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

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Abstract

We study the interaction between economic conditions and health on an individuals' decision to apply for Social Security Disability Insurance (SSDI). Within our quantitative framework, we allow these factors to be correlated: there are multiple sectors that differentially expose workers to health and economic risks. These forces interact in the household's decision and also within the SSDI institutions because acceptance criteria consider workers' economic conditions. We use the calibrated model to decompose the rise in SSDI after 1980 into changes in institutions, economic conditions, and the composition of workers of different ages, health, and occupation. With this structural model, we compute counterfactual employment rates and projections for the future.

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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 force[1]. This expansion occurred at a time when rules of the program remained virtually unchanged. Further, the magnitude of the expansion is much higher than can be attributed to obvious factors: expanded eligibility for benefits resulting from increased female participation and the aging of the baby-boom cohort. On the other hand, earlier empirical work has suggested that worsening economic conditions for low-skilled workers accounts contributed to this trend (e.g. Autor et al. (2013) and Duggan et al. (2006)). However, it is important to sort out quantitatively the impact of economic conditions by identifying specific types of changes and channels through which they affected SSDI. Does it matter who was affected? What is the role of the business cycle versus structural decline? Answering these question provides insight as to whether improvements in economic conditions could reverse past trends or if SSDI rolls will continue to grow.

In this paper, we consider how economic forces, demographic forces, and their *interaction* affect SSDI claims. While economic conditions are changing the value of remaining in the labor force, a worker's response also depends upon his health and demographics. We would expect a greater response from those already on the margin of participation: older workers and those in poor health. Yet, economic and health prospects are not unrelated: one's occupation is an important determinant of both. Therefore, it is not clear cut to assign blame for changes in the SSDI rolls to economic conditions or demographics: the pain a worker is willing to tolerate to continue to work is different in recessions than in booms.

[1]Sources: SSA and BLS (CPS) estimates.

The aggregate implications of these choices boils down to the quantitative question: how sensitive to economic forces is the decision to apply for SSDI for workers of different health at different stages of life? In other words, how do workers consider the disability option?

We put structure around individuals' SSDI 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 bring to this model individual-level microdata over the period in which SSDI was rising most steeply. We infer from individuals' lifetime occupational histories a portion of the health risks they have faced and the economic risks associated with their occupational skill set. We connect these risks to worker's labor-force participation decisions. This reveals how realized health and economic status—along with future prospectives for them—affect the labor supply trade-off. 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.

There is ample evidence that SSDI interacts with economic conditions, the literature on which we summarize below. We add to this literature evidence that averse macroeconomic trends have affected disproportionately workers already on the margin of the SSDI decision: older workers of poor health. For example, workers in production occupations are disproportionately older, have skills that are increasingly obsolete, and have deteriorated physical health from a life-time of labor in their trade. However, there are sizable exceptions, such as health service occupations, that also take a large toll on workers' health but have expanded steadily over the past decades. This variation is useful for identification. If these exceptions have different disability outcomes, we can address whether the increase in SSDI was a one-off

confluence of particular factors or whether high enrolment will be sustained in the future.

To make such projections and understand the developments thus far, we build into an overlapping generations model our theory of how individuals' occupation history affects their SSDI choice. It features multiple occupations each with differential health risks, sensitivity to the business cycle, and long run structural paths. The upshot is that disability is not just a constant random risk; rather, a worker's choice to apply to SSDI is affected by economic shocks. The logic is that longterm health problems may make many workers potential applicants to SSDI, but when the value of working is high, they will not apply. However, facing an averse economic shock, particularly a long lasting one, they may find SSDI a better option than to wait for it to revert. To have a good quantitative measure of these incentives, we incorporate both the cyclical and long-run prospects of various occupational skill sets. Age is another important factor. Older workers are more likely to have health problems and they have a shorter time horizon before retirement. Entering SSDI and cutting working life short is less costly the older the worker is. Finally, economic conditions interact with age to provide evolving demographics of past occupational exposure to health deterioration and occupational skill sets of the cohorts in the economy.

Throughout our analysis, we take care to incorporate realistic program rules. In particular, some SSDI program rules interact with the economic margin in our analysis. As we will discuss further, the acceptance criteria is designed to be more lenient to older workers and for those whose skills have become obsolete. On the other hand, strong economic factors would dissuade workers with strong economic prospects from applying, such as the requirement that a worker be nonemployed for 5 months prior to application and the modest benefit rate that is a redistributive function of past wages. These rules have an important effect on how workers application decision interacts with economic shocks.

The rest of the paper is organized as follows. In the next section we review some of the literature and then in Section 3 we present some motivational evidence. 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.[2] Our paper belongs to the second literature. We first review the relation to this literature and provide evidence supporting our contribution from the former reduced-form 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 a different factor. 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. Our paper focuses on the correlation between the health and economic risks individuals face and how the SSDI acceptance criteria consider health and

[2]There 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.

economic prospects jointly. Our main question also differs in that it is not normative; we do not consider what the program should look like. Instead use the model to measure the role Macroeconomic factors have played in the rise of DI enrollment and consider counterfactual scenarios.

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 a novel way of modelling short versus long-term unemployment to better capture the importance of the persistence of economic shocks for SSDI. We allow agents some control over their health and economic risks through occupational choice. Finally, we also are the first, that we are aware of, to examine a non-stationary environment.

Empirical Studies Connecting SSDI and the Macroeconomy Several reduced form papers have studied the relationship between Macroeconomic factors and SSDI applications or enrollment. One causal hypothesis is that changes in the Macroeconomy changes SSDI application incentives. A notable study is Duggan et al. (2006) who examine trends in SSDI and the Macroeconomy since 1980. They claim that the rise in SSDI benefits relative to falling wage prospects 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. They find that permanent structural decline has greater impact that transitory shocks. The intuitive result that persistence matters motivates our choice to include both types of shocks in the

model. We take the question one step further by how much the magnitudes of these findings depend on how these shocks affect the occupational structure of the economy and differential exposure of individuals in each occupation to health risks putting them on the margin of DI.

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.[3] 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.[4] The structural model allows us to look deeper into this behavior to uncover whether those who return to work were not truly disabled, have improved Macroeconomic conditions, or are truly disabled but choose to suffer the pain of work because of lack of other options.

3 Motivating Evidence: Economic Risk of Those on the Margin of SSDI

Poor health and old age put people on the margin of applying for SSDI. In this section we provide evidence that this group has also been particularly vulnerable to adverse Macroeconomic

[3]For 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.

[4]For 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)

outcomes. This includes both long-run declines in real wages and employment prospects as well as cyclical volatility of the two. These facts motivate our analysis because they suggest the SSDI application rate has been more responsive to Macroeconomic conditions over the past 20 years as a consequence of unique demographic and structural factors.

We use two sources of variation to identify the correlation between the health and economic risks people face: occupations and geography.

3.1 Occupational Bundling of Health and Economic Risks.

In a previous paper, we showed life-time occupational exposure accounts for 42% of the variation in poor health outcomes leading to work limitations and SSDI enrollment (Michaud and Wiczer (2014)). We did this using various metrics of health outcomes and occupational exposure for individuals in the Health and Retirement Survey (HRS).[5] For the present analysis, we link health risk to 16 broad occupational categories using our preferred measure from the HRS: proportion of workers aged x-x who list that occupation as their longest held and experience a difficulty in an Activity of Daily Living (ADL).[6] 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.[7] Our measure of structural decline is a 10-year rolling window (reported statistics correspond

[5] We showed robustness to various measures of outcomes: any difficulty in activities of daily living (ADL), number of ADLs, any work limitation, self-rated health, SSDI enrollment; and measures of occupational exposure: longest held occupation, restricting the sample to those with an occupation more than 10 years, and instrumenting for occupation with place of birth. See the manuscript for further details.

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

[7] We 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.

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

Figure 1 shows the correlation of health risk and long-run employment growth by occupation.[8] Figure 2 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.[9] Occupations with low health risks (Figure 1) 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 2) 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.[10] 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

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

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

[10] Full time series show in extended appendix.

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

3.2 Geographic Concentration of Poor Health, Bad Job Prospects, and SSDI Claims.

Geographic variability in SSDI claimants provides further evidence for the role of correlated risks and demographics. Table ?? provides data for the states with the highest and lowest SSDI beneficiary rate. High SSDI incidence is associated with various combinations of aged demographics, high non-employment, and objectively measured poor health outcomes. For example, Kentucky and Alabama are in the top decile of states for cancer and heart disease deaths per capita. Alabama also has poor health outcomes, but has an even worse economic climate with low employment and many blue collar jobs. Maine's case, on the other hand, seems particularly driven by its aging demographics. Converse patterns emerge for the states with the lowest SSDI rates. One commonality between the two groups is the median benefit which does not differ substantially.

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 $\tau \in \{0, 1, 2...T\}$. 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 $j \in \{1, 2...J\}$. They then draw a permanent δ^i related to their personal health deterioration risk and an initial α^i, an idiosyncratic wage component. The characteristic δ^i is drawn from an occupation-specific distribution $G_j(\delta)$. The initial α^i is drawn independently from an identical distribution F_α. Each subsequent period of $\tau \in \{1, 2...T-1\}$ 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 Wages

Wages are exogenous. They depend on agents' idiosyncratic component α^i, their current age τ and extent of disabilities d, as well as a current occupation-wide productivity z^j and their sensitivity to it, β^i. The full specification is:

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

Movements in z^j will provide agents macroeconomic-related pecuniary motives to file for disability. Wages are assumed to be non-increasing in d. This 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^i, β^i provide variation in wages and the SSDI application decision 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. Whereas β^i is a fixed characteristic over time, α^i evolves stochastically.

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: $\Pi_\tau(d, d'; \delta^i)$, where δ^i is an individual-specific parameter of the transition probabilities. Disability states are ordinal: an agent of $d = 2$ is considered to be of worse health than and 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, respectively[11] 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 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.[12] An agent's DI application is accepted with probability $\xi(d)$, assumed to be non-decreasing in the agent's disability extent d. 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.

[11] Some 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.

[12] SSDI 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. (2013) who find cyclical UI extensions have no significant effect on the timing or level of SSDI applications.

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 $\beta \in (0,1)$.

4.6 Agents' Decisions

We define the problems agents face, recursively, yielding a set of value functions: working agent $V^W_{j,\tau}(a,e,d,z)$, unemployed $V^U_{j,\tau}(a,e,d,z)$, long-term unemployed $V^N_{j,\tau}(a,e,d,z)$, disability beneficiary $V^D_{j,\tau}(a,e,d)$, and retiree $V^R_{j,\tau}(a,e,d)$. 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.

$$V^R(d,e,a) = \max_{c,a} u^N(c,d) + \beta\phi_T V^R(d,e,a')$$
$$\text{st} \quad c + a' \leq SSI(e) + Ra \qquad a' \geq 0$$

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.

$$V^D_\tau(d,e,a) = \max_{c,a} u^N(c,d) + \beta \sum_{\tau'} [\phi(\tau,\tau')V^D_{\tau'}(d,e,a')]$$
$$\text{st} \quad c + a' \leq SSDI(e) + Ra \qquad a' \geq 0$$
$$V^D_{\tau'}(d,e,a) = V^R(d,e,a) \text{ if } \tau' = T$$

The Decision to Work An agent who is neither retired nor disabled has the choice of working or rest unemployment each period. For notational convenience, we combine the exogenously-determined idiosyncratic states into a single vector $s = (\alpha, \beta, e, d)$. The optimal choice yields value:

$$V_{j\tau}(\alpha,\beta,e,d,a;z) = \max\{V^W_{j\tau}(\alpha,\beta,e,d,a;z), V^U_{j\tau}(\alpha,\beta,e,d,a;z)\}$$

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 as summarized by value function $V(\cdot)$.

$$
\begin{aligned}
V^U_{j\tau}(\alpha,\beta,e,d,a;z) = & \max_{c,a} u^N(c,d) + \\
& \beta \sum_{\tau'} E[\phi(\tau,\tau') \int_{z'} \varphi V^N_{j\tau'}(\alpha',\beta',e',d',a';z') + (1-\varphi) V j\tau'(\alpha',\beta',e',d',a';z') \\
\text{st} \quad & c + a' \leq UI(e) + Ra \qquad a' \geq 0 \\
& e' = e, \quad d' = d \\
& \alpha' = \alpha_l \ w/\Pr \ \pi(\alpha_l|\alpha) \\
& z' = z_k \ w/\Pr \ \zeta_j(z_k|z) \ \forall z_k \in \mathcal{Z} \\
& V^N_{j\tau'}(\alpha',\beta',e',d',a';z') = V_{j\tau'}(\alpha',\beta',e',d',a';z') = V^R(d',e',a') \text{ if } \tau' = T
\end{aligned}
$$

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.

$$
\begin{aligned}
V^N_{j\tau}(\alpha,\beta,e,d,a;z) = & \max_{c,a,m} u^N(c,d) - m\nu + \\
& + \beta m \sum_{\tau'} \phi(\tau,\tau')[\xi_{d\tau} V^D_{\tau'}(\alpha',\beta',e',d',a') + (1-\xi_{d\tau}) E[V^N_{j\tau}(\alpha',\beta',e',d',a';z')] \\
& + \beta(1-m) \sum_{\tau'} \phi(\tau,\tau')[E\left[\rho V_{j\tau'}(\alpha',\beta',e',d',a';z') + (1-\rho) V^N_{j\tau'}(\alpha',\beta',e',d',a';z')\right] \\
\text{st} \quad & c + a' \leq b + Ra \qquad a' \geq 0 \qquad m \in \{0,1\} \\
& e' = e, \quad d' = d \\
& \alpha' = \alpha_l \ w/\Pr \ \pi(\alpha_l|\alpha) \\
& z' = z_k \ w/\Pr \ \zeta_j(z_k|z) \ \forall z_k \in \mathcal{Z} \\
& V^D_{\tau'}(\alpha',\beta',e',d',a') = V_{j\tau'}(\alpha',\beta',e',d',a';z') \\
& = V^N_{j\tau'}(\alpha',\beta',e',d',a';z') = V^R(e',d',a') \text{ if } \tau' = T
\end{aligned}
$$

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: $\mathbf{E}[V^N_{j\tau'}(\alpha',\beta',e',d',a';z')]$. If the agent does not apply, there is a probability ρ he or she will have the opportunity to work again next period: $\mathbf{E}[V_{j\tau'}(\alpha',\beta',e',d',a';z')]$; 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. For simplicity of notation, we combine the set of idiosyncratic exogenously determined variables into $s = (\alpha, \beta, e, d)$

$$\begin{aligned} V^W_{j\tau}(\alpha, \beta, e, d, a; z) = & \max_{c,a} u^W(c, d) + \beta \sum_{\tau} \phi(\tau, \tau') E[V_{j\tau'}(\alpha', \beta', d', e', a'; z')] \\ \text{st} \quad & c + a' \leq w_{j\tau}(d, z) + Ra \ : \ a' \geq 0 \\ & e' = H_\tau(e) \\ & \alpha' = \alpha_l \ w/ \Pr \ \pi(\alpha_l|\alpha) \\ & d' = d_i \ w/ \Pr \ \delta^i(d_i|d, \tau) \\ & z' = z_k \ w/ \Pr \ \zeta_j(z_k|z) \ \forall z_k \in \mathcal{Z} \\ & V_{j\tau'}(\alpha', \beta', e', d', a'; z') = V^R(d', e', a') \text{ if } \tau' = T \end{aligned}$$

4.7 Stationary Equilibrium

4.8 Discussion

Should I explain our assumptions about how disability vs economic conditions can affect things here? Any notes on simplifying assumptions? (ie: no health investment, death independent of health, etc.) Also that disability only evolves during work. Alternatively, should I explain this sort of stuff before the value functions and explain the tradeoffs in the decisions here? Help!

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 interest rate is set to 4% per year.

Demographics Individuals age through 5 age groups: 23-45, 46-55, 56-59, 60-62, 63+. The latter age groups are finer to allow us to test the hypothesis that individuals very close to retirement are more sensitive to the business cycle. The final age group is retirees that have health dependent mortality risks estimated from the PSID sample. The size of new entrants grows 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:

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

We choose $\theta = -0.448$ and $\eta = -0.185$ following Low et al. (2015).[13] 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.[14] We set $\gamma = 2$, within the standard range. [15] We choose β 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.

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.[16] 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.[17] Second, the applicant must have been non-employed for five months prior to application and not have earnings exceeding a low

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

[14] Or 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.

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

[16] The 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.

[17] The 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.

threshold of substantial gainful activity.[18] 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. [19] This figure 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.[20] 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

[18] $1090/month in 2015.

[19] We 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 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).

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

through our modelling 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 togo 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).

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.[21] Research examining this issue has found that SSDI screening produces high levels of both false positives and false negatives.[22] 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.[23] As a result of these complexities, even if we accept individuals reporting a severe

[21]The 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.

[22]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.

[23]The SSA has explicit guidelines. They construct a determination "grid" that lists extent of work limi-

work limitation as meeting the SSDI criteria, we do not set their acceptance probability to one. Instead, we appeal to a study of **?**. 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 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 Macroeconomic 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. [24] 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.

tation, 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.

[24] We 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.

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:[25]

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

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.[26] 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

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

[26] This 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.

updated for the last two age groups if it provides an increase.

$$e' = \begin{cases} e \times (1 - \frac{2}{10\times12}) + w\frac{2}{10\times12} & e < \text{age 25-45} \\ e \times (1 - \frac{6}{5\times30\times12}) + w\frac{6}{5\times30\times12} & e < \text{age 46-55} \\ \max\{e, e \times (1 - \frac{35}{32.5\times35\times12}) + w\frac{35}{32.5\times35\times12}\} & e < \text{age 56-59} \\ \max\{e, e \times (1 - \frac{40}{35\times40\times12}) + w\frac{40}{35\times40\times12}\} & e < \text{age 60-62} \end{cases}$$

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.[27] These workers would be eligible for UI.[28] 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.

[27] Indeed, 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.

[28] For 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.

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.[29] 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.[30] 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 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.[31] To

[29]The 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.

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

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

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 occupation[32] Additional regressors include dummies for age, education, and race.

Results in Table 3 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 employment 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 3, the coefficient on the Mills ratio is positive in the wage regression, confirming our conjecture that selection biases wages upwards.[33] Omitting the selection correction also biases the effect of poor health on wages significantly towards zero for severe limitations.[34]

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

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

[34]There 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

The idiosyncratic component α^i is persistent. With probability ρ_α it remains unchanged. Otherwise a new value is drawn from the log-normal distribution. One reason workers enter unemployment is if they have a low α^i realization that does not compensate for the disutility of work. The variance of α^i is chosen such that the model provides an average unemployment rate of 5%.

The occupation specific component z_j will be discussed in paragraph on Macroeonomic 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:

$$\begin{pmatrix} 1-\pi_0 e^{\phi_{0\tau}+\delta} & \pi_0 e^{\phi_{0\tau}\tau+\delta} & 0 \\ \pi_{10} e^{\phi_{10\tau}+\delta} & 1-\pi_1 e^{\phi_{1\tau}+\delta} - \pi_{10} e^{\phi_{10\tau}\tau+\delta} & \pi_1 e^{\phi_{1\tau}+\delta} \\ 0 & 0 & 1 \end{pmatrix}$$

The variables π_d are the baseline transition risks. They are equal to the mean transition probability after removing age and occupation-related risks. The impact of age on health is the same for all workers and given by ϕ_τ. Finally, δ is the individual's health risk, which is related to their occupation.

without a severe limitation today who have a severe work limitation in the following year work today).

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.[35] 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.[36] The results are presented in 4. The variance of disability risk distributions are constant across occupations.

Macroeconomic Risks Macroeconomic risks in the model are provided through the occupation-specific component of wages: z_j. However, because of issues dealing with selection highlighted in our wage regression analysis, we do not target wages to uncover the process for z_j. We instead target employment statistics given that the employment decision is driven by wage dynamics in the model.

For each occupation, z_j follows a four-state Markov process. The first two states represent a steady state of the 1980s. The latter two states represent a steady state post 2000. Fluctuations between states one and two, and between three and four, provide business cycle dynamics within these steady states. Transition between states 1/2 to states 3/4 is

[35] We 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.

[36] We exclude workers whose longest held occupation duration is less than 8 years.

interpreted as structural change. The complete Markov matrix is explicitly written as:

$$\begin{pmatrix} z \setminus z' & z_{j1} & z_{j2} & z_{j3} & z_{j4} \\ z_{j1} & \pi_{11} & \pi_{12} & \pi_{j13} & 0 \\ z_{j2} & \pi_{21} & \pi_{22} & 0 & \pi_{j24} \\ z_{j3} & 0 & 0 & \pi_{33} & \pi_{34} \\ z_{j4} & 0 & 0 & \pi_{43} & \pi_{44} \end{pmatrix}$$

The business-cycle component of risk is correlated across occupations.[37] All occupations have the same probability of experiencing a recession π_{12} or π_{34} and recovery π_{21} or π_{43}. These values are chosen to match the incidence and duration of NBER dated business cycles from 1980-2015. However, the magnitude of the impact of the recession z_{j2}/z_{j1} or z_{j4}/z_{j3} is occupation specific. The ratios z_{j2}/z_{j1} and z_{j4}/z_{j3} will be chosen to target the cyclical volatility of employment in each occupation for the 1980's and Great Recessions, respectively.

Structural change is captured by the transition between the first two and latter two states. The relative value of z_{j1} and z_{j3} will determine whether the occupation is in long-run decline or expansion. The probabilities of structural change, π_{j13} and π_{j24}, are occupation specific. They are important because they govern expectations surrounding the speed at which structural change occurs and whether it occurs more rapidly during a recession.[38] These expectations affect behavior even before the shock is realized. We use variation in the behavior of the young and the old to identify these beliefs versus actual realizations. In the model, entry of young into an occupation is more sensitive to expectations of long-run

[37] This is virtually a tautology.

[38] It has been documented that manufacturing employment follows a "step" pattern: flat during expansions and sharp declines without recovery during recessions. Health related employment, on the other hand, shows acyclical sustained long-run growth.

decline while the old react primarily to realizations. Therefore, identification of expectations versus realizations comes from separately targeting changes in occupational composition of the young and occupational composition of the old. z_{j1} is restricted to be common across occupations (as a normalization) and the additional target is the aggregate employment to population ratio of the 1980s.

5.3 Parameter Choice and Calibration

In total, we need to estimate technologies $g(\tau)$,$\{\xi_0, \xi_1, \xi_2\}$, $\phi_0, \phi_1, \pi_0, \pi_1$, preference parameters $\nu, \eta, \theta, \gamma$ and distribution parameters $\{\lambda_{\delta,j}\}$,$\rho_\alpha, \mu_\alpha, \sigma_\alpha$,$\sigma_{\upsilon,j}$,$\kappa_\rho, \kappa_{\rho,\lambda}, \kappa_\sigma, \kappa_{\sigma,\lambda}, \sigma_\varpi$. We will estimate the model in segments.

First, we create a measure of health status from which we can directly estimate transition probabilities $\{\xi_0, \xi_1, \xi_2\}$ and the distribution parameters $\{\lambda_{\delta,j}\}$.

Then we will estimate a probit for participation:

$$Pr[particpate] = \sum_{\tau} \beta^p_\tau \mathbb{I}_\tau + \sum_{d} \beta^p_d \mathbb{I}_d + \sum_{j,t} \beta^p_{j,t} \mathbb{I}_{j,t} + \sum_{j,t} \beta^p_{j,t+1} \mathbb{I}_{j,t+1} + u$$

Using this, we will perform a wage regression in which the inverse Mills ratio from the previous regression corrects for the omitted variable bias associated with the endogenous selection.

$$w = \sum_{\tau} \beta^w_\tau \mathbb{I}_\tau + \sum_{d} \beta^w_d \mathbb{I}_d + \sum_{j,t} \beta^w_{j,t} \mathbb{I}_{j,t} + +e$$

For identification we need more terms in the selection model than in the wage model. This is where the occupation-time lead effects are particularly useful and they also meaningfully contribute to participation but not contemporaneous wages. If we could observe them in

data, leads of individual health would also be useful.

Clearly, we can't fit all of the occupation-time effects exactly because the sequence of shock realizations will not be the same in the model as the data. Instead, we will fit joint distribution statistics of the parameters $\{\beta^p_{j,t}\}$

6 Risky Occupations and the Rise in Disability Insurance

In this section, we use our model to measure the contribution of several factors to the rise in DI application rates from 1985-2005. As in previous studies, we consider: (i) changes in the DI system, (ii) long-run changes in real wages, and (iii) demographics. What is unique to our study is that we consider how the variation in long-run changes in real wages across occupations interacts with the demographics, the health and age structures, within those occupations. In other words, we address how much of the magnitude of the increase in DI applications was from real wage declines in occupations of persons on the margin: the old and those of poorer health.

The transition in this exercise will be driven by changes in occupation-specific wage components. We choose three values of these wage components for each occupation $\{z_{tj}\}^{3,J}_{t=0,j-1}$. The response of agents within the model to these changes depend on their expectations about when these shocks will occur and how persistent they will be. We model agents as forward looking with expectations according to the following occupation-specific markov chain:

$$\zeta_{j,z'z} = \begin{array}{c} \\ z_{j,0} \\ z_{j,1} \\ z_{j,2} \end{array} \begin{array}{c} \begin{array}{ccc} z_{j,0} & z_{j,1} & z_{j,2} \end{array} \\ \begin{pmatrix} \rho_{j,0} & 1-\rho_{j,0} & 0 \\ 0 & \rho_{j,1} & 1-\rho_{j,1} \\ 0 & 0 & 1 \end{pmatrix} \end{array}$$

Changes in these wage components cannot be directly observed in the data because they will be biased by issues of censoring and selection. Specifically, we do not see the wages of workers leaving the occupation and these workers are selected in terms of other traits also contributing to wages such as health and age. To deal with this problem, we estimate the appropriate $z'_{tj}s$ and $\xi'_{j,z'z}s$ within our model by indirect inference. In this way, the model predictions of wages and flows will be generated by the same issues of censoring and selection as in the data. In particular, we choose the levels of z_{tj} such that the model generated data provides changes in the occupation size consistent with empirical observations along the transition. We choose the persistence parameters of the Markov process targeting the proportion of persons leaving the occupation who apply for DI as in the data.[39] The level of the first state is chosen to match statistics for 1985, the level of the second state and transition probability is chosen to match statistics for 1995, and the third state and transition probability is chosen to match statistics for 2005.

The contribution of demographics is included in the exercise in the following ways. We begin with occupation-age structures taken directly from 1985 data. We generate distributions of stocks of health-cross-age in each occupation by simulating the model with expectations given by our inferred Markov chains, but choosing realizations of occupation wage shocks to always be z_0. We simulate the transition of the model freely without further adjusting these

[39]Lifetime occupation of workers leaving occupations and of those applying for DI will be assigned using propensity score matching techniques outlined in the prior section.

demographics.[40]

We should mention the role of one institutional detail not modeled: the issue of DI eligibility. We calculate changes in eligibility directly using the 2006 Earnings Public-Use Microdata File, a one-percent random sample of earnings histories of all Social Security numbers, released by the SSA. We find that the eligibility of men in their 50's has fallen an average of two percentage points- from 95% to 93% since the mid-1980s.[41] This implies that our analysis may over-state the increase in SSDI enrollment by 2 percentage points.

7 Accounting for the Rise

Occupational Age Structure We evaluate the effect of the occupational age structure by running the simulation with a common age structure in each occupation equal to the aggregate age structure in the US labor force in 1985.

Occupational Health Risks We evaluate the effect of the occupational health risks by running the simulation with individual health risks drawn from the unconditional distribution (not occupation conditional).

Occupational Wage Risks We evaluate the effect of the heterogeneity in occupational wage risks by running the simulation for a re-estimated Markov wage-risk process. We estimate this process via indirect inference by the same procedure as for occupation-specific processes except targeting the equivalent aggregate moments.

[40] Exogenous changes in demographics including migration or differential mortality will contribute to variation unexplained by the model.

[41] The eligibility of women has grown substantially over the time period- from 80 to 90%, but we exclude them from our present analysis. The male trend also shows lagged cyclical components.

SSDI System Design We evaluate the effect of changes in the design of the SSDI system by running the simulation, fixing the replacement rate and acceptance probabilities to 1985 levels. We now use the model to implement two sets of counterfactual exercises to evaluate two directions of SSDI reform: changing the generosity of SSDI benefits and changing the stringency of disability evaluation to qualify for DI.

8 Forecasts

TBA

9 Conclusion

TBA

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10 Figures

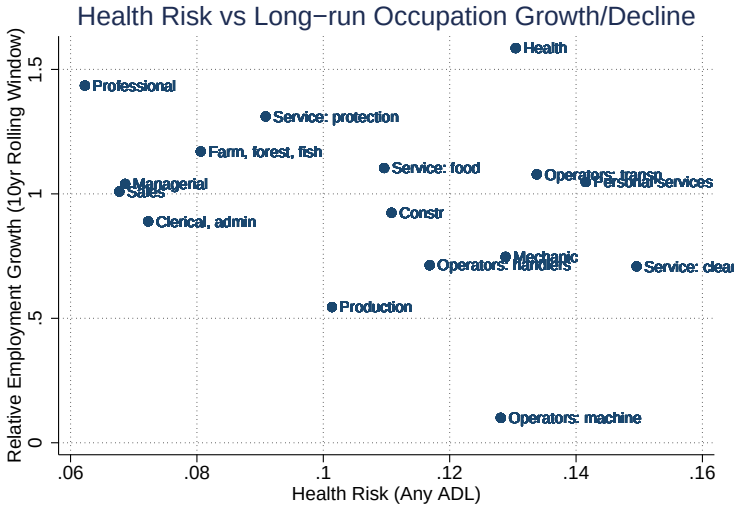


Figure 1: The correlation between health risk and long-run job growth.

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%

Table 2: States with the Most and Least SSDI Rates- 2013

State	%SSDI†	%Disabled*	Med Benefit†	Emp/Pop**	Blue Collar‡	Med Age‡	Heart Dis.◇	Cancer ◇
W.Va	8.9	18.6 (1st)	$1063	49.7	58 (37th)	41.7 (4th)	193.7 (12th)	199.6 (2nd)
Alabam	8.5	16.4 (6th)	$1056	52.9	66 (2nd)	38.3 (20th)	193.7 (12th)	187.4 (8th)
Arkan.	8.4	16.9 (3th)	$1024	53.4	63 (10th)	37.8 (27th)	214.1 (4th)	191.1 (6th)
Ky	8.2	16.9 (3rd)	$1029	54.8	64 (7th)	38.5 (18th)	203.4 (7th)	200.9 (1st)
Miss.	7.9	16.7 (5th)	$1018	54.9	62 (15th)	36.6 (36th)	240.0 (1st)	196.8 (3rd)
Maine	7.7	15.7 (7th)	$989	60.5	58 (37th)	44 (1st)	152.3 (33rd)	181.7 (12th)
Alaska	2.8	10.9 (40th)	$1027	63.3	42 (37th)	33.1 (50th)	135.0 (49th)	176.1 (19th)
Hawaii	2.8	11.1 (38th)	$1097	59.0	66 (2nd)	38.1 (24th)	139.0 (47th)	138.2 (50th)
Utah	3.0	9.3 (51st)	$1046	65.4	59 (31st)	30.2 (51st)	149.0 (39th)	125.6 (51st)
Calif.	3.2	10.1 (49th)	$1074	57.7	38 (15th)	35.7 (47th)	151.8 (34th)	151.8 (46th)
Colo.	3.3	10.0 (50th)	$1077	64.6	56 (44th)	36.4 (39th)	125.7 (50th)	143.9 (49th)

(Rank among 50 states + DC)
† Social Security Administration. Reference population is ages 18-64.
*American Community Survey- ADL or sensory/ cognitive impairment. Reference population: ages 18-64.
** Bureau of Labor Statistics
‡ Current Population Survey/Census
◇ Kaiser Family Foundation, deaths per 100,000

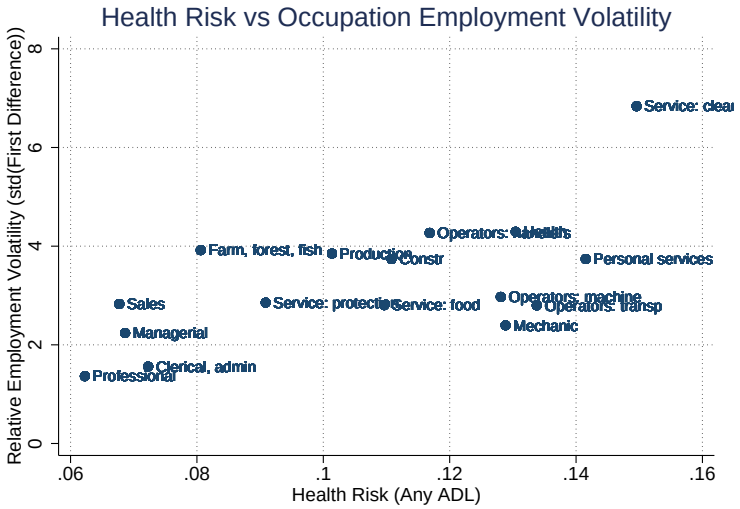


Figure 2: The density across occupations of the incidence of difficulties with ADLs

Table 3: Wage Equation Estimation

Variable	Employment equation	Wage w/out selection	Wage w/ selection
Severe Limitation (t)	-0.107**	-0.219**	-0.358**
	0.011	0.062	0.086
Moderate Limitation (t)	-0.319**	-0.134**	-0.164**
	0.015	0.028	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 4: 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	0.587	0.014	0.02
	0.048	0.326	0.008	0.012
Age 45-55	1.150**	0.536*	1.309**	1.481**
	0.066	0.202	0.104	0.160
Age 56-60	1.386**	0.306**	2.092**	1.980**
	0.106	0.129	0.194	0.277
Age 61-65	2.023**	0.253**	2.262**	1.980**
	0.144	0.135	0.225	0.307
Occupation Risk	2.537**	0.915	5.700**	3.797**
	0.186	0.692	0.588	0.558

Standard errors in parentheses.
**Denotes statistical significance at the 1%level.
*Denotes statistical significance at the 10%level.