacement rate

	Overall	Heterogeneity			
		Less-educated workers	More-educated workers	Young workers, 25-42	Old workers, 43-60
$\log(\widehat{RDI})$	0.0963***	0.111***	0.0539***	0.0509***	0.177***
	(3.06e-05)	(7.96e-05)	(3.05e-05)	(3.13e-05)	(5.32e-05)
$\log(\widehat{UD})$	0.0248***	0.0274***	0.0182***	0.00728***	0.0236***
	(1.96e-05)	(3.50e-05)	(2.08e-05)	(1.83e-05)	(3.73e-05)
constant	0.0526***	0.0670***	0.0224***	0.0399***	0.149***
	(5.95e-05)	(0.000114)	(6.21e-05)	(5.62e-05)	(0.000115)
state and year effects	✓	✓	✓	✓	✓
observations	650,506	277,148	373,358	348,215	302,291

Notes: This table is based on the CPS-ASEC of 2001-2021. The standard errors of the estimated coefficients are in parentheses.

Table C.3: Logit marginal effects with demographic characteristics

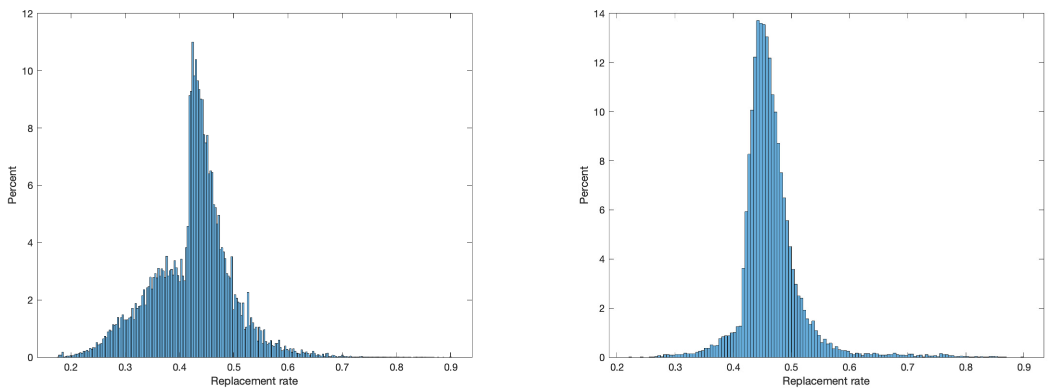
	Overall	Heterogeneity			
		Less-educated workers	More-educated workers	Young workers, 25-42	Old workers, 43-60
$\log(\widehat{RDI})$	0.0689***	0.115***	0.0467***	0.0298***	0.0966***
	(4.20e-05)	(9.32e-05)	(3.88e-05)	(4.24e-05)	(7.28e-05)
$\log(\widehat{UD})$	0.000877***	0.00176***	-3.94e-05	-4.08e-05**	0.00369***
	(2.23e-05)	(3.85e-05)	(2.43e-05)	(2.05e-05)	(4.29e-05)
$\log(RUI_s)$	0.00529***	0.00594***	0.00238***	0.00217***	0.0104***
	(7.38e-05)	(0.000139)	(7.46e-05)	(7.09e-05)	(0.000135)
age	-0.00151***	-0.00389***	-0.000338***	0.00185***	-0.0132***
	(4.94e-06)	(9.37e-06)	(4.98e-06)	(1.48e-05)	(4.26e-05)
$\text{age}^2/100$	0.0049***	0.0091***	0.0024***	-0.00055***	0.0166***
	(5.81e-06)	(1.11e-05)	(5.84e-06)	(2.21e-05)	(4.15e-05)
years of schooling	-0.00297***	-0.00136***	-0.00217***	-0.00163***	-0.00442***
	(2.29e-06)	(5.66e-06)	(2.75e-06)	(2.25e-06)	(4.09e-06)
marital status	-0.0302***	-0.0426***	-0.0182***	-0.0194***	-0.0442***
	(1.22e-05)	(2.26e-05)	(1.27e-05)	(1.17e-05)	(2.27e-05)
constant	0.148***	0.210***	0.0900***	0.0228***	0.506***
	(0.000145)	(0.000274)	(0.000150)	(0.000264)	(0.00110)
state and year effects	✓	✓	✓	✓	✓
observations	650,506	277,148	373,358	348,215	302,291

Notes: This table is based on the CPS-ASEC of 2001-2021. The standard errors of the estimated coefficients are in parentheses.

C.6 Figures

Figure C.1: Distributions of the replacement rate of DI benefits

(a) non-DI beneficiaries **(b)** DI beneficiaries



Notes: These figures are based on the CPS-ASEC of 2001-2021.