

The Disability Option: Labor Market Dynamics with Macroeconomic and Health Risks

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Abstract

In recent decades, Social Security Disability Insurance (SSDI) claims have risen rapidly. We evaluate the importance of changing macroeconomic conditions in shaping this trend. Our quantitative framework considers that economic conditions interact with individuals' health status in their decisions to apply for SSDI. Crucially, these factors are correlated through the nature of work: multiple sectors differentially expose workers to health and economic risks. Decomposing factors driving SSDI growth in a calibrated model, we find the deteriorating economic conditions and concentration of health risks account for about half of the increase in SSDI claims predicted by the model, about a third overall.

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1 Introduction

The number of U.S. Social Security Disability Insurance (SSDI) beneficiaries has risen consistently for the past 30 year years, nearly without abatement. In 1985 there were 3,907,169 individuals receiving SSDI benefits, 2.2% of the labor force. By 2015 beneficiaries swelled to total 10,931,092, 6.6% percent of the labor force¹. This expansion was probably not a caused by changes in program rules; the last major overhaul was completed in the early 1980s. Nor is it easily accounted for by obvious demographic factors: expanded eligibility for benefits resulting from increased female participation and the aging of the baby-boom cohort contribute to less than a third of the rise (See Figure 1).²

Empirical evidence suggests that a third theory, worsening economic conditions for low-skilled workers, has contributed to this trend (e.g. Autor et al. (2013) and Duggan and Autor (2006)). However, the quantitative impact of economic conditions on SSDI awards and the channels through which they operate remain unclear. For example, does it matter which demographics were most exposed to worsening economic conditions? What is the role of the business cycle versus structural decline? Answering these questions are critical to understand why SSDI grew and whether coming shifts in demographics and economic conditions will alleviate or exacerbate future growth.

In this paper, we consider how economic forces, demographic forces, and their *interaction* affect SSDI claims. These forces are intertwined in important ways. First, the response of each individual’s SSDI application decision to changing economic conditions depends on

¹Sources: SSA and BLS (CPS) estimates.

²Predicted changes are constructed as the weighted sum of predicted new awards across 14 age cross gender demographic cells. Predicted new awards at the demographic cell level are the product of share of insured workers; application rate of workers; aggregate award-to-application rate. We hold all these rates and the weight of each cell to the 1985-89 average and introduce the actual time series changes cumulatively: first changing the share of insured in each cell, then the total demographic share (weights) on each cell, and finally the observed award rate. Details explained in the appendix

their demographics. When facing the same economic prospects, we would expect a greater response from those already on the margin of participation: older workers approaching poor health. Second, an individual's demographics affect his or her exposure to economic shocks. These marginal workers, those older and in poor health, are disproportionately represented in declining sectors such as manufacturing. Third, institutional rules determining the likelihood a SSDI claim is granted explicitly condition on vocational factors: worker's demographics and the economic shocks they face; as well as health outcomes. Therefore, it is not clear how to divide the blame for changes in the SSDI rolls between economic conditions and demographics. To what extent do healthy workers misrepresent themselves as disabled to apply when economic prospects are poor? To what extent is it the opposite side of the coin: that poor economic prospects have come down mostly on those already in legitimate pain, but who had been tolerating it in order to work when prospects were good. To understand aggregate SSDI outcomes, we must understand who in the economy is sensitive to economic shocks and why. In other words, how do workers of different demographics consider the disability option?

We put structure around individuals' SSDI application decisions to provide insight into the forces shaping them. We develop a quantitative framework in which individuals face correlated economic and health risks as they age. We discipline the quantitative predictions of this structure using individual-level microdata over the period in which SSDI was rising most steeply. We exploit the fact that occupations bundle tasks differently, and as a result impose differential health and economic risks across individuals. This allows us to infer from individuals' lifetime occupational histories a portion of the health risks they have faced and the economic risks associated with their occupation. We connect these risks to worker's labor-force participation decisions. Variation across workers with different occupations reveals

how realized health and economic status—along with future prospectives for them—affect the labor supply trade-off. It also suggests that changing occupational demographics impact aggregate outcomes. We calibrate parameters of our model such that the behavior of agents replicates moments summarizing the patterns of individuals’ behaviors that we document. We then use the model to predict how changes in the occupational and demographic structure along with differential exposure to economic risk contributed to the rise in SSDI applications.

An empirical literature we summarize below has evaluated whether SSDI interacts with economic conditions. Our structural model complements these empirical studies by evaluating the differential impact on individuals with different health and demographics. As mentioned, this is difficult to understand without a structural model because economic shocks used in the literature disproportionably affect certain demographics. For example, trade shocks disproportionably affect older males in manufacturing industries who, on account of the nature of their work, are likely to be of worse health than average.

A second difficulty, another reason to use a structural model, is that SSDI acceptance rules explicitly consider demographics besides health. These so called “vocational considerations” explicitly include education and age, and also leave some grey area to consider regional or industrial economic prospects. The implication is that not only to different demographics have different exposure to economic shocks, they also have different SSDI acceptance probabilities even for individuals of the same health. Data show the percentage of new SSDI awards in which the grounds for acceptance included vocational considerations, not just health, has increased from 25% in late 1980’s to almost 60% after 2010. This indicates that understanding how vocational considerations affect individuals’ application considerations and whether they exacerbate the role of changing demographics and economic conditions is vital for understanding aggregate trends. Moreover, it is not clear whether the rising im-

portance of vocational considerations stems from increasing de facto leniency of the awards process or a change in the demographics of who is applying. With the use of our structural model we can evaluate how the vocational rules affect incentives to apply and then ask whether the trend in vocational awards can be accounted for by changing demographics and economic conditions alone or if there is room for de facto changes in the institutions themselves. All of these things are important to address whether the increase in SSDI was a one-off confluence of particular factors or whether high enrolment will be sustained in the future, counterfactuals that are not obvious from inspection of data where all forces we’ve discussed are inseparable.

Our main results decompose the rise in SSDI due to long-term economic trends, differences in health exposure and aging: we find that cyclical fluctuations contribute quantitatively insignificantly.

The rest of the paper is organized as follows. In the next section we review related literature. In Section 3 we motivate our approach by presenting evidence that occupations bundle health and economic risks and explain how the SSDI awards process considers each factor. We then introduce the model and our estimation procedure in Sections 4 and 5. Section 6 presents our results and several experiments. Finally, Section 7 concludes.

2 Literature

Topically, our paper belongs to a literature studying the incentives and circumstances determining whether individuals apply for Social Disability Insurance. The methodology employed by this literature is divided between reduced form strategies and quantitative analysis

of structural models.³ We employ the latter methodology, but conduct exercises explicitly designed to relate our approach to findings in the empirical literature.

Structural Life-Cycle Models of Social Security Disability in the United States.

The structural model implemented in our paper builds upon two key works: [Kitao \(2014\)](#) and [Low et al. \(2015\)](#). These papers and our own conduct quantitative studies of the SSDI application decision, but each focuses on different factors. Kitao studies program interactions, in particular how much Medicare benefits accompanying SSDI incentivize applications. [Low et al. \(2015\)](#) analyze details of the SSDI institutions, paying particular attention to estimating individuals' preferences and the risks they face using panel data on individuals' joint consumption and income paths. Whereas these papers study stationary models, our paper focuses on understanding the role of changing economic conditions in the rise of SSDI through transitional dynamics.

We maintain useful ingredients from these works- for example preferences from [Low et al. \(2015\)](#) and the modelling strategy of SSA earnings indices from [Kitao \(2014\)](#). We abstract from other ingredients in order to maintain tractability while accommodating innovations necessary to answer the specific question we are after. We abstract from explicit health investment and insurance as in [Kitao \(2014\)](#), but maintain most of the properties of [Low et al. \(2015\)](#). Our new features include: sectors with differential health and economic risks; a variety of economic risks including cyclical job finding and displacement rates, long-run wage decline/growth, and heterogenous idiosyncratic wage risk; and a realistic SSDI acceptance criteria that includes vocational considerations.

³There is also an interesting theory literature on optimal program design. We omit discussion of this literature because our paper is distanced by our methods as we focus on quantitative and positive analysis.

Empirical Studies Connecting SSDI and the Macroeconomy Several reduced form papers have studied the relationship between Macroeconomic factors and SSDI applications or enrollment. The first causal hypothesis is that worsening economic conditions increase SSDI applications. Generally, empirical studies find persistent declines in economic prospects significantly raise applications, but cyclical increases in unemployment do not. [Duggan and Autor \(2006\)](#) present an analysis of national data. They conclude the steady rise in SSDI benefits relative to falling wage prospects since the early 1990s is a key driver in the secular increase of those on the DI rolls. [Black et al. \(2002\)](#) study specific labor markets. They use prices shocks in mining industries measure the impact of employment and wage prospects on SSDI participation. [Autor et al. \(2013\)](#) relate declining economic prospects to import competition. They exploit geographical variation in historic shares of employment in manufacturing sub-industries more exposed to import competition to identify its effect on employment and SSDI outcomes. they find areas exposed to an additional 4.5 percent fall in the number of manufacturing employees experience a 0.8 percentage point larger reduction in the employment to population rate of which 10% are awarded SSDI benefits. [Mueller et al. \(2016\)](#) and [Rutledge \(2011\)](#) each exploit variation in unemployment insurance extensions during the great recession and fail to find evidence that disability insurance substitutes for unemployment insurance. We take these questions several steps further by evaluating how much the magnitudes of these findings depend on how these shocks affect the demographic/occupational structure of the economy and differential exposure of individuals in each demographic/occupation to health risks putting them on the margin of DI. This is particularly important in relation to the work of [Autor et al. \(2013\)](#). We hypothesize that their analysis of the manufacturing sector over-estimates the contribution of trade competition to aggregate DI trends because workers in this sector are precisely those on the margin of

exiting the labor force to begin with: they are older and on a consequence of the nature of their work they are in worse health.

The other causal direction posits that SSDI claiming behavior has an effect on aggregate employment- specifically that some SSDI claimants would return to work, not non-participation, if the program was inoperable or less generous.⁴ We return to this literature as an external validity test of our model. We compare the outcomes of individuals rejected from the program in our simulations to those in the data. Further we seek to reconcile seemingly conflicting empirical results by considering differential behavior in both recessionary periods and in the changing structural climate of the 1980s versus 2000s.⁵ The structural model allows us to look deeper into this behavior to uncover the types of rejected applicants across health and economic margins that choose to return to work.

3 Motivation

Our goal is to decompose SSDI trends into changing demographics, economic conditions, and institutions. To do so, we must understand how different demographics respond to economic shocks within the differential institutions that they face. In this section we provide evidence of ample variation in the long-run employment and wage prospects of demographics likely to be on the margin of SSDI— those in occupations associated with poor health outcomes. We then explain how SSDI acceptance criteria is explicitly more lenient to certain

⁴For example: [Von Wachter et al. \(2011\)](#), [French and Song \(2014\)](#), and [Chen and Van der Klaauw \(2008\)](#). The last paper analyzes those rejected for vocational reasons (they are deemed to be able to work in some job in the national economy) and finds only 20% would return to work. They also note a secular increase in those accepted for vocational reasons from the 1980's to 1990's.

⁵For example, [French and Song \(2014\)](#) study employment of applicants rejected in 2006. They acknowledge that their results are specific to the time period, particularly in the face of the ensuing Great Recession. See also: [Bound et al. \(2014\)](#)

demographics— the old, the less educated, and those with limited occupational experience in declining industries.

3.1 Occupations Provide Correlation in Health and Economic Risks.

In a previous paper, we presented evidence life-time occupational contributes significantly to the variation in poor health outcomes that leading to work limitations and SSDI enrollment (Michaud and Wiczer (2014)). We measured health by various metrics and used the physical requirements of the workers’ longest-held occupation to measure exposure. The data on health and occupational history came from the Health and Retirement Survey (HRS), to which we linked the O*NET for physical requirements.⁶ For the present analysis, we link health risk to 16 broad occupational categories using our preferred measure from the HRS: proportion of workers who list that occupation as their longest held and experience a difficulty in an Activity of Daily Living (ADL) prior to age 65.⁷ We pair this health risk metric to wage and employment data from the Current Population Survey disaggregated into the matching occupational categories.

The time period we consider in 1980-2014, with data collected at an annual frequency.⁸ Our measure of structural decline is a 10-year rolling window (reported statistics correspond to year 5) of employment growth in each occupation relative to aggregate employment growth over the time period. Our measure of cyclical volatility is the first difference in the natural log of employment in the occupation from the prior year. Employment is always measured

⁶We showed robustness to various measures of outcomes and instrumented the endogeneity of occupational choice by using non-physical requirements. See the manuscript for further details.

⁷ADLs are used as a core indicator by the SSA for determining whether an individual has a severe work limitation.

⁸We begin in 1980 as our analysis will focus on the rise in SSDI following a major purge of claimants and accompanying reforms in the early 1980’s.

as the number of full-time (≥ 30 hours/week) full-year (≥ 50 weeks) workers constructed using appropriate weights.

Figure 2 shows the correlation of health risk and long-run employment growth by occupation.⁹ Figure 3 shows the correlation of health risk and employment volatility. Employment in both figures is limited to workers aged 45-65; those comprising the vast majority of SSDI claimants.¹⁰ Occupations with low health risks (Figure 2) tend to be growing. Only clerical work has low health risk and is in decline. On average, occupations with high health risks are shrinking. However, there is ample variation in long-run growth of occupations with high health risk. The fastest growth category- machine operators. health has similar health risk to the fastest shrinking category- machine operators. Differences in SSDI claim behavior across these groups will inform the relative importance of long-run decline in Economic prospects. Employment volatility (Figure 3) is mildly positively correlated with health risk. Cleaning and household services are an important outlier with high volatility and high health risk. We will be particularly interested in the SSDI behavior of workers in this occupation.

Since recessions vary in their causes and consequences, we provide Table ?? highlighting employment changes by occupation in the great recession.¹¹ Occupations are ordered by their health risks. There were large declines in employment in occupations across the risk spectrum: Sales (low risk), Construction and Operators (medium risk), and Cleaning and Maintenance services (high risk). Further, there is variation in the recovery of these occupations: Sales, Cleaning, and some Operators recovered while Construction/Extraction and other categories of Operators did not. The table also reinforces the pattern that most occupations with good economic prospects have low health risks. The exception is health

⁹Full time series plots by the 16 occupation groups and by ADL and DI risk quartiles are included in the extended appendix.

¹⁰We also exclude those self-employed or in the military. See Appendix for great detail.

¹¹Full time series show in extended appendix.

services which had the highest employment growth over the time period.

3.2 SSDI Award Criteria Consider both Health and Vocation.

The SSDI award criteria directly distorts the incentive to apply for SSDI across demographics, particularly through explicit rules called “vocational considerations”, (key SSA terms defined in 2). Vocational considerations are the last step in the four-stage sequential decision process the Social Security Administration uses to determine whether or not to award a disability claim (see 4). Claims made by uninsured workers are rejected in the first stage. To be insured, a worker must have accumulated a sufficient number of SSA work credits.¹² Claims made by insured workers currently engaged in substantial gainful activity are rejected in the second stage. In 2016, the threshold for substantial gainful activity was having earnings greater than \$1,130 per month. Health is considered at the third stage. Claims are accepted at this stage if the applicant provides proof of a severe medical condition expected to last for at least one year or result in death, that meets or is equivalent to a condition the SSA’s listing of impairments.

Claims that pass the first two stages and are *not* accepted at the third stage move on to the final stage in which vocational factors are considered. First, the residual functioning capacity (RFC) of the applicant is evaluated in order to identify the types of work the individual is capable of in spite of their disability. If it is deemed the applicant is capable of performing their recent past work, their application will be denied. Otherwise, it will be considered whether the applicant has the vocational skills to adapt to new work feasible

¹²Up to four Social Security work credits may be earned per year. In 2016, one credit is awarded for each \$1,260 in wages or self-employment income earned. The required number of work credits to be insured under SSDI increases with age. There are also restrictions on when during the lifetime the credits were earned. For example, at age 62 the total number of credits required is 40, of which 20 must have been earned within 10 years of disability onset.

given their (RFC). Crucially, from here forward health is no longer considered in the accept/reject conditions. The set of possibilities is explicitly narrowed by expected vocational adaptability. First, age and education are considered according to a vocational grid (see ??). The grid defines explicit age categories at 18-44, 45-49, “approaching advanced age” at 50-54, and “advanced age” at 55+. Rules dictate that older applicants are limited in vocational adaptability and should be more likely to receive an award compared to younger applicants with similar RFC. Education is evaluated along three dimensions: formal education, literacy, and ability to communicate in English. Similarly older applicants, those with limited education are also ruled to be less able to adapt to new vocations and more likely to get an award. Second, an individual’s past work experience is considered. Specifically, it is evaluated whether skills they used in the past are easily transferable to other occupations. After the set of occupations to which the applicant can be expected to adapt are narrowed by RFC and vocational considerations, the SSA can only reject the claim if it can provide evidence that job openings in significant numbers in such occupations. Otherwise the claim will be awarded.

Figure 5 shows the role of the Vocational stage in SSDI claim outcomes has changed in important ways over the past decades. In the late 1980’s 80% of denials were based upon the decision that work suited to the applicants residual functioning capacity was available. This share rose to 90% in the 1990s before falling to less than 70% in the 2010s. Moreover, the share of awards based upon the decision that suitable work was *not* available rose monotonically from 25% in the 1980s to 60% after 2010. Yet the share of all decisions, awards and denials, with vocational considerations only rose 10 points. This implies that a larger/smaller portion of denials/awards are taking place at the medical stage. What is not clear is whether these trends are indicative of the award rate at the vocational stage reacting

to changing economic conditions or whether economic conditions changed the demographics of the types of workers who file SSDI claims. Likely, it is both. This motivates our inclusion of separate medical and vocational award stages in our model so that we may disentangle the two for a deeper understanding of how much and why economic conditions are important for SSDI claims.

4 The Model

The model features overlapping generations of agents that spend a portion of their lives with the option of participating in labor markets and a portion of their lives in retirement. Agents differ in the extent of their disability, wages, age, and labor market history. At the beginning of their career, agents choose a lifetime occupation. Occupations affect future wage and disability outcomes. Throughout their career, agents choose whether to participate in the labor market, whether to apply for disability payments, and how much of their income to save. We start by describing the problem of an arbitrary agent over the life course for an arbitrary occupation choice. We then describe the occupation choice at the beginning of life.

4.1 Demographics

The model is populated by agents of various ages $\tau \in \{0, 1, 2 \dots T\}$. Agents age sequentially; at each age τ they progress to $\tau + 1$ with probability ϕ_τ . Agents of age $\tau = T$ and health status d die with probability $\tau_T(d)$ and are replaced by an equal measure of new-born agents of age $\tau = 0$. Agents begin life employed in an occupation $j \in \{1, 2 \dots J\}$. They then draw a permanent δ^i related to their personal health deterioration risk. The characteristic δ^i is

drawn from an occupation-specific distribution $G_j(\delta)$.

Each subsequent period of $\tau \in \{1, 2 \dots T - 1\}$ agents choose whether to continue working or move into unemployment. Unemployed agents become long-term unemployed with probability φ . Otherwise, they choose whether to go back to work or remain unemployed in the following period. Long-term unemployed chose whether to apply for SSDI or search for a job. Agents of age $\tau = T$ are retired. Retired agents and agents receiving SSDI cannot work; they consume from their savings a and social security retirement payment $SSI(e)$ or disability payment $SSDI(e)$, where e is a measure of their prior labor market earnings.

4.2 Income

Wages are exogenous. They depend on agents' idiosyncratic component α , their current age τ and extent of disabilities d , as well as a current occupation-specific productivity $z(j)$. The full specification is:

$$\log(w) = \alpha + h_d + g(\tau) + z_j$$

Movement in z_j provides the occupation-specific, economic motive and evolves according to function ζ . Wages depend on d through h_d , which provides health-related pecuniary motives to file for disability. The dependence of wages on age affects the life-cycle timing of disability application, an important characteristic of the data. Finally, α provides variation across individuals who have the same health status d and occupation j . This assumption can be thought of as capturing omitted individual factors such as firm effects or differences in local labor markets. α evolves stochastically, according to a process we will described by π_α .

The business cycle is indicated by y , which determines the unemployment risk. For

notational parsimony, we fold the exogenous unemployment state into α , the lowest state of which becomes an indicator that the worker was exogenously separated. The rate of entering and exiting this state varies by y and j , therefore, π_α depends on y, j . $\mathcal{Y}$ are the probabilities for the Markov chain governing y .

4.3 Disability

The extent of agents' disabilities d takes three values $d \in \{0, 1, 2\}$. Each agent is born healthy without disabilities: $d = 0$. Each period of life, an agent's disability extent evolves according to an age and individual-type specific Markov process: ${}_1d(d, d'; \tau, \delta^i)$, where δ^i is an individual-specific parameter of the transition probabilities. Disability states are ordinal: an agent of $d = 2$ is in worse health than an agent of $d = 1$.

4.4 Social Transfer Programs: Unemployment, Disability, & Retirement

Non-employed agents receive exogenous social transfers, $UI(e)$, $SSDI(e)$, and $SSI(e)$, according to their state: unemployed, disability beneficiary, or retired, respectively¹³. In line with the US systems, these transfers depend on an index of agents' prior earnings: e . This index is updated when an agent works according to their current wage, age, and past earnings: $e' = H_\tau(w, e)$. Retirees automatically receive old age insurance $SSI(e)$. Newly unemployed agents receive $UI(e)$ until, with Poisson probability φ , the individual becomes long-term

¹³Some agents chose unemployment when wages are sufficiently low, which can be thought of as a lay-off. Others do so because of changes in health, which may be thought of as a quit. We simplify the problem by providing all agents choosing unemployment with temporary unemployment benefits because we do not model a clear distinction between quits and lay-offs.

unemployed and unemployment benefits are terminated. Disability benefits $DI(e)$ are only paid to agents who are apply and are accepted as beneficiaries. In accordance to SSDI rules, only long-term unemployed can apply for DI benefits. The application process takes one period and applicants incur a psychic cost ν .¹⁴ An agent’s DI application is accepted with probability $\xi(d, \tau, w)$. The SSDI decision criteria include health status in addition to age and economic status, and so we model these aspects as well. An agent who is accepted as a beneficiary must permanently leave the labor force and will collect DI benefits until they age into retirement and switch to SSI.

4.5 Preferences

Agents have preferences over consumption which depend on the extent of their disability d and whether or not they are working. Denote $u^W(c, d)$ as the flow utility of consumption c for an agent who works in the current period and has disability extent d . Denote $u^N(c, d)$ similarly for an agent who does not work in the current period (ie: a non-participant, retiree, or enrolled as a disability beneficiary). We assume these functions satisfy standard regularity conditions for each value of d . Agents are also impatient and discount the future at rate $\beta \in (0, 1)$.

¹⁴SSDI program rules stipulate an applicant must not have worked in the previous 5 months. This is close to the median duration of unemployment benefits across US States during “normal” times: 26 weeks. While unemployment benefit duration is highly cyclical, we do not include this variation in the model as motivated by [Mueller et al. \(2016\)](#) who find cyclical UI extensions have no significant effect on the timing or level of SSDI applications.

4.6 Agents' Decisions

We define the problems agents face, recursively, yielding a set of value functions: working agent $V_{j,\tau}^W(\alpha, a, e, d; z, y)$, unemployed $V_{j,\tau}^U(\alpha, a, e, d; z, y)$, long-term unemployed $V_{j,\tau}^N(\alpha, a, e, d; z, y)$, disability beneficiary $V_{j,\tau}^D(a, e, d)$, and retiree $V_{j,\tau}^R(a, e, d)$. To economize on notation, we suppress the fact that value functions are also indexed by agents' type i . We proceed backwards with the terminal value of retirement, then the irreversible disability beneficiary, and finally the unemployed, long-term unemployed, and working agent as well as the choice between work and unemployment.

A Retiree's Problem Retirement is boring. Agents' disability extent and earning index do not change in retirement. The only choice agents make is a consumption versus savings decision given their asset holdings and SSI income. This problem repeats until death occurs with probability ϕ_T .

$$V^R(d, e, a) = \max_{c,a} u^N(c, d) + \beta \phi_T V^R(d, e, a')$$

$$c + a' \leq SSI(e) + Ra \quad a' \geq 0$$

A Disability Beneficiary's Problem A disability beneficiary's problem is also boring. Agents' disability extent and earning index do not change, but they do continue to age. The only choice agents make is a consumption versus savings decision given their asset holdings and SSDI income. This problem repeats until the agent exogenously ages into retirement

$\tau = T$. Of the individual state, d, e are constant and α, β do not matter.

$$V_{\tau}^D(d, e, a) = \max_{c, a} u^N(c, d) + \beta \sum_{\tau'} [\phi(\tau, \tau') V_{\tau'}^D(d, e, a')]$$

$$c + a' \leq SSDI(e) + Ra \quad a' \geq 0$$

The Decision to Work An agent who is neither retired nor disabled has the choice of working or rest unemployment each period. The optimal choice yields value:

$$V_{j\tau}(\alpha, e, d, a; z, y) = \max\{V_{j\tau}^W(\alpha, e, d, a; z, y), V_{j\tau}^U(\alpha, e, d, a; z, y)\}$$

An Unemployed Agent's Problem An agent who chooses unemployment faces only the consumption-savings choice. As he makes this choice, he considers that, with probability φ , he will become long-term unemployed (with value V^N) in the next period. Otherwise, α and z continue to evolve and he will be able to choose again between work and unemployment in the next period.

$$\begin{aligned} V_{j\tau}^U(\alpha, e, d, a; z, y) &= \max_{c, a} u^N(c, d) + \\ &\quad \beta \sum_{\tau'} E[\phi(\tau, \tau') \varphi V_{j\tau'}^N(\alpha', e', d', a'; z', y') + (1 - \varphi) V_{j\tau'}^U(\alpha', e', d', a'; z', y')] \\ c + a' &\leq UI(e) + Ra \quad a' \geq 0 \\ e' &= e, \quad d' = d \quad z' = \zeta(z) \end{aligned}$$

A Long-Term Unemployed Agent's Problem An agent who becomes long-term unemployment faces two decisions: a consumption versus savings choice and whether to search for a job or apply for disability benefits.

$$\begin{aligned}
V_{j\tau}^N(\alpha, , e, d, a; z, y) &= \max_{c, a, m} u^N(c, d) - m\nu + \\
&+ \beta m \sum_{\tau'} \phi(\tau, \tau') [\xi(d, \tau, w) V_{\tau'}^D(\alpha', e', d', a') + (1 - \xi(d, \tau, w)) E[V_{j\tau'}^N(\alpha', e', d', a'; z', y')]] \\
&+ \beta(1 - m) \sum_{\tau'} \phi(\tau, \tau') [E[\rho V_{j\tau'}^N(\alpha', e', d', a'; z', y') + (1 - \rho) V_{j\tau'}^N(\alpha', e', d', a'; z', y')]] \\
c + a' &\leq b + Ra \quad a' \geq 0 \quad m \in \{0, 1\} \\
e' &= e, \quad d' = d \\
z' &= \zeta(z)
\end{aligned}$$

Application for SSDI benefits is a discrete choice: $m = 1$ if the agent applies and is zero otherwise. If the SSDI application is accepted (with probability ξ_d), the agent becomes a disability beneficiary for the rest of life until retirement. If the application is not accepted, the agent remains long-term unemployed: $\mathbf{E}[V_{j\tau'}^N(\alpha', e', d', a'; z', y')]$. If the agent does not apply, there is a probability ρ he or she will have the opportunity to work again next period: $\mathbf{E}[V_{j\tau'}^N(\alpha', e', d', a'; z', y')]$; and with probability $(1 - \rho)$ remains unemployed. In other words, agents can only spend time searching for a job or applying for DI. Finally, observe the long-term unemployed receives a flow of real income b , which can be considered a combination of home production and broader social transfers (food stamps, TANF, etc).

A Worker's Problem An agent who chooses to work faces a consumption-savings choice during the current period.

$$\begin{aligned}
V_{j\tau}^W(\alpha, e, d, a; z, y) &= \max_{c, a} u^W(c, d) + \beta \sum_{\tau'} \phi(\tau, \tau') E[V_{j\tau'}(\alpha', d', e', a'; z', y')] \\
c + a' &\leq w_{j\tau}(d, z) + Ra \quad : \quad a' \geq 0 \\
e' &= H_{\tau}(e) \quad z' = \zeta(z)
\end{aligned}$$

4.7 Stationary Equilibrium

4.8 Discussion

The crucial decision within the model is whether to apply for Disability or not. In particular, the decision within the model depends on the health and age of a worker and also the incipient wage she could make if employed. To show how these factors affect the policy decision, Figures 6 and 7 plot the latent value of applying for SSDI. For positive values, where

$$E [\xi(\cdot) V^D(\alpha', e', d', a') + (1 - \xi(\cdot)) V^N(\alpha', e', d', a'; z' y') - \nu] > E [V^N(\alpha', e', d', a'; z', y')] \quad ,$$

eligible workers apply for DI.

At progressively worse levels of health, workers are more likely to apply for disability: which we see in Figure 6. Even while sitting in non-employment, they are still observing innovations to α , and so at any moment there is some positive probability that they may

next period decide to apply even if this period they did not. In Figure 6, we hold fixed the distribution of SSDI wealth at its mean and z at an expansion level. Assets are chosen towards the top of the distribution, the XX percentile, which makes workers with moderate health more likely to apply. In this figure we are looking at relatively young workers, aged 52.

Figure 7 turns now to the way the application decision varies with age, taking $d = 1$, moderate health. Notice that it is not just a monotone increase. In fact, at 52 a worker may be less likely to apply than at 47, given the same state. This is because the earnings profile peaks in one's 50's, making work relatively more attractive. The next stage, once one crosses 55, however, application becomes quite a bit more attractive because acceptance probability makes a discrete jump, a feature of the system to which we will return in the calibration section. We purposely do not plot the policy among 62 year-olds because that can be quite unstable across states. For some, it makes perfect sense to continue working, given that application times are relatively long and retirement is close. For others, the value of work is even lower than in earlier years simply because the terminal date T is approaching.

5 Calibration

To chose parameters for this model, we use data from wages, health status and, most importantly, labor market flows. On the model side, we have parameters governing preferences, wages, occupation-specific disability risk and the evolution of occupations' conductivities. Here we explain our chosen parametric forms and then describe how we choose parameter values to replicate features of individuals' behavior and the Macroeconomy.

5.1 Externally Set Parameters- Preferences and Demographics

The time period is one month. The discount rate is set to 4% per year.

Demographics Individuals age through 5 age groups: 23-45, 46-50, 51-55, 56-60, 60-65 and a final age group of retirees. The new entrants arrive at a constant rate of 1%.

Preferences Preferences follow [Low et al. \(2015\)](#), in which workers value consumption, leisure and health. For participants and non participants, the utility is:

$$u^W(c, d) = \frac{(ce^\theta d\eta)^{1-\gamma}}{1-\gamma} \quad u^N(c, d) = \frac{(ce^\theta d)^{1-\gamma}}{1-\gamma}$$

We choose $\theta = -0.448$ and $\eta = -0.185$ following [Low et al. \(2015\)](#).¹⁵ This implies disability and work both increase the marginal utility of consumption. In other words, disabled individuals must have higher general consumption expenditure to maintain the same utility. Quantitatively, this implicitly captures the higher health expenditures of those in poor health which we do not model explicitly.¹⁶ We set $\gamma = 2$, within the standard range.¹⁷ We choose the interest rate such that the wealth level of the 56-62 age group is equal to four times the economy average as is targeted in [Kitao \(2014\)](#) to match the corresponding statistic from the Survey of Consumer Finance.

¹⁵They identify these parameters using consumption data. We maintain these preferences in our paper for comparability.

¹⁶Or what can be interpreted as expenditures net of insurance coverage and payments. We do not capture heterogeneity in these details, and potential correlation with other model features.

¹⁷[Low et al. \(2015\)](#) show results for $\gamma = 1.5, 3$; [Kitao \(2014\)](#) uses $\gamma = 2$.

5.2 Social Insurance Institutions

Social Security Disability Acceptance Screening The Social Disability Insurance (DI) program in our model is designed to replicate realistic features of the US Social Security Disability Insurance (SSDI) program.¹⁸ The SSDI program provides partial earnings replacement to covered individuals unable to work because of a health-related work limitation. Award of insurance payment upon the onset of disability is subject to meeting several sequential criteria. First, the individual must be eligible: they must meet an work requirement on prior earnings and file an application.¹⁹ Second, the applicant must have been non-employed for five months prior to application and not have earnings exceeding a low threshold of substantial gainful activity.²⁰ Third, the applicant must demonstrate a physical or mental impairment resulting in the ‘inability to engage in substantial gainful activity’ and is expected to last for one year or terminate in death. Fourth, it must be deemed that the applicant can neither perform the job they did previously nor can they be “expected to adjust to other work that exists in the national economy”.

With regards to the first criteria, we consider the work requirement only for young workers (age 25 to 45) in our model. Using the large representative sample of the SSA’s Earnings Public-Use File, we compute the average share of males age 25-45 working in the current year who meet the work requirement for eligibility over the years 1984-2006.²¹ This figure

¹⁸The program underwent major changes in the late 1970’s and early 1980’s. However, it has been surprisingly unchanged since the 1984 reforms. As such, our analysis begins at 1984.

¹⁹The work requirement applies only to individuals over age 31. The requirement is satisfied if 20 credits have been earned in the past ten years or X credits have been earned ever where X is dependent on age (for example: 20 for age 40; 40 for age 60+). In 2015 a credit was awarded for approximately each \$1200 of SSI taxed income. A maximum of 4 credits can be earned per year.

²⁰\$1090/month in 2015.

²¹We include the requirement for younger workers under the assumption that gaps in their work history are provided by factors outside the model such as education. Not including the requirement for older workers is not a pivotal assumption given that we focus on males. Authors’ calculations from SSA earnings credit files show that between 93% and 95% of men age 50-59 meet the work requirements between 1980 and

is 63.8%. We do require agents to submit an application by imposing a utility cost of doing so. This utility cost is proportional to the expected gain from receiving disability benefits. In practice this cost includes physical and/or mental examination, a court hearing, and very often appeals.²² It is not unreasonable to think these costs are increasing in the expected gain from receiving disability benefits as one would expect these to be the people who incur costs to appeal. In the model, this cost is a key parameter determining whether the marginal individuals who become long-term unemployed as a result of bad luck apply for SSDI or wait until they exit long-term unemployment and can go back to work. Therefore, we choose this cost to match the proportion of long-term unemployed that return to Employment.

We capture the second criteria of a 5 month non-employment period prior to application through our modeling of rest unemployment and long-term unemployment. When workers choose rest unemployment instead of work, there is a probability that they will become “long-term” unemployed. Once they are long-term unemployed, they no longer receive unemployment benefits and receive no job offers, but can apply for SSDI. Accordingly, we choose the probability of long-term unemployment to match an average rest unemployment duration of 5 months. Stochastically, long-term unemployed receive the option to go back to work. We choose the probability this option occurs to match the exit rate of workers unemployed for more than five months. Altogether, this is a simple recursive formulation that captures key economic incentives affecting the SSDI application decision for long-term unemployed workers versus short term unemployed. It is harder for the long-term to find work, they no longer receive unemployment benefits, and they are eligible to apply for SSDI (whereas short term unemployed are not).

2005. However, eligibility displays both trends (a decline from 1980 to 2000) and procyclicality. Eligibility of women in the same demographic rose from 77% in 1980 to 90% in 2005. (Graphs available upon request).

²²For example legal fees to disability attorneys totaled over \$1 billion in 2014. See also [Benitez-Silva et al. \(1999\)](#) for further discussion on the costs of the application process.

The third criteria, that of a severe work limitation, is neither verifiable by the SSA with respect to applicants nor by the authors with respect to the PSID sample.²³ Research examining this issue has found that SSDI screening produces high levels of both false positives and false negatives.²⁴ Further, administrative acceptance criteria of the SSA consider more factors than work limitation status alone. The fourth criteria: ability to do any type of work in the economy, brings age into play. The SSA considers older individuals to be less likely to be able to “adjust to other work” compared to younger individuals with the same work limitation.²⁵ As a result of these complexities, even if we accept individuals reporting a severe work limitation as meeting the SSDI criteria, we do not set their acceptance probability to one. Instead, we appeal to a study of [Lahiri et al. \(1995\)](#). They compute the marginal effects of various factors in a logit regression on SSDI application acceptance using data from the Survey of Income and Program Participation (SIPP) matched with SSA administrative data. The former data contains demographic data and variables relating to ADL difficulties. The latter contains detailed data on whether an applicant was accepted and on what grounds: on health conditions only or because of vocational considerations. We mimic this two step process in our model. We impose an acceptance probability for each health status cross age group in our model using the base acceptance rate at this stage and marginal effects of health and age found in their paper. Next we allow applicants not accepted for health reasons alone to be accepted for vocational considerations. Their paper shows the base

²³The validity and interpretation of self-reported work-limitation is not uncontroversial. We, and other researchers, find that self-reported work limitation in the PSID is a strong predictor of observable outcomes such as high medical spending and death. Therefore, we are comfortable with our assumption that self-reported work limitation implies lower marginal utility of consumption and lowers wages (as we documented), the two channels through which disability affects choices in our model.

²⁴[Benitez-Silva et al. \(2004\)](#) estimate that 70% of applicants are legitimately work limited, but screening errors are substantial: a lower bound of 16% false awards and 52% false rejections.

²⁵The SSA has explicit guidelines. They construct a determination “grid” that lists extent of work limitation, education, work experience, and age, the so-called “medical-vocational” guidelines. Older age results in lower thresholds for the other categories, particularly over the age of 50.

conditional probability of vocational acceptance is 17.14% in 1993. A follow up paper shows this conditional probability is 39% in 2010. We interpret this change as reflecting how economic conditions can affect the decision whether an individual can perform “any work in the national economy” through the vocational considerations. Whether or not a worker’s skills are relevant depends on whether they are in a declining occupation or industry.

As such, we impose that the vocational acceptance probability is linear in z_j , the occupation productivity shock, and bounded at these thresholds.²⁶ Finally, we adjust the vocational acceptance probability of workers over 55 to be an additional 12.4 percentage points higher consistent with the marginal effect in their regression and the descriptive age considerations of the SSA policy.

SSDI and SS Retirement Payment Schedules SSDI benefits and SS retirement both replace past earnings at the same piecewise linear rate set according to the formula used by the Social Security Administration. Past earnings are defined by an index e of the individual’s 35 highest annual earnings. In 2015 the bend points in terms of monthly income, were:²⁷

$$SSDI(e) = \begin{cases} 0.9 \times e & e < \$826 \\ 743 + 0.32 \times (e - 826) & \$826 \leq e < \$4980 \\ 2072 + 0.15 \times (e - 4980) & \$4980 \leq e \end{cases}$$

²⁶We set acceptance rates to be constant over the business cycle following [Coe and Rutledge \(2013\)](#), who document constant acceptance rates once correcting for demographics and types of limitations of applicants. The exception is the Great Recession where acceptance rates rose by 20%. We consider this as a non-targeted statistic and see whether the mix of occupations in decline following the Great Recession can deliver this result through the model on its own.

²⁷Bend points are designed to be consistent with 1979 bend points adjusted for the average wage index two years prior to the calendar year.

The average wage index for the given points is \$44,888. We convert these bend points to real "model dollars" by targeting the ratio of the bend points relative to the average wage, not the nominal value.

We use an age-dependent recursive formulation to keep track of past earnings as follows.²⁸ We compute the updated earnings index by weighting the previous index as though the individual is at the midpoint of the age group. For example, the age group 25-45 spans 20 years and the prior index is weighted by $1 - 2/(10 \times 12)$ or .983, consistent with the median individual in this age group, one in her 35th year (10th year of work). The index is only updated for the last two age groups if it provides an increase.

$$e' = \begin{cases} e \times (1 - \frac{2}{10 \times 12}) + w \frac{2}{10 \times 12} & e < \text{age 25-45} \\ e \times (1 - \frac{6}{5 \times 30 \times 12}) + w \frac{6}{5 \times 30 \times 12} & e < \text{age 46-55} \\ \max\{e, e \times (1 - \frac{35}{32.5 \times 35 \times 12}) + w \frac{35}{32.5 \times 35 \times 12}\} & e < \text{age 56-59} \\ \max\{e, e \times (1 - \frac{40}{35 \times 40 \times 12}) + w \frac{40}{35 \times 40 \times 12}\} & e < \text{age 60-62} \end{cases}$$

Unemployment Insurance The US unemployment insurance program pays benefits to workers who are separated from their job by no fault of their own (ie: they did not quit and were not fired). We do not distinguish between different types of separation in our model. Workers chose "rest" unemployment when their wages fall below an acceptable threshold or if they decide to apply for SSDI. The drop in wage of the former group can be considered a termination for economic reasons (job destruction) because of low productivity.²⁹ These

²⁸This allows for a consistent earnings index in the presence of the stochastic aging environment. Both are key to easing the computational burden of the life-cycle dimension.

²⁹Indeed, in many models of labor markets (such as search models) the distinction between a quit and layoff is not clear. The match ends because the worker and the firm cannot agree to a wage that would justify continuing the match.

workers would be eligible for UI.³⁰ Unemployment benefits average 45% of workers’ wage in the job they lost and a duration of 6 months. To conserve state variables, we impose a replacement rate of 45% of the earnings index of average lifetime earnings e , used also to calculate individuals’ SSDI and SS retirement benefits. Unemployment benefits are only paid while individuals are in short-term of “rest” unemployment. We set the probability an individual is forced from rest to long-term unemployment to provide an expected duration of rest unemployment of 6 months, consistent with the average maximum duration of UI payments.

Other Social Welfare Schemes and Transfers Coe et al. (2013) document that SNAP benefits (food stamps) are an important source of consumption for SSDI applicants- more than 30% receive SNAP during the application process out of the 50% who are eligible.³¹ An additional 7% receive worker’s comp and 7% receive SSI. Other transfers come from informal networks. Since we are not interested in program interactions and reform (as opposed to Kitao (2014) and Low et al. (2015)), we model all other transfers as a fixed payment for the non-employed. We chose the size of this transfer to be 30% of the median earnings in the model, consistent with the typical poverty threshold for a single household.³² In reality, there is a threshold on liquid asset holdings below which individuals are eligible for SNAP benefits and other in-kind transfers. We have no analogy in the model since there is only one asset primarily used for retirement (ie: no pensions, houses, etc). Therefore, we do not

³⁰For tractability, we do not preclude the SSDI filers from receiving UI even if their behavior is interpreted as a quit. This is not an extreme assumption as Coe et al. (2013) document more than 60% of workers who apply for SSDI were eligible for UI in the months before their application.

³¹The next highest sources of income is borrowing from credit cards- 17% borrow at a mean of \$3,400 in the month they apply. Introducing unsecured credit greatly complicates the model because we would also have to include a bankruptcy option to capture the behavior of individuals using this coping strategy.

³²SNAP benefits per person are approximately 5% of median earnings of a single-person household over our sample.

abstract from asset testing in the model.

Wages The wage of an employed individual i (or shadow wages for an unemployed individual) is given by the function:

$$w_{j,\tau}(d, z) = g(\tau) + h(d) + \alpha^i + z_j$$

Here the age profile is $g(\tau)$ and the direct effect of health status on wages is given by $h(d)$. These values are chosen directly from empirical regressions. Wages in both the model and PSID data are censored as a result of endogenous choices of whether to participate.³³ To produce unbiased estimates of the effect of age and health on wages, we use a standard two-step Heckman selection correction. We first estimate a probit on employment as a selection equation. The regressors include dummies for reported work limitations in the current *and* following period to capture selection on health. To capture selection on economic factors, we include one year and five year differences in log employment in the longest held occupation³⁴ Additional regressors include dummies for age, education, and race.

Results in Table 4 show poor health has a strong effect on employment. A severe/moderate work limitation has a marginal effect of reducing employment likelihood by 46%/18% when all other variables are evaluated at their means. Both cyclical and longer run declines in aggregate occupational employment are also associated with a decline in individual employment likelihood. Moreover, shrinking occupations have higher risk of poor health outcomes: the correlation coefficient of health risk with the one/five year aggregate occupational em-

³³Our PSID sample for the calibration includes men ages 30-62 over the years 1983-1996.

³⁴We restrict the sample to those holding the longest held occupation for at least 8 years. This is consistent with our modeling of a lifetime occupational set of skills that are non-transferable. Five year difference is centered at the current year to capture expectations.

ployment growth is -0.084/-0.129.

The wage equation is a typical Mincer regression. It includes dummies for work limitations in the current period only, dummies for education and race, a quadratic in age, and occupation cross year dummies for our 16 occupation groups. We correct for selection by including the inverse Mills ratio from the first step selection equation. It is a proxy for the probability of employment, conditional on the selection regressors. As shown in Table 4, the coefficient on the Mills ratio is positive in the wage regression, confirming our conjecture that selection biases wages upwards.³⁵ Omitting the selection correction also biases the effect of poor health on wages significantly towards zero for severe limitations.³⁶

The idiosyncratic component α^i is an persistent, auto-regressive process. We estimate a simple restricted income process, $\alpha^{i'} = \rho_\alpha \alpha^i + \sigma_\alpha \epsilon^{i'}$ on residual wages after having run our Mincer regression, which controlled for age, health and occupation-specific effects.

The occupation specific component z_j will be discussed in section on macroeconomic risks.

Occupation Health Risks Each individual i draws a permanent disability risk from an occupation-specific distribution

$$\delta_i \sim F_{\delta,j}(\delta) = 1 - e^{-\lambda_{\delta,j}\delta}$$

characterized by the parameter $\lambda_{\delta,j}$. Given a risk level δ , the three disability states—no disability, moderate, and severe—evolve according to the Markov transition matrix. The

³⁵The average truncation effect is 0.073 log points or 3.2% of the mean log wage (2.29).

³⁶There are 289 wage observations of individuals with severe limitations (14.4% of workers with a severe limitation work) and 403 observations with a severe limitation in the following year (41.68% of individuals without a severe limitation today who have a severe work limitation in the following year work today).

baseline risks for each age τ are given by

$$\begin{pmatrix} \pi_{00,\tau} & \pi_{01,\tau} & \pi_{02,\tau} \\ \pi_{10,\tau} & \pi_{11,\tau} & \pi_{12,\tau} \\ 0 & 0 & 1 \end{pmatrix}$$

Occupations affect the gradual depreciation rate of health by multiplying $\pi_{01,\tau}$, $\pi_{02,\tau}$ and $\pi_{12,\tau}$, so the final probability of transiting down a stage is $\pi_{dd',\tau}e^{\delta_j}$.

The first choice we make is to restrict our notion of a severe-limitation to one that is an absorbing state. This is consistent with the SSDI definition of a disability- a work-limitation expected to last more than one year or result in death.³⁷ The mean effects are estimated using a Cox proportional hazard regression. We use age dummies that correspond to model age groups. We include an occupational health risk variable which equals our preferred measure of occupation ADL risk assigned to PSID individuals according to their longest held occupation.³⁸ The results are presented in 5. The variance of disability risk distributions are constant across occupations.

To summarize the differences across occupation in their relative health risk, Figure 9 shows the distribution of the probability of a severe limitation. Because the realized rate of disability within an occupation may reflect selection into that occupation, we use the estimated disability effect from [Michaud and Wiczer \(2014\)](#). These implied effects use the physical task-component of each occupation and instrument for selection into physical task-intensive occupations by using other tasks. In both the implied and actual disability rates, there is significant variation and a very long-tail of health risk.

³⁷We adjust the data accordingly by recoding reports of a “severe” limitation to moderate if the individual reports a moderate or no limitation in the following year. Details are found in the appendix.

³⁸We exclude workers whose longest held occupation duration is less than 8 years.

Macroeconomic Risks There are two sources of macroeconomic risk: long-term changes to wages and short-term fluctuations in unemployment probability. Both of these are occupation-specific. Long-term changes in wages, those which were described by ζ , are chosen to match the median wage changes within each occupation. Recall that wages are endogenous within our model because of the composition effects from α, d : when workers chose to participate or not they can change the median wage within their occupation. Figure 8 plots the sequence of $\{z_{j,t}\}$ that match period-wise the median wages for each of the 16 occupations.

6 Results from the Quantitative Model

In this section, we evaluate how well elements of the the model capture the disability decision and then use this model to understand the forces behind the rise. We designed the model to include many of the factors that would affect an individual’s decision to apply for disability insurance and to allow them to interact. In our numerical work, we will simulate agents making these decision given a health, income and asset state. To begin, we feed in the occupation and age distribution and chose occupation-specific finding, separation and wage-trends to match those observed in data.

Central to the model’s predictions about disability receipt is that it interacts with economic risk, in that worse economic prospects make SSDI more tempting. In Table 6 we show characteristics of the population that applies and eventually is awarded SSDI. A large portion or the applicants were separated from their last employer involuntarily, but far fewer of those who are actually awarded SSDI. The intuition is that an exogenous separation may affect a relatively healthy workers. If she is unlucky enough to stay unemployed until eligible,

it is attractive to apply because the cost of application is relatively low and the distribution of reemployment wages are somewhat averse. However, because acceptance criteria condition on health, they are less well represented among total awards. In the next two rows of Table 6, we see that applications and awards go to workers in the bottom of the income distribution. Very few have had life-time incomes, measured by AIME, in the top half. About $\frac{4}{5}$ had wages in the bottom quintile prior to displacement.

We also capture, roughly speaking the age profile of SSDI receipt. Older workers are more likely to receive SSDI both because of their increasing willingness to apply and because of they are increasingly likely to receive SSDI. Purely mechanically, older worker’s state evolves in a way to increase the attractiveness of SSDI. Over time, their health deteriorates and the age-profile of wages increases their AIME and hence the benefits they will receive. Because SSDI is an absorbing state, the young are also relatively less likely to apply because of the option value of working in the future. For young workers facing temporarily averse circumstances, they will often chose not to apply because when α reverts they will want to work again. Older workers do not feel this motive. Figure 10 shows the model-generated age profile next to that in the data, both in 2010.

Recall, from Figure 7 that the latent value of application was not monotone in age because, at a given state, the peaking of the earnings profile may make work more attractive. However, health deteriorates monotonically with age and as seen from 6, health is the largest determinant of the value of application. The transition rates for d are crucial for getting correct that age-SSDI profile.

Turning to Table 7, we see that recessions increase the number of “incidental” applicants from those exogenously separated. This is not surprising, given that recessions increase the number of exogenous separations and also make the probability of exiting unemployment

less likely. The application rate goes up in general, but the profile of applicants stays largely the same, though becoming slightly more affluent.

Indeed, SSDI is surprisingly insensitive to business-cycle conditions. It is, however, quite responsive to long-term changes affecting an occupation. To illustrate this point, we estimate a Logit within our model

$$Pr[DI] || Pr[Apply] = f(\beta_z \log z_{j,t} + \beta_u u_t + \beta_s \mathbb{I}_{sep} + \sum_d \mathbb{I}_d) . \quad (6.1)$$

On the left-hand side we have either disability receipt or disability application. Because applications may be lagged because of eligibility requirements and disability may be lagged by the application time, we measure both a year forward. On the right-hand side, we include the occupation's wage trend component, $z_{j,t}$, the aggregate unemployment rate u_t and an indicator for whether the individual was separated exogenously $\mathbb{I}_{sep}$. We also include dummies for the health level d .

Table 8 gives the estimates from the regression in Equation 6.1, with the elasticities listed in percentage. The application probability is very slightly counter-cyclical, but only if we do not control for the individual unemployment status. To the extent that high unemployment rates increase the probability of an individual becoming unemployed, they increase the probability of applying for disability. But, once we condition on whether the worker was unemployed herself, this small effect from the aggregate goes away.

The long-term effects from wage trends, $z_{j,t}$, are strongly linked to disability receipt and, even more strongly to applications. Bad prospects for one's occupation bring in more applicants. To the extent that these applicants are in better health than those applying purely for health reasons, we would expect applications to be less likely to result in receipt.

This difference in composition along with the delay between application and receipt result in SSDI being less sensitive to $z_{j,t}$ than is application.

6.1 Components of the Rise

In this section, we use the model to try to understand the mechanisms behind the rise in SSDI. The model allows us to isolate different factors that potentially played into the rise in SSDI since the early 1980's. By constraining wage or health risks to be uniform across this period, we can create counter-factual SSDI paths. We will see that both contribute meaningfully: constraining wage trends knocks the rise in SSDI down by 25% whereas keeping health constant across occupations takes away about $\frac{1}{2}$ of the rise over this period. To interpret these, when we constrain health, we are saying that wage trends and aging alone can generate half of the trend.

To understand the rise in SSDI, we begin with the state matching as closely as possible the US in 1980-1985. Particularly, we set the distribution of occupation, age and health groups. We cannot see the asset or AIME distributions in this period, though both will factor into the application decision. Instead, when we create agents at the beginning of the simulation, we will draw assets and AIME from ergodic distributions of these distributions. ν is left without an obvious empirical counter-part and so we chose it to get the overall rate of SSDI applications correct. In every subsequent period, we match exactly the fraction of new entrants who chose each occupation. This ensures that we have the right number of workers exposed to the occupation-specific risks throughout the transition.

Figure 11 shows the model's success in matching the rise in SSDI over the period since 1985. In general, it gets the magnitude correct but misses many of the smaller features. For instance, just before the Great Recession the model predicts a period of very slow SSDI

growth that was not also observed in the data. The model also shows visual upticks in SSDI in each recession though the data is relatively smooth in the every recession except the most recent Great Recession.

Within the model, we can isolate the forces driving the rise by holding constant either wages or health risk. Two linked narratives may drive the rise. In one, some occupations carry more health risks than others and as the population in these occupations ages they are likely to move into SSDI to exit the labor force. In the other, long-term wage trends have diminished the value of work in some occupations, making SSDI relatively attractive. The narratives are linked because many of the occupations that have high health risks have also experienced long-term declines in their economic prospects.

In Table 9 we “turn off” occupation-specific differences in health risk, occupation-specific differences in the wage trend and demographic changes. In the first experiment, we make the probability of health deterioration in all occupations equal to the mean. This affects particularly the high-risk occupations in the tail of the risk distribution (recall Figure 9). In the next we set all wage trends to zero so that the only economic risks are the idiosyncratic innovations on wages and cyclical unemployment risk. This takes the tangle of trend lines from Figure 8 and sets them all flat. To create the Shapley-Owen decomposition, we perform each experiment, comparing the SSDI rate to the the baseline with all of the driving forces. We then compute the SSDI level with only one of the driving forces and then contribution to the SSDI rate associated with one additional driving force if only one other is in play. We average each measure of the contribution.

The column labeled $\pi_{j,\tau} = \pi_\tau$ labels the differential health risk across occupations, j . We are collapsing each $\pi_{j,\tau} = \pi_\tau$ to a simple, age-based health transition matrix. In the column $z_j = 0$ we have set all of the long-term economic shocks to 0. $\Pr[\tau|t] = \Pr[\tau]$ refers

to changes in the age structure.

The model accounts for a 1.4 percentage point rise, 63% of the total rise during that period. This is the result of many known drivers that we did not model, e.g. changes in mental health qualification, female eligibility, and also potential differences in tastes and preferences. However, it is incorrect to say that these omitted factors contribute 37% because if they were included they would interact non-linearly with the factors we included, just as they did with each other.

Separating the forces, notice the large role that demographics play. This is in part due to its interactions with the other forces: aging brings with it worse health and greater sensitivity to health shocks. Hence, the insights of the model allow us to attribute more to demographic change than would be seen with a purely statistical decomposition. Furthermore, both economic shocks and differential health risks are important drivers. The relatively large role of differential health risk is particularly interesting, because it suggests that the tail of the distribution is particularly important: Disability risk is spread unevenly and those who are particularly susceptible are particularly important to its rise.

7 Forecasts

TBA

8 Conclusion

TBA

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9 Figures

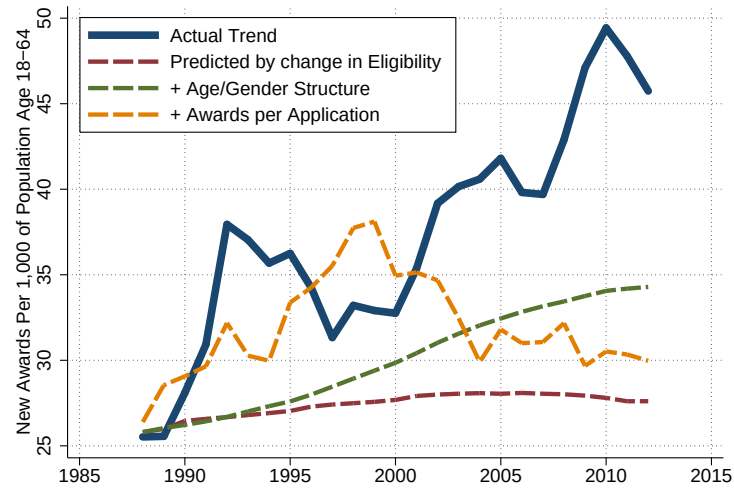


Figure 1: New Awards as predicted by Changing Demographics. (See extended appendix for details)

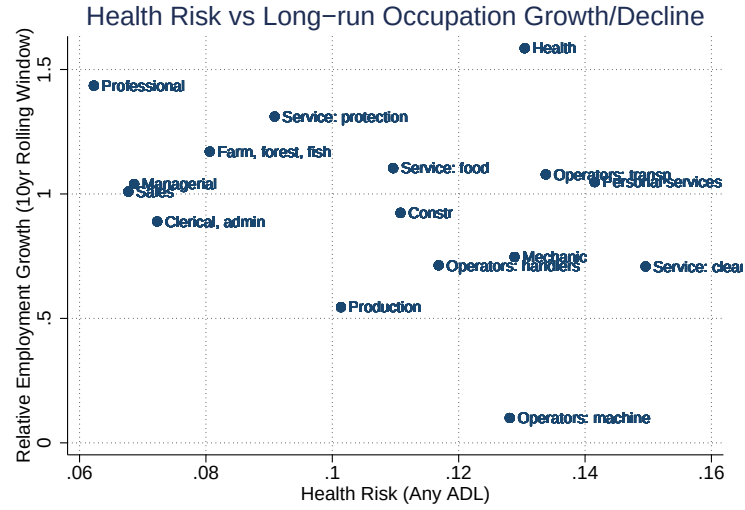


Figure 2: The correlation between health risk and long-run job growth.

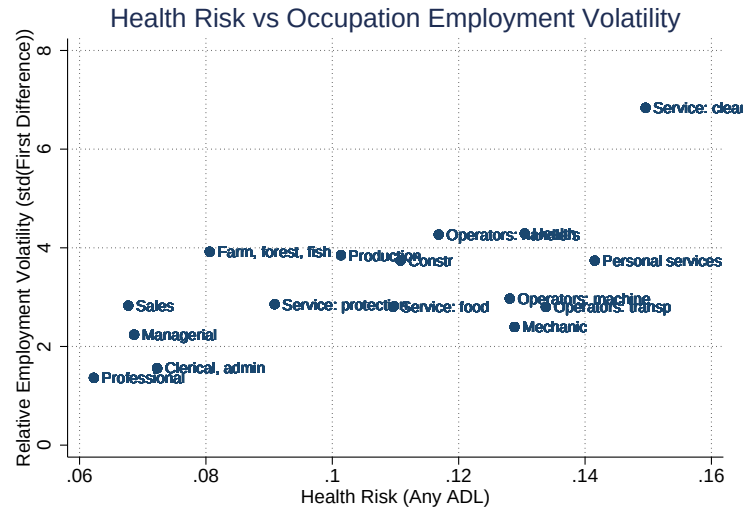


Figure 3: The density across occupations of the incidence of difficulties with ADLs

Table 1: Occupational Bundling of Health and Economic Risks

Occupation	Health Risk	Empl. share 2006	Trough vs. 2006	2014 vs. 2006
Professional	0.062	21.0%	0.0 %	+14.7%
Sales	0.068	10.3 %	-10.3 %	-0.9 %
Managerial	0.069	15.0%	0.0 %	+12.8%
Clerical, admin	0.072	15.3%	-6.2%	-5.8%
Farm, fish, forest	0.080	6.5%	0.0 %	+14.8%
Service: protect	0.091	2.5%	0.0 %	+5.4%
Precision production	0.101	1.9%	-8.6%	-9.4%
Service: food	0.110	4.0%	0.0 %	+5.2%
Construction/extractors	0.111	4.7%	-33.0%	-28.8%
Operators: handlers	0.117	3.2%	-21.5%	+0.1%
Operators: machine	0.128	5.4%	-27.8%	-12.2%
Mechanics	0.129	4.1%	-10.4%	-4.6%
Service: health	0.130	2.6%	0.0 %	+21.0%
Operators: transport	0.134	4.5%	-13.3%	-5.1%
Service: personal	0.142	4.0%	-4.4%	+1.0%
Service: clean/maint	0.150	8.5%	-13.4 %	+9.3%

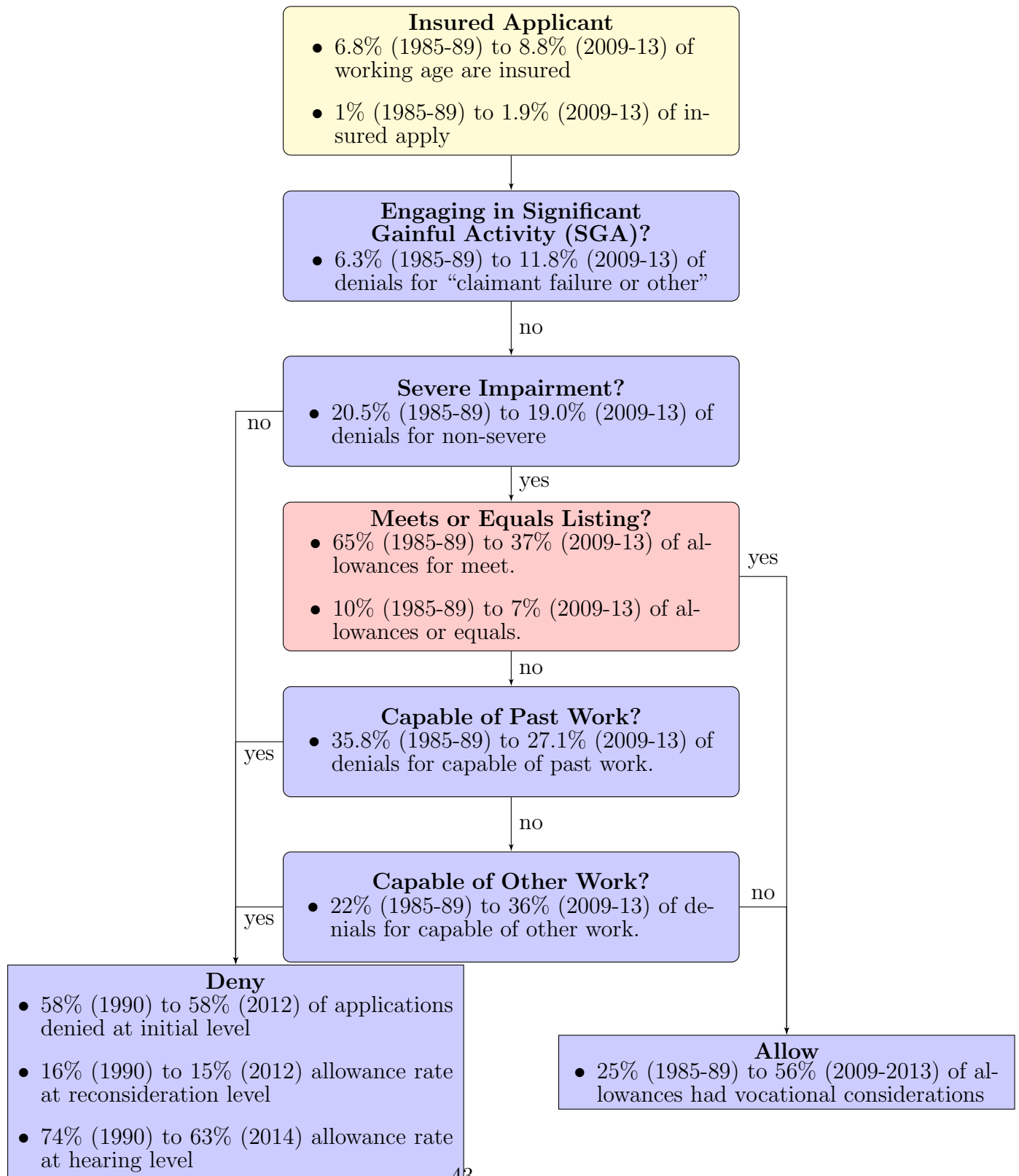


Figure 4: Initial decision process. Allowances from the red step “Meets or Equals the Listing” do not consider ability to work, all other steps do.

Table 2: SSA Decision Process Details

Factor	Description
<i>Substantial Gainful Activity (SGA)</i>	Max monthly earnings • ex: \$1,200 in 2012 • aligned with SSA <i>work oriented</i> notion of disability.
<i>Severe Impairment</i>	Medically determined to limit work. • Combination of non-severe impairments may be deemed severe.
<i>SSA's Listing of Impairments</i>	• Can be mental and/or physical. Medical conditions with objective tests. • "meets" if is on the list • "equals" if limitation is equal to a listed impairment • result in award without considering vocational factors.
<i>Residual Functioning Capacity</i>	Tasks capable of despite impairments. • ex: walking, standing, lifting.
<i>Past/Usual Work</i>	• ex: understand, remember, and carry out instruction. Significant work in past 15 years • Does not consider additional vocational factors: age, education, etc.

Table 3: Condensed Vocational Grid- Capability for Unskilled, Sedentary Work

Age	Education	Work Experience	Decision
50+	less than High School	Unskilled	Disabled
	less than High School	Skilled, not transferable	Disabled
	less than High School	Skilled, transferable	Not Disabled
	High School or more	Unskilled	Disabled
	High School or more	Skilled, not transferable	Disabled
	High School or more	Skilled, transferable	Not Disabled
45-49	illiterate/no English	Unskilled	Disabled
	less than High School	Any	Not Disabled
	High School or more	Any	Not Disabled
18-44	Any	Any	Not Disabled

Full grid: Appendix 2 to Subpart P of Part 404 of Code of Federal Regulations
“Individuals approaching advanced age (age 50-54) may be significantly limited in vocational adaptability if they are restricted to sedentary work.”

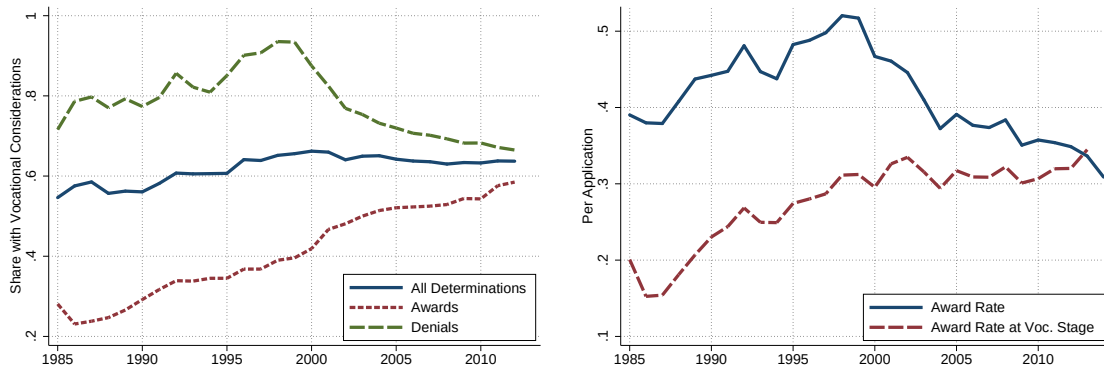


Figure 5: Role of Vocational Considerations in SSDI Trends)

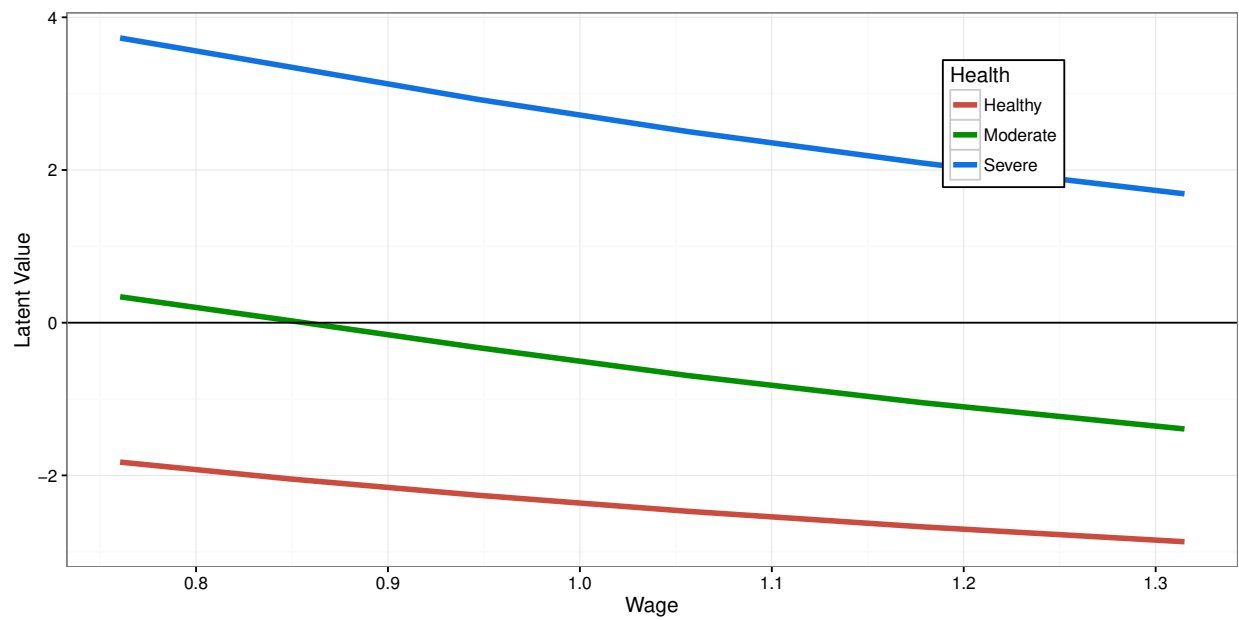


Figure 6: Latent value of disability application, all but health & income constant

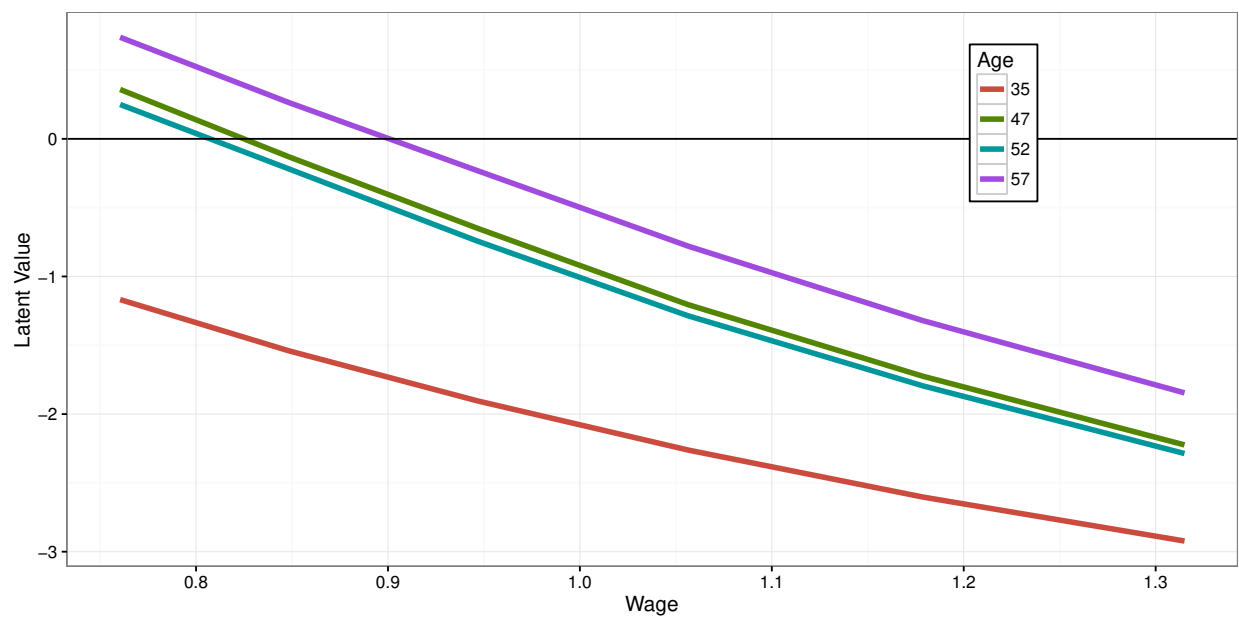


Figure 7: Latent value of disability application, all but age & income constant

Table 4: Wage Equation Estimation

Variable	Employment equation	Wage w/out selection	Wage w/ selection
Severe Limitation (t)	-0.107** 0.011	-0.219** 0.062	-0.358** 0.086
Moderate Limitation (t)	-0.319** 0.015	-0.134** 0.028	-0.164** 0.041
First dif Occ Employment	-0.267 0.169		
Fifth dif Occ Employment	0.244** 0.072		
Mills Ratio			0.113** 0.046
N	16,931	13,884	13,884

Standard errors in parentheses.

**Denotes statistical significance at the 1%level.

*Denotes statistical significance at the 5%level.

Probit results reported as Marginal Effects

See appendix for additional controls in each regression.

Table 5: Health Transition Hazard (Cox Regression)

Variable	$P(d' = 1 d = 0)$	$P(d' = 0 d = 1)$	$P(d' = 2 d = 1)$	$P(d' = 2 d = 0)$
Base	0.074 0.048	0.587 0.326	0.014 0.008	0.02 0.012
Age 45-55	1.150** 0.066	0.536* 0.202	1.309** 0.104	1.481** 0.160
Age 56-60	1.386** 0.106	0.306** 0.129	2.092** 0.194	1.980** 0.277
Age 61-65	2.023** 0.144	0.253** 0.135	2.262** 0.225	1.980** 0.307
Occupation Risk	2.537** 0.186	0.915 0.692	5.700** 0.588	3.797** 0.558

Standard errors in parentheses.

**Denotes statistical significance at the 1%level.

*Denotes statistical significance at the 10%level.

	% of Applicants	% of Awards
Exogenous Separation	69.3	44.1
AIME > Median	19.2	20.1
Wage < 20 pctl	81.2	83.4

Table 6

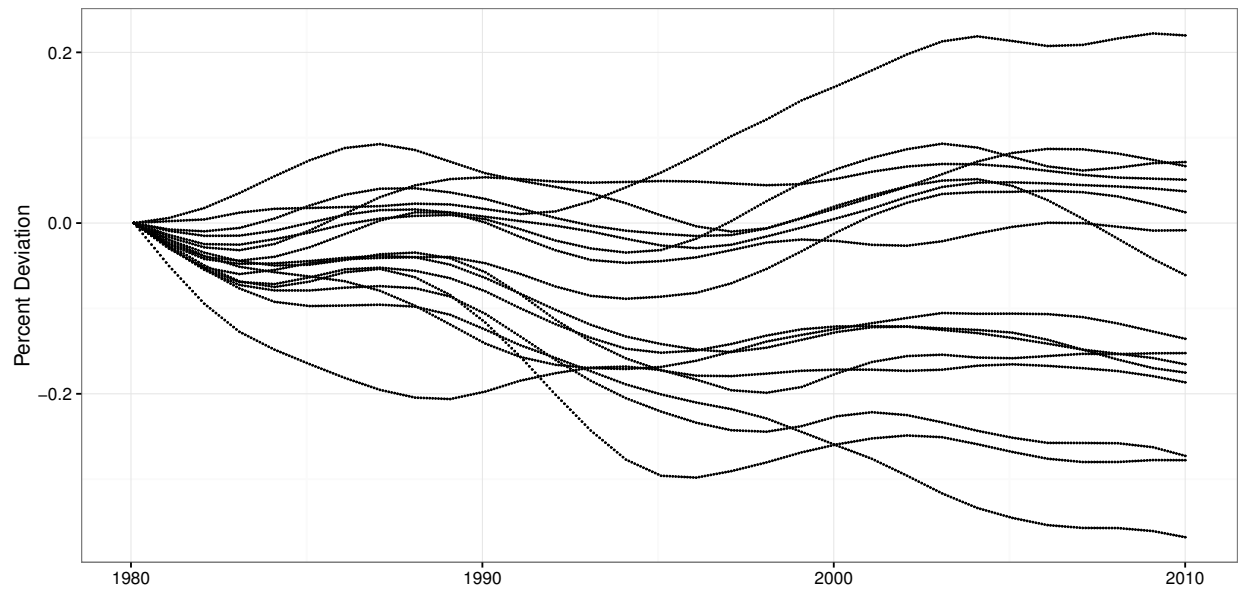


Figure 8: Occupations' wage trends

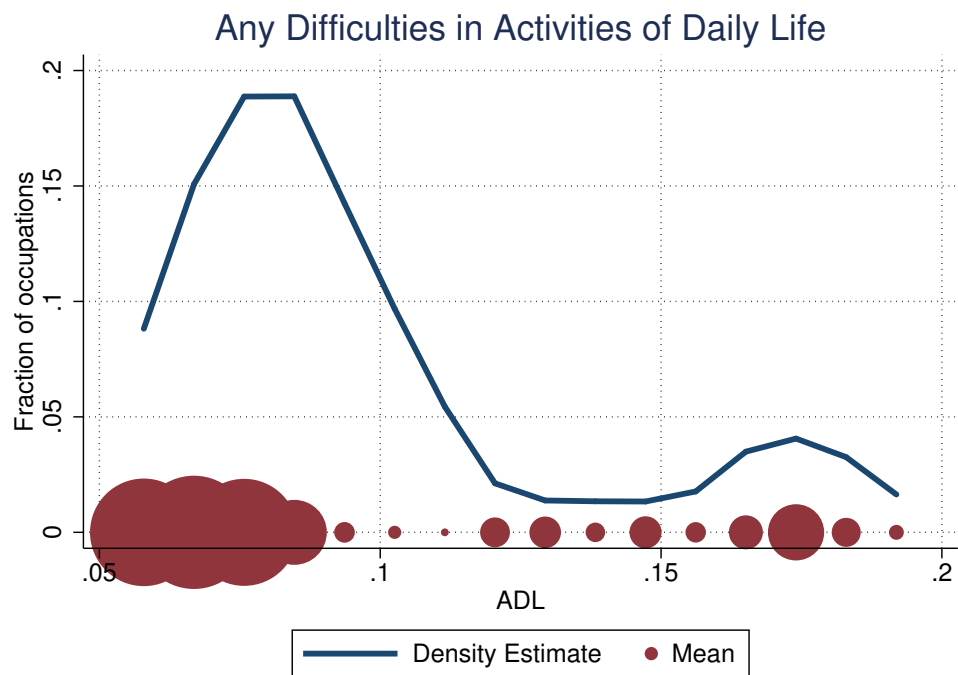


Figure 9: Occupations' mean health-risk

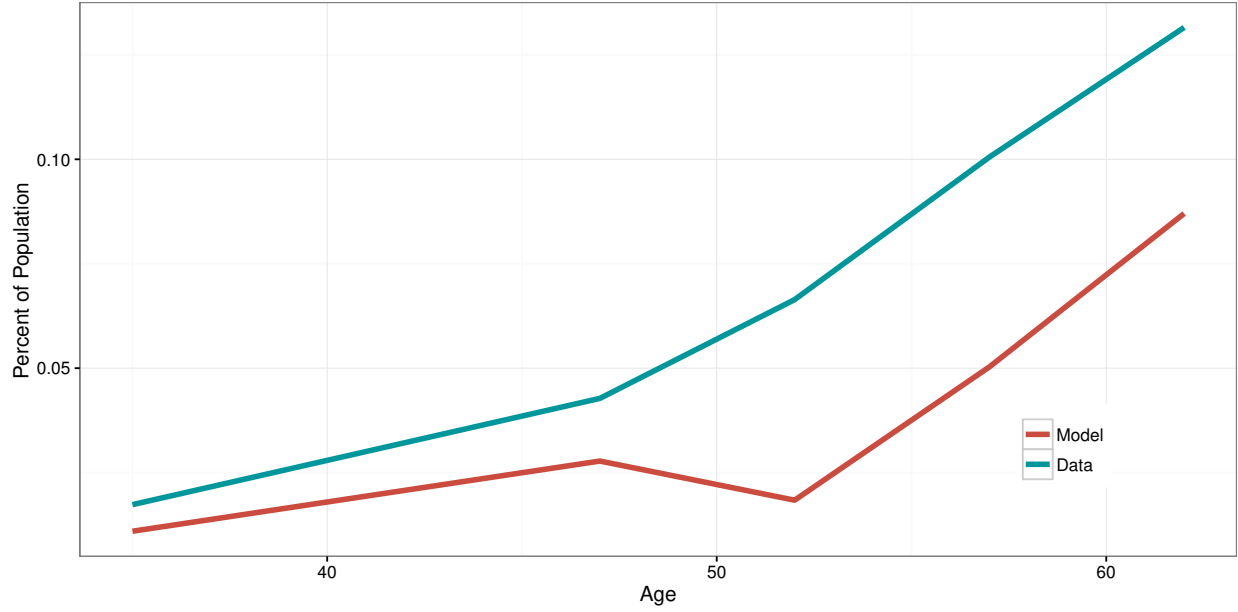


Figure 10: The fraction of eligible population on SSDI in 2010

	% in Recession	% in Expansion
Exogenous Separation	70.6	67.9
AIME > Median	19.1	19.6
Wage < 20 pctl	81.2	81.6
Application Rate	1.56	1.23

Table 7

	DI	Apply	Apply
z_j	-9.4	-36.0	-35.7
u_t	0.1	0.1	0.0
$\mathbb{I}_{sep}$	3.7		12.1

Table 8: Elasticity implied by coefficients (percent)

	Baseline	$\pi_{j,\tau} = \pi_\tau$	$z_j = 0$	$\Pr[\tau t] = \Pr[\tau]$
Total Rise in DI	1.40 pp	0.70 pp	1.05 pp	0.83 pp
1980 - 1990	0.27 pp	0.28 pp	0.26 pp	0.24 pp
1990 - 2010	1.13 pp	0.43 pp	0.79 pp	0.59 pp
Shapely-Owen		32%	22%	46%

Table 9: Demographics are most important driver. Scenarios differ most in the 1990-2010 period. $\pi_{j,\tau} = \pi_\tau$ labels the differential health risk across occupations, j . $z_j = 0$ is long-term economic shocks and $\Pr[\tau|t] = \Pr[\tau]$ refers to changes in the age structure.

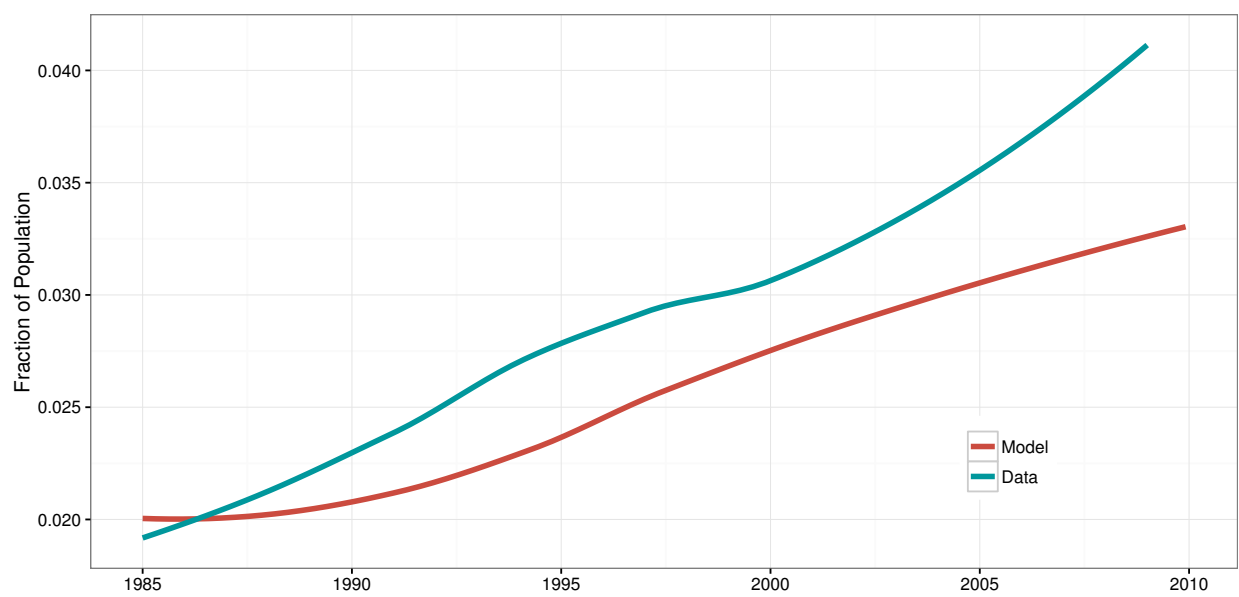


Figure 11: The fraction of 25-64 on SSDI