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**by**

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

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**Abstract**

We evaluate the contribution of changing macroeconomic conditions and demographics to the increase in Social Security Disability Insurance (SSDI) over recent decades. Within our quantitative framework, multiple sectors differentially expose workers to health and economic risks, both of which affect individuals' decisions to apply for SSDI. Over the transition, falling wages at the bottom of the distribution increased awards by 27% in the 1980s and 90s and aging demographics rose in importance thereafter. The model also implies two-thirds of the decline in working-age male employment from 1985 to 2013, three-fourths of which eventually goes on SSDI.

## 1 Introduction

The number of U.S. Social Security Disability Insurance (SSDI) beneficiaries has risen consistently for the past 30 years. 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

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labor force.[1] This expansion was not a consequence of changes in program rules; the last major overhaul was completed in the early 1980s. Nor is it directly attributable to broad demographic factors, like the aging of the baby-boom cohort or expanded eligibility for benefits resulting from increased female participation.[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, aggregate impact of economic conditions on SSDI awards and the channels through which they operate remains unclear. The answer depends not only on the trends in economic conditions themselves, but also the age and occupation demographics that were exposed to to them. And given that outflows from SSDI are rare, do business cycles may also ratchet up the rolls? Quantifying how these forces can explain why SSDI grew is critical to understand whether coming shifts will alleviate or exacerbate the trend and what role institutional features of SSDI play.

In this paper, we consider how economic forces, demographic forces, and their *interaction* affect SSDI claims and drive their rise.[3] These forces are intertwined in several important ways. First, the response of each individual's SSDI application decision to changing economic conditions depends on 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 their 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 that determine if a SSDI claim is awarded explicitly condition on vocational factors—workers' 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 have individuals who are healthy enough to work when economic prospects are good decided to apply for disability when their prospects worsened? 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

[1] Authors' estimates from Social Security Administration (SSA) and Current Population Statistics (CPS) data.

[2] Our statistical accounting is in the online appendix and corroborates a similar analysis in Liebman (2015).

[3] Although Supplemental Security Income (SSI) also rose steeply, we restrict our study to SSDI because the mechanisms driving applications appear to differ. The programs differ in intended beneficiaries: SSI is means tested and SSDI is not; and the conditions of beneficiaries differ widely: over 60% of SSI beneficiaries have Mental or Psychiatric disorders whereas less than 20% of SSDI beneficiaries do.

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 model in which individuals face correlated economic and health risks as they age. We discipline the quantitative predictions of this model using individual-level microdata over the period in which SSDI was rising most steeply. Our insight is that occupations bundle tasks differently, and thus differentially expose individuals to heath and economic risks. As we show in the data, occupations, and the joint health and economic risks they bring, determine workers' labor force participation and disability decisions in the model.

We use the model to decompose how changes in the occupational and demographic structure of the United States coupled with economic trends contributed to the rise in SSDI awards. To do so, we feed in changes in the age-occupation structure of the population, occupational-specific, secular wage declines and business cycle fluctuations in job loss/finding rates. With these shocks, the model's predicted flows onto DI closely follow the data except for an over-prediction of awards in the late 1980s and under prediction in the early 2000s. The more-than one percentage point rise in awards predicted for the 1990s is driven by the response to wage declines for occupations with high health risks, though it was mitigated by youthful demographics. Though wage-trends continue to matter, the aging of the baby-boom generation is the largest contributor to the rise from the mid-2000s onward. Cyclical fluctuations contribute quantitatively insignificantly. However, this result is tempered by the running theme of the paper: it matters which demographics experience these shocks.

Our structural model complements empirical studies analyzing whether economic conditions affect SSDI by evaluating the differential impact on individuals with different health and demographics. For example, we find an average elasticity of applications to secular wage declines of about 20%. This is slightly lower than empirical estimates, but ours is an aggregate figure whereas the empirical literature has focused on shocks that disproportionately affect certain demographics such as declines in coal or oil prices.[4] We also find mixed evidence that poor economic conditions induce fraudulent applications of healthy people. Following a secular wage decline, the increase in the likelihood of applying for a worker in good health is less than one-fifth of that for a worker in

[4]For example, Charles et al. (2018) and Black et al. (2002).

poor health. However, their responses to a job loss are similar.

Changing economic conditions interact with the SSDI program to increase non-employment by more than the rise in disability beneficiaries.[5] Rising applications provide 18% of the 4.3 percentage point increase in non-employment from 1984-2013 implied by the model. Applications are more sensitive to wage trends than awards. While secular wage declines drive applications to rise in both the 1990s and mid-2000s onward, rejections also rise during these periods. This makes applications more important than awards in increasing non-employment for those with high and rising rejection rates: younger individuals in their 30s and 40s and those in occupations with the lowest health risks.

# 2 Literature

Topically, our paper belongs to a literature studying the incentives and circumstances determining whether individuals apply for public DI. The methodology employed by this literature is divided between reduced form strategies and quantitative analyses of structural models.[6] 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 and Pistaferri (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.[7] Low and Pistaferri (2015) analyze details of the SSDI institutions and welfare program interactions, paying particular attention to estimating individuals' preferences and the risks they face using panel data on individ-

[5] In this way, we relate to the puzzling rise in very long jobless spells among the low skilled over our period of study as discussed in Elsby et al. (2018).

[6] There is also an interesting theory literature on optimal program design. We omit discussion of this literature because our methods in this paper are more suited to quantitative and positive analysis.

[7] Kitao writes: "Given the high dimensionality of the model populated with heterogeneous agents, which is essential for the current paper, we do not compute transition dynamics and explore the implications of DI for changes in the labor market over time. This is an important avenue of research which is left to be explored in future work." As such, our model abstracts from Medicare aspects of her analysis in order to focus on transition dynamics.

uals' joint consumption and income paths.[8] The principal distinction between these papers and our own is that these papers study stationary models, while our paper focuses on the role of changing economic conditions in the rise of SSDI, tracing the transitional dynamics.[9]

We maintain key ingredients from these works and add a few innovations necessary central to our specific question. These innovations include: sectors with differential health and economic risks; a variety of heterogeneous economic risks including cyclical job finding and loss rates and long-run wage declines and growth; and a realistic SSDI acceptance criteria that includes vocational considerations.

**Empirical Studies Connecting SSDI and the Macroeconomy** Generally, empirical studies find persistent declines in economic prospects significantly raise applications, but cyclical increases in unemployment do not. Duggan and Autor (2006) 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, finding that areas exposed to a 4.5 percent fall in employment in manufacturing will experience a 0.8 percentage point larger reduction in the employment to population rate and of which 10% are awarded SSDI benefits. But the evidence of substitution from unemployment is more mixed: Mueller et al. (2016) and Rutledge (2011) each exploit variation in unemployment insurance extensions during the Great Recession and fail to find evidence that SSDI substantially substitutes for unemployment insurance. Our model lets us further investigate these findings, allowing a bevy of different shocks and all affecting different demographics. This is particularly important to understand Autor et al. (2013). Our results would suggest that the contribution of trade competition to overall DI trends is less than in the manufacturing sector because workers in this sector are already on the margin of exiting the labor force: they are older and, given the nature of their work, in worse health. While we will

[8] The conclusion of Low and Pistaferri (2015) highlights one of our relative contributions: "A second restriction is in terms of the stochastic process for work limitations, which we take to be exogenous. The probability of receiving a negative shock to the ability to work is likely to be partly under the individuals control, through occupation choice and other decisions on the job." Here, we explore exactly this bundling of health and economic risks.

[9] Also worth noting in this vein, Kim and Rhee (2018) study SSDI within a macroeconomic context, but from the opposite perspective: while we focus on the causal effect from aggregate conditions on SSDI growth, they study the equilibrium effects SSDI has on aggregate conditions.

# 3 Motivation

**Occupations Provide Correlation in Health and Economic Risks.** To motivate our analysis, we link health and economic risks to 16 broad occupational categories. The time period we consider in 1980-2014.[10] We use data from the Current Population Survey to measure employment within an occupation and data from the Panel Study of Income Dynamics to link individuals' life-time occupational exposure and health outcomes.[11] We measure occupational exposure by an individual's longest held occupation.[12] Our health outcome measure is the proportion of individuals in a given life-time occupation who report a "severe work limitation" by age 60.[13]

Figure 1 shows ample variation in health outcomes across occupations.[14] It also shows that labor income decline is not isolated to occupations with higher likelihoods of poor health outcomes. There are healthier occupations, such as clerical, that have experienced wage declines and there are less healthy occupations, such as those in the service sector, that have experienced wage growth. However, a large share of prime age male employment is concentrated in sectors with both high likelihood of poor health and low income growth. The possibility that the correlated nature of these outcomes push workers onto SSDI is central to our analysis.

The relationship between health and higher job displacement risk is also potentially important to flows into SSDI. The idea is that workers in poor health are more likely to be tipped over the margin of applying by a job loss. Table 6 shows that occupations with poor health outcomes have higher job loss risk (EU flows), generally. These include: construction, transport operators, and farming, forest, and fishing. These occupations as well as handlers, precision production, and some service industries also have higher standard deviations of these rates implying they are more adversely affected by recessions.

[10] 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.

[11] Further details, including our sample selection, can be found in our extended data appendix.

[12] This is the same as the current occupation for 80% of individuals aged 60-63. For this measure, we drop individuals whose longest held occupation is less than 9 years in duration. The extended data appendix shows robustness for all of our analysis to alternative thresholds and provides a successful placebo test using current occupation.

[13] See Low and Pistaferri (2015) for a presentation on the reliability of this self-report using correlates with objective health outcomes.

[14] In these figures employment is defined as full-time ($\geq$ 30 hours in the reference week) and full year ($\geq$ 50 weeks/year).

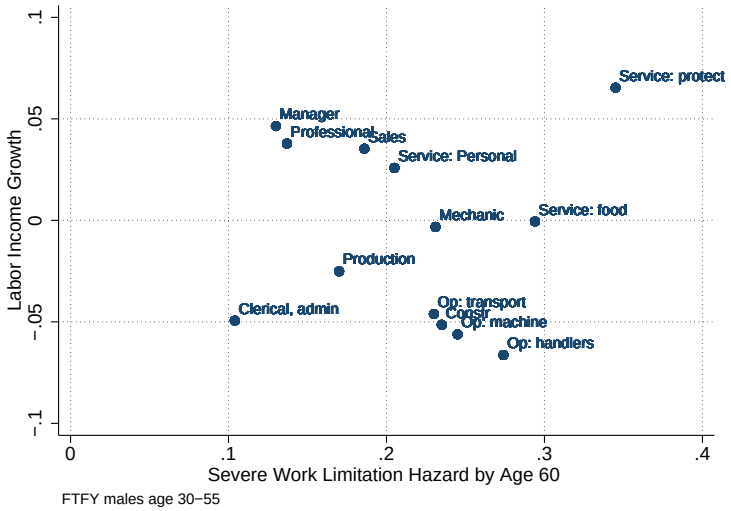



Figure 1: The correlation between health and long-run wage growth.

**SSDI Award Criteria Consider both Health and Vocation.** The SSDI award criteria directly distorts the incentive to apply for SSDI across demographics through explicit rules called "vocational considerations".[15] Vocational considerations are the last step in the four-stage sequential decision process the SSA uses to determine whether or not to award a disability claim. Claims made by uninsured workers (those with limited work experience) are rejected in the first stage.[16]Claims made by insured workers currently engaged in substantial gainful activity are rejected in the second stage.[17] Health is considered at the third stage. An award is made if the applicant proves they have a severe medical condition equivalent to a condition on the SSA's list that is expected to last for at least one year or result in death.

Claims that pass the first two stages and are not accepted at the third (health) 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 the RFC prevents an applicant from performing his

[15]See the online appendix for a glossary of key administrative terms and a simplified vocational grid.

[16]To be insured, a worker must have accumulated a sufficient number of SSA work credits. Up to four 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 and these credits must have been earned sufficiently recently.

[17]Substantial gainful activity was defined as earnings greater than $1,130 per month in 2016

past work, a vocational grid is used to determine if he can adapt to another type of work possible with his RFC. The grid defines explicit age categories and dictates that older applicants, especially "advanced age" above 55, are less like to be able to adapt and, therefore, more likely to receive an award. Other factors considered are past work experience and education. After RFC and vocational considerations narrow the set of occupations to which the applicant can be expected to adapt, the SSA rejects the claim if it can provide evidence of significant numbers of job openings in these occupations and otherwise awards the claim, thus tying the award process to Macroeconomic conditions.

The role of the vocational stage in SSDI awards has changed in important ways over the past decades. 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. To assess this quantitatively within our model, we include separate medical and vocational award stages in our model. This distinction from past work is important to understand 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. At birth, agents are assigned a life-time occupation that affects wage, employment and disability risks. Over their work-life, agents will differ in the extent of their disability, wages, age, and labor market history. 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.

**Demographics** The model is populated by agents aged $\tau \in \{0, 1, 2...T\}$ who advance to the next age with probability $1 - \phi^{age}(\tau'|\tau)$. Agents of age $\tau$ and health status $d$ die with probability $1-\phi^{death}(\tau, d)$, denoting the joint probability of neither dying nor aging as $\phi(\tau'|\tau, d)$. Agents begin life employed in an occupation $j \in \{1, 2...J\}$ and draw a permanent $\delta^i$ related to their personal

health deterioration risk. The characteristic $\delta^i$ is drawn from an occupation-specific distribution $G_j(\delta)$.

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 $\varphi$. 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 $SS(e)$ or disability payment $SSDI(e)$, where $e$ is a measure of their prior labor market earnings.

**Income** Wages are exogenous. They depend on agents' idiosyncratic component $\alpha$, their current age $\tau$ and health status $d$, 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 $\mathcal{Z}$. Wages depend on health status $d$ through $h_d$. Poor health lowers workers' wages which provides health-related pecuniary motives to file for disability. The dependence of wages on age $g(\tau)$ changes pecuniary incentives to apply for disability over the life-cycle. Finally, $\alpha$ provides variation across individuals who have otherwise identical demographics. This assumption can be thought of as capturing omitted individual factors such as firm effects or differences in local labor markets. Component $\alpha$ is a markov process with transitions $\pi_\alpha$.

**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: $\pi_d(d, d'; \tau, \delta^i)$. Disability states are ordinal: an agent of $d = 2$ is in worse health than and agent of $d = 1$.

**Social Transfer Programs: Unemployment, Disability, & Retirement** Non-employed agents receive exogenous social transfers, $UI(e)$, $SSDI(e)$, and $SS(e)$, according to their state: unem-

ployed, disability beneficiary, or retired, respectively[18] 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 receive old age social security insurance $SSI(e)$. Newly unemployed agents receive $UI(e)$ until, with Poisson probability $\varphi$, the individual becomes long-term unemployed and unemployment benefits are terminated. Disability benefits $SSDI(e)$ 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 $\nu$.[19] An agent's SSDI application is accepted with probability $\xi(d, \tau, z)$. 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 SSDI benefits until they age into retirement and switch to SSI.[20]

In line with Social Security rules, agents will be provided the option of early retirement before the full (mandatory in the model) retirement age starting at age 62. Agents choosing early retirement will receive 80% of full retirement benefits and we adjust $e$ to $e'$ accordingly, $SS(e') = 0.8 * SS(e)$.

**Exogenous Employment Transitions** Occupations differ in exogenous job destruction rates and exogenous rates at which unemployed workers find job opportunities. The business cycle is indicated by $y$, which determines unemployment risks. For computational tractability, we fold the exogenous unemployment state into $\alpha$, 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, $\pi_\alpha$ depends on $y, j$. $\mathcal{Y}$ are the probabilities for the Markov chain governing $y$. Upon realizing an unemployment exit shock, the worker draws a new $\alpha$ from the conditional distribution of

[18] 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 with temporary unemployment benefits.

[19] 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. (2016) who find cyclical UI extensions have no significant effect on the timing or level of SSDI applications.

[20] The monthly payments from SSI are equal to SSDI if the individual retires at full retirement age. If the individual retires early, the SSI payments are less than SSDI.

workers exiting unemployment which has a lower mean than workers continuing employment.[21]

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

**Agents' Decisions** We define the problems agents face, recursively, yielding a set of value functions: working agent $V^W_{j,\tau}(\alpha,a,e,d;z,y)$, unemployed $V^U_{j,\tau}(\alpha,a,e,d;z,y)$, long-term unemployed $V^N_{j,\tau}(\alpha,a,e,d;z,y)$, 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' types $i$. Further, the states $d,\tau,\alpha,z,y$ will be continuously evolving which we denote with the expectations operator. To be explicit, these are defined by

$$\begin{aligned}
\Pr[d' = d_j|\tau,\delta] &= \pi_d(d,d_j,\tau,\delta) \\
\Pr[\alpha' = \alpha_l|\alpha,y,j] &= \pi_\alpha(\alpha_l|\alpha;y,j) \\
\Pr[\tau' = \tau|d,\tau] &= \phi(\tau|\tau,d) \\
z' = \mathcal{Z}(z)\,; &\quad \Pr[y' = y_i] = \mathcal{Y}(y_i|y)\,.
\end{aligned}$$

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** 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

[21] This is in line with the empirical evidence on "wage scars" as in Jacobson et al. (1993) and others.

and SSI income. This problem repeats until death occurs with probability $1 - \phi(T|T, d)$.

$$V^R(d, e, a) = \max_{c,a'} u^N(c, d) + \beta\phi(T|T, d)E_d[V^R(d', e, a')]$$
$$c + a' \leq SSI(e) + Ra\ ; \quad a' \geq 0$$

**A Disability Beneficiary's Problem** Agents' earning index does not change, but their $d$ continues to evolve, they continue to age and face differential mortality given their disability $d$.[22] The only choice agents make is a consumption versus savings decision given their asset holdings and SSDI income. This problem repeats until the agent ages into retirement $\tau = T$. Earnings components $\alpha, \beta$ are no longer relevant and earnings index $e$ is constant.

$$V^D_\tau(d, e, a) = \max_{c,a'} u^N(c, d) + \beta \sum_{\tau'} [\phi(\tau'|\tau, d)V^D_{\tau'}(d, e, a')]$$
$$c + a' \leq SSDI(e) + Ra\ ; \quad a' \geq 0$$

**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:

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

if $\tau < T - 1$ and for $t = T - 1$ the opportunity to retire early is given by $\phi^R$ and this choice makes $e' = SS^{-1}(0.8SS(e))$.

$$V_{jT-1} = \phi^R \max\{V^W_{j\tau}(\alpha, e, d, a; z, y), V^U_{j\tau}(\alpha, e, d, a; z, y), V^R(d, e', a)\}$$
$$+(1 - \phi^R) \max\{V^W_{j\tau}(\alpha, e, d, a; z, y), V^U_{j\tau}(\alpha, e, d, a; z, y)\}$$

**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 $\varphi$, he will become

[22] It is important $d$ continues to evolve to avoid an application motive to time their disability application when health is relatively good.

long-term unemployed (with value $V^N$) in the next period. Otherwise, $\alpha$ and $z$ continue to evolve and he will be able to choose again between work and unemployment in the next period.

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

**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. If an agent applies for SSDI benefits, then $m = 1$, and $m = 0$ otherwise.

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

A SSDI application is accepted with probability $\xi(\cdot)$. If accepted, then benefits last until retirement. If not accepted, the agent remains long-term unemployed ($V^N$). If the agent does not apply, there is a probability $\rho$ he or she will have the opportunity to work again next period ($V$). Only then can they become re-employed.[23] Finally, 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.

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

[23] This is how we model a friction that provides duration dependence in unemployment.

# 5 Calibration

Here we explain our chosen parametric forms and then describe how we choose parameter values to replicate features of US social insurance institutions, features of individuals' outcomes calculated from microdata, and features of the Macroeconomy most relevant for the analyses we conduct.[24]

## 5.1 Externally Set Parameters- Preferences and Demographics

**Demographics and time** A model period is a month. Individuals progress through five age groups: 30-44, 45-49, 50-54, 55-59, 60-64 and a final age group of retirees. When we simulate the transition, we choose the entry rate of the young age group to replicate its share of the US population over time. Agents in all age groups die randomly by a probability following their health-specific death rate.[25]

Agents are assigned a lifetime occupation at birth among the 16 2-digit SOC codes. The fraction in each occupation in the initial period is chosen to match CPS data on this distribution in 1984. Through the transition, we assign entrants an occupation to exactly match their occupation shares among the 30-44 year-olds in that year.

**Preferences** Preferences follow Low and Pistaferri (2015), in which workers value consumption, risk, leisure and health. For employed and non employed, 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 $\eta = -0.185$ as in Low and Pistaferri (2015).[26] 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

[24] Great detail on all of these calculations are presented in the on-line appendix accompanying this manuscript.

[25] In other words, we exactly match the evolution of annual population demographics calculated using linear interpolation on decennial census data. Health specific death hazards for each age group are calculated from PSID data.

[26] See Low and Pistaferri (2015) for details on how consumption data is used to identify these parameters using consumption data.

explicitly. We set $\gamma = 1.5$, within the standard range of risk-aversion and the baseline for Low and Pistaferri (2015). The interest and discount rate are set to 1.6% and 2.5%, as in Low and Pistaferri (2015), and they provide endogenous median wealth inline with the PSID and SCF in our model as well.

## 5.2 Social Insurance Institutions

**Social Security Disability Acceptance Screening** The DI program in our model is designed to replicate realistic features of the US Social Security Disability Insurance program. While the program underwent major changes up through early 1980s, it has been mostly stable since the 1984 reforms and, as such, our analysis begins at 1984. SSDI uses four sequential criteria to award benefits.

First, the individual must be eligible: they must meet a work requirement on prior earnings and file an application.[27] Our calibration considers the work requirement only for young workers (age 30 to 44) in our model. Using the large representative sample of the SSA's Earnings Public-Use File, we compute the average share of males age 30-44 working in the current year who meet the work requirement for eligibility over the years 1984-2006. [28] This figure is 83.4% and so we reduce the probability of an award for this group by 16.6%.

Second, the applicant must have been non-employed for 5 months prior to application and not have earnings exceeding a low threshold, $1090/month in 2015, of substantial gainful activity. Implementing this in our model, agents can only apply for SSDI when in long-term unemployment, but they can only enter long-term unemployment by first transiting through rest unemployment. The stochastic transition probability, $\psi = \frac{1}{5}$, to set the average duration prior to long-term unemployment. Once in long-term unemployment, agents may receive the option to return to work, the arrival rate of these options matches the relative exit rate of workers unemployed for more than 5 months. Altogether, this recursive formulation captures key economic incentives affecting the

[27] 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.

[28] 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).

SSDI application decision for long-term unemployed. It is harder for the long-term unemployed to find work, they no longer receive unemployment benefits, and they are eligible to apply for SSDI (whereas short-term unemployed are ineligible).

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. This criteria, that of a severe work limitation, is not verifiable by the SSA among applicants nor verifiable by the authors in the PSID sample.[29] Research examining this issue has found that SSDI screening produces high levels of both false positives and false negatives, e.g. Benitez-Silva et al. (2004) estimates 16% of awards and 52% of rejections are false. Further, administrative acceptance criteria of the SSA consider more factors than work limitation status alone. This brings age and work experience into play through the fourth, vocational criteria: whether an applicant is able to do any type of work in the economy. 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. The SSA has explicit guidelines, a determination "grid" that lists extent of work limitation, education, work experience, and age, the so-called "medical-vocational" guidelines, described further in Chen and Van der Klaauw (2008) or Michaud et al. (2018).

To capture the complexities if the screening process in the third and fourth steps, we estimate the following SSA "decision rule":

$$\xi(d,\tau,z) = 1 - \left(1 - \sum_j \zeta_j \mathbb{I}_{d=j}\right)^{1/\zeta_T} + 1 - \left(1 - e^{\zeta_\tau \mathbb{I}_{\tau \geq 55}} \zeta_V \frac{\bar{z} - z}{\bar{z} - \underline{z}}\right)^{1/\zeta_T}$$

The dummies, $\zeta_j$ are the health-related acceptances and we take these directly from Lahiri et al. (1995) who estimate the marginal contribution of a moderate or severe limitation to a DI acceptance using administrative data linked to survey data that elicits the same self-reported measure of work limitation as we use elsewhere. We assume that the vocational acceptance probability is increasing in $\frac{\bar{z}-z_{jt}}{\bar{z}-\underline{z}}$, where $\bar{z}, \underline{z}$ are the max and min of the realizations of $z_{jt}$ used to normalize the occupation productivity shock. There is no explicit business cycle component, consistent with

[29] There is a measure of self-reported work limitation in the PSID but its validity and interpretation 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 higher marginal utility of consumption and lowers wages.

Coe and Rutledge (2013), who document constant acceptance rates once correcting for the composition of applicants. $\zeta_\tau$ allows the vocational acceptance probability to be higher for workers over 55, "advanced age" in the vocational grid. Finally, we use $\zeta_T$ to adjust for the expected time an application will take using the calculations from Autor et al. (2015).[30] To emphasize the point, $\zeta_V$ and $\zeta_\tau$ must be inferred such that the endogenous predictions of the model match the proper number of new awards given for vocational reasons and to those with "advanced age."

**SSDI and SS Retirement Payment Schedules** SSDI benefits and SS retirement at full retirement age both replace past earnings at the same piecewise linear rate set according to the formula used by the Social Security Administration. The key input into the formula is the average indexed monthly earnings (AIME) of an individual's 35 highest annual earnings (state variable $e$ in the model). We use an age-dependent recursive formulation that is standard in the literature (Low and Pistaferri (2015); Kitao (2014)) to keep track of $e$ and we explain it in the online appendix. In 2015 the bend points in terms of AIME monthly income, were:[31]

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

We convert these bend points to real "model dollars" by targeting the ratio of the bend points relative to the mean wage, not the nominal value.

The Social Security rule for early retirement allows individuals to collect social security retirement benefits at ages below the full-retirement age starting at age 62, but their benefits will be paid at a discounted rate. This is an important program feature to include in our model since workers aging into full retirement age from SSDI will receive full retirement benefits for the rest of their lives, whereas their benefits are permanently reduced if the choose early retirement instead. We calibrate the arrival rate of the option for early retirement for our 61-65 by setting $\phi^R = \frac{4}{5}$ to match

[30] It might be reasonable to make $\zeta_{T1}$ and $\zeta_{T2}$ different values for vocational considerations allowances because they are determined at a "later stage." Evidence from Autor et al. (2015) suggests they take slightly longer on initial review, but no information about potential time in further adjudication, which is the largest portion of potential processing time.

[31] Bend points are designed by the SSA to be consistent with 1979 bend points adjusted for the average wage index two years prior to the calendar year. Therefore we do not need to adjust the bend points over time.

the eligibility of ages 62-65. Exercising the option cuts $e'$, $SSDI(e') = 0.8 * SSDI(e)$.

**Unemployment Insurance** Cash unemployment benefits in the US average 40-45% of workers' wage in the job they lost and last an average maximum duration of 6 months. However, workers have many other sources of income beyond these explicit cash benefits, especially considering take-up rates in the US are quite low. Hence, we use estimates from Ganong and Noel (2017) on the drop in consumption after job separation using high-frequency, detailed consumption data from JP Morgan-Chase. To conserve state variables and for parsimony, we convert these consumption declines to replacement rate of 80% of the earnings index of average lifetime earnings $e$. Ganong and Noel (2017) show a discrete consumption decline after the expiration of benefits, which generally happens after 6 months. We capture this by dropping the income to $60\%$ of $e$ once the worker becomes long-term unemployed. We do not preclude SSDI filers from also receiving UI in the period prior to their filing, even though they quit, which is in line with Coe et al. (2013) document more than 60% of workers who apply for SSDI were eligible for UI in the months before their application. The 60% replacement rate is also conistent with evindence in Coe et al. (2013) that SSDI applicants use a variety of non-UI resources such as SNAP, informal networks and credit cards.[32]

## 5.3 Occupations: Health, Wages, and Employment.

To motivate our analysis, we linked health and economic risks to 16 broad occupational categories. We now introduce a task-based approach to interpret how these categories classify the nature of individuals' work in order to interpret the role an occupation plays in determining these risks. The O*NET, a US Department of Labor database, provides a measure of the content of each occupation. We condense the 120 Knowledge, Skill and Ability descriptors into 2: the first principal component of the 19 physical tasks and the first component of the remaining descriptors. The following paragraphs describe how we use these skill measures to calibrate health, wage, and employment risk in the model. Table 6 summarizes how these vary across occupations.

[32] 30% receive SNAP during the application process out of the 50% who are eligible. The next highest sources of income is borrowing from credit cards- 17% borrow at a mean of $3,400 in the month they apply. While we do not pursue it here, a very interesting extension would be to introduce unsecured credit and bankruptcy into our framework.

**Wages- Age, Health, and Individual Effects** To calibrate the components of wages in the model, we regress wages on age, health, and individual effects. This first estimation step is distinct from the second wage regression we use as an auxiliary model to establish the relationship between time, occupation, and their interaction on wages. We do this in two steps to better estimate the impact of health on wages, which exploits the detailed, individual-level health data at the annual frequency in the PSID, but this ended in 1997. We use the whole sample for the second regression, described below. The log-wage of an employed individual $i$ (or shadow wages for an unemployed individual) aged $\tau$, in occupation $j$, and with health $d$ at time $t$ is given by the expression:

$$ln(w^i(\tau, d, j, t)) = g(\tau_t^i) + h(d_t^i) + \mathbf{O_j}'\beta_O + \mathbf{t}'\beta_T + \mathbf{x_{i,t}}'\beta_x + \gamma\Phi^{-1} + \bar{\alpha}^i + \alpha_t^i \qquad (5.1)$$

We separate the individual fixed effect, $\bar{\alpha}^i$, from the individual idiosyncratic shock, $\alpha_t^i$. An age-profile ($g(\tau)$) and the direct effect of health status on wages ($h(d)$) are common to all workers of a given age or health status. The effect of an individual's occupation on her wages is $\mathbf{O_j}'\beta_O$ where $\mathbf{O_j}$ is a vector of O*NET task components summarizing the occupation: the first principal component of physical and the first component of knowledge-skill-ability.[33] The time effect common to all workers is $\mathbf{t}'\beta_t$, a cubic in time. $\mathbf{x_{i,t}}'\beta_x$ are additional demographic controls and $\gamma\Phi^{-1}$ is the inverse mills ratio explained in the next paragraph.

Wages in both the model and PSID data are censored as a result of endogenous choices of whether to participate. 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. We then calculate from this the inverse Mills ratio reflecting how much wages are truncated by endogenous participation for use in the second-step wage equation. The regressors in the first-step probit include dummies for reported work limitations in the current period to capture selection on health. To capture selection on economic factors, we use one year and five year differences in log full-time, full-year national employment in the individual's age-education group as exclusion restrictions.[34] These trends are exogenous at the individual level, not directly related to health outcomes, but workers with different health levels will respond differently.

[33] These continuous measures are more parsimonious than occupation dummies, which helps with the small sample sizes and are consistent with the definition of an occupation used to estimate occupational specific health-risk.

[34] See the data appendix for further definitions, explanation of additional demographic controls and robustness on the exclusion restriction.

Table 1: Wage Equation Estimation

| Variable | Employment equation | Wage w/out selection | Wage w/ selection |
|---|---|---|---|
| Severe Limitation (t) | -0.649** | -0.008 | -0.266** |
| | 0.020 | 0.027 | 0.101 |
| Moderate Limitation (t) | -0.197** | -0.031* | -0.097** |
| | 0.015 | 0.014 | 0.030 |
| First dif Occ Employment | -0.058† | | |
| | 0.097 | | |
| Fifth dif Occ Employment | 0.982** | | |
| | 0.000 | | |
| Mills Ratio | | | 0.255** |
| | | | 0.094 |
| N | 32,092 | 19,056 | 19,056 |

Probit results reported as Marginal Effects
$^{\dagger}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, standard errors provided.
See appendix for additional controls in each regression.

Table 1 summarizes the first and second steps. Full results are in the online appendix. The first step shows that poor health strongly affects employment. A severe (moderate) work limitation has a marginal effect of reducing employment likelihood by 65% (20%) when all other variables are evaluated at their means. The second step shows that both moderate and severe work limitations significantly lower wages by 0.26 and 0.97 log points, respectively.[35] These estimates are very close to Low and Pistaferri (2015) who instead use potential welfare payments as an exclusion restriction.

The idiosyncratic component $\alpha_t^i$ is an persistent, auto-regressive process. We estimate a simple restricted income process, $\alpha_{t+1}^i = \rho_\alpha \alpha_t^i + \sigma_\alpha \epsilon_t^i$ on residual wages after having run our second-step Mincer regression. On top of this we impose that, for workers leaving involuntary unemployment, a new $\alpha_t^i$ is drawn to replicate the average wage losses of workers exiting involuntary unemployment as in Michaud (2018).

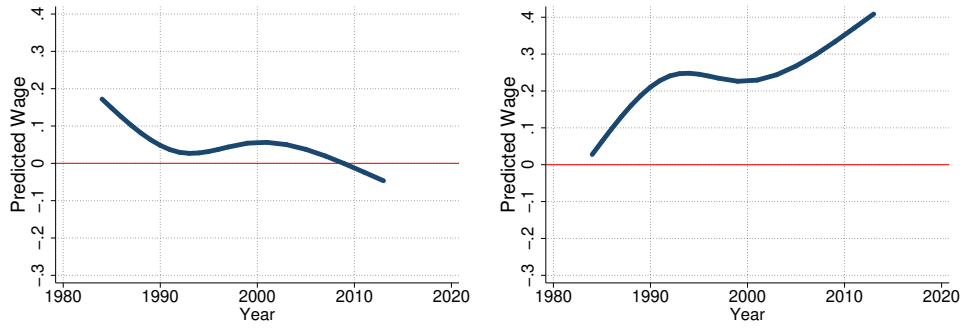
**Wages- Occupation-Time Trends** The next objective is to estimate long-term wage trends for each occupation. We maintain our view of an occupation as a collection of physical and knowledge-

[35] As shown in Table 1, the coefficient on the Mills ratio is positive in the wage regression, confirming our conjecture that selection biases wages upwards. The average truncation effect is 0.25 log points or 9.4% of the mean log wage (2.66) in 1999 dollars. Omitting the selection correction would bias the effect of poor health on wages significantly towards zero for severe limitations.

skill tasks, summarized by the O*NET descriptors. We run the following regression to attribute wages to common time trends and to the task composition of occupations over time.

$$ln(w_{it}) = \mathbf{X_{it}}'\beta^d + \mathbf{O_j}'\beta_O + \mathbf{t}'\beta_T + \beta^{ot}\mathbf{T_t} \times \mathbf{O_i}$$

The first regressor is a vector of demographic variables; the second $\mathbf{T_t}$ is a spline in annual time; the third $\mathbf{O_i}$ comprises of the first principle component of each the O*NET physical and knowledge-skill tasks.[36] The final term is an interaction of the time-spline with each of the O*NET tasks.




(a) Physical Tasks (b) Knowledge-Skill-Ability Tasks

Figure 2: Predicted change in occupational task-skill component of wages.

The decomposition of occupational wages into the hedonic price paid to each task-skill can be seen in Figure 2. The first principle component of Knowledge-Skill-Ability tasks has been a driver of wage growth. However, different occupations have different mixes of these components. Figure 3 groups the 16 SOC codes into quartiles of 4 occupations according to their physical task intensity. The most physically intensive occupations have suffered the largest predicted wage declines. This is important for our analysis because the physical task intensity of an occupation is a strong predictor of a reported work limitation.

**Job Finding and Job Loss Probabilities.** Cyclical risk is created by time-varying job finding and separation rates. For each occupation and phase of the cycle, $y$, we calculate the job separation

[36] Our motivation to use lifetime occupation is to capture the fact that individuals whose life-time occupation has declining wages over-time are still paid less than otherwise similar workers when they switch to an occupation whose wages are not in decline. To this end, we find that life-time occupation is a better predictor of wages than current occupation for those over age 50.

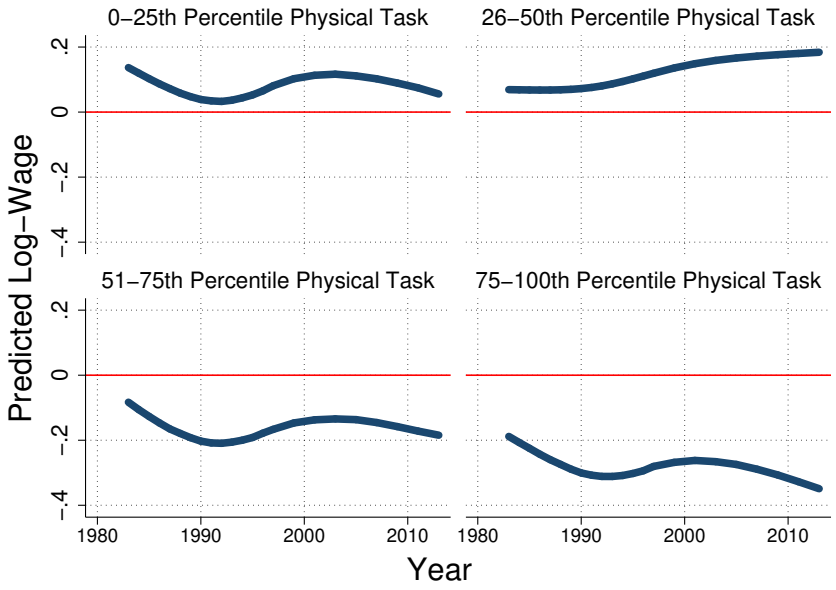



Figure 3: Predicted change in wages by occupation.

rate into unemployment and job finding rate from unemployment. We use the CPS in the 1984-2013 sample period and correct for monthly time aggregation following Elsby et al. (2009). Because the CPS is a relatively short sample, we cannot compute the life-time occupation, and so we use the self-reported occupation from which the worker originated before the unemployment spell.

We cannot directly feed observed transition rates into the model as shocks because some transitions in the model are endogenous. We instead calibrate two parameters that scale the separation and finding rates. Recall the first element of the idiosyncratic wage component, $\alpha$, indicates exogenous unemployment. Then, the job finding rate is the complementary probability of the first element of $\pi_\alpha$, which we parameterize as

$$1 - \pi_{\alpha,11} = e^{\lambda_0 + \lambda_y \mathbb{I}_{y=2} + \sum_j \lambda_j \mathbb{I}_j}.$$

The first term $\lambda_0$ must be adjusted to get the average flows correct while $\lambda_y$ adjusts for the cycle and $\lambda_j$ for the occupation effect. Separation rates occur from any current $\alpha$ state $r$ and are given by

$$\pi_{\alpha,r1} = e^{\iota_0 + \iota_y \mathbb{I}_{y=2} + \sum_j \iota_j \mathbb{I}_j}.$$

Again, the first term $\iota_0$ must be adjusted to capture the average flows while $\iota_y$ adjusts for the cycle and $\iota_j$ for the occupation effect.

**Health Risks** We estimate the effects of age and occupation on health transitions using a linear probability model on observed health dynamics in the PSID. We use age dummies that correspond to model age groups. In estimating the effect of occupation on health, we must consider that the realized rate of health limitations within an occupation may reflect selection into that occupation on unobservable factors. To address this issue, we use the strategy developed in Michaud and Wiczer (2018). The health risk component of an occupation is linearly increasing the intensity of physical tasks in that occupation. We then instrument for selection into the occupation using other non-physical tasks bundled in that occupation.[37] The effect of occupation is strongest in raising the probability of a transition to a greater work limitation, but also reduces the probability of recovery.[38] Consistent with realized outcomes, production, construction/extraction, and some service occupations have the highest risks of adverse transitions. Table 6 summarizes the occupational variation in health hazards by providing the estimated hazards of having work limitations by age 60.

We must ensure the distribution of health is stationary over the simulated transition paths, otherwise SSDI may rise due to a spurious trend towards worse health in the population. We use a variant of the RAS-method to impose row and column constraints on the estimated Markov transition matrices. This minimizes the log-difference between the directly estimated Markov transition matrices for each age and health risks and the a transition matrix the satisfies these constraints. The column constraints are that rows add to 1 minus the death rate. The row constraints impose that the cross-sectional health distribution matches the observed age-health distribution.

**Model Fit.** Table 2 shows the model's fit to targeted moments. We match all but one of our targeted moments very well. We over predict the fraction of new awards to workers of advanced age, over 55, even with $\zeta_\tau = 0$, which was supposed to capture the vocational grid's preference. This is because of the other model mechanisms, e.g. the declining option value of work, and because older workers tend to be in worse health.

[37] See the online appendix for further explanation and tests of instrument validity.

[38] The full health transition table is provided in the online appendix.

Our model is quite rich in its labor market characteristics, and the benefit is that we capture well important but not-targeted labor market features. For example, the share of employment to unemployment flows that are exogenous in the model are not too far from the flows reported as involuntary in the PSID: 51% and 36%, respectively. The share of long-term unemployed ($>$ 25 weeks) among the unemployed matches perfectly: 48% in both model and data. This statistic is important to match because it determines the at-risk population who might apply for SSDI with economic motives. In the following section we discuss the model's fit to the non-targeted moments with regards to who goes on DI.

| Parameter | Value | Moment | Target | Model | Source |
|---|---|---|---|---|---|
| $\nu$ | 0.05 | 1984-86 DI Awards | 0.0337 | 0.0337 | Social Security Administration (2013) |
| $\zeta_{V,0}$ | 0.02 | Voc DI Awards | 0.25 | 0.25 | Social Security Administration (2013) |
| $\zeta_{\tau}$ | 0.0 | Adv Age DI Awards | 0.41 | 0.55 | Social Security Administration (2013) |
| $F_0$ | 0.20 | $d = 1$ LFP difference | -0.20 | -0.20 | PSID |
| $F_2$ | 0.61 | $d = 1$ LFP difference | -0.65 | -0.65 | PSID |
| $\lambda_0$ | 2.40 | Unemp Duration | 3 | 3 | CPS |
| $\iota_0$ | 1.35 | Unemp Rt | 0.055 | 0.055 | CPS |
| $\zeta_T$ | 13.5 | Application Duration | | | Autor et al. (2015) |
| $\theta$ | -0.448 | Preference for health | | | Low and Pistaferri (2015) |
| $\eta$ | -0.185 | Preference for leisure | | | Low and Pistaferri (2015) |
| $\gamma$ | 1.5 | Risk Aversion/IES | | | Low and Pistaferri (2015) |
| $\beta$ | 0.9979 | Time Preference | 2.5% | | Low and Pistaferri (2015) |
| $R$ | 1.0013 | Return on Savings | 1.6% | | Low and Pistaferri (2015) |
| $\{\lambda_{j,y}\}$ | | Occupational finding rates | | | CPS |
| $\{\iota_{j,y}\}$ | | Occupational separation rates | | | CPS |

Table 2: Calibration parameters and targets. Below the line, parameters are set outside of the model.

# 6 Results from the Quantitative Model

## 6.1 Determinants of The Disability Option

In this section, we explore how the model predicts economic and health shocks contribute to DI applications and awards in the cross-section.[39] We begin by analyzing the elasticities of individuals' DI application and award propensity with respect to three sources of adverse economic prospects: a long-run decline in wages; an incidence of involuntary job loss; and the effect of a

[39]We focus on aspects central to our study. The online appendix includes empirical counterparts and validation the model replicates more standard statistics such as age.

recession. We estimate a simple probit on the working age population in the model simulated data. The independent variables are the three variables of interest and a cubic of time. For dependent variables, we define an award as anyone receiving SSDI 18 months after the reference period. Table 3 summarizes the results for the full model simulation of our period of study, 1984-2013.

| | Model | | Empirical Literature |
|---|---|---|---|
| | Individuals' Applications | New Awards | |
| Wage Trend | -0.20 | -0.15 | (-0.29,-0.4) |
| Exogenous Job Loss | 0.07 | 0.00 | (0.17, 0.34) |
| Unemployment Rate | 0.01 | 0.00 | n/a |
| $d > 0$ | | | |
| Wage Trend | -1.16 | -0.79 | |
| Exogenous Job Loss | 0.17 | 0.04 | |
| Unemployment Rate | 0.07 | -0.00 | |
| $d = 0$ | | | |
| Wage Trend | -0.19 | -0.16 | |
| Exogenous Job Loss | 0.14 | 0.03 | |
| Unemployment Rate | 0.01 | -0.01 | |

Table 3: Panel (1): Empirical and model elasticities with respect to adverse economic shocks. Panels (2), (3) split the sample between $d > 0$ and $d = 0$ among the age$> 45$.

It is interesting to compare the magnitude of these elasticities to the empirical literature. Whereas reduced-form empirical strategies focus on the populations most vulnerable to SSDI uptake, lower income workers in occupations with high health risks, the model estimates consider the response of the entire population to a shock. Given this different approach, it is natural that we find a lower elasticity than studies such as Black et al. (2002) and Charles et al. (2018). The former finds an elasticity of awards of $-0.3$ to $-0.4$ and the latter finds an elasticity of awards of -0.293 (standard error of $0.069$) using, respectively, coal prices in the 1970's and 80s and oil and gas prices over 1970-2011 as exogenous shocks to local income. In short, the samples and types of shocks chosen in these studies likely attenuate the effect of wage decline on SSDI uptake relative to the population in general.

Section IV of Autor and Duggan (2003) studies the response of low-skilled workers' applications to adverse employment shocks using geogrpahic variation in the U.S. to industrial composition changes. They find an application elasticity of -0.17 to -0.34 in their baseline specification. Our model predicts a smaller elasticity, 7%. This is possibly because the design of Autor and Duggan (2003) may attenuate the impact of a job loss if they are not able to disentangle secular wage

declines from job losses. We can cleanly separate the two in our model and find the response to more permanent secular wage declines to be larger than a transitory job loss, even when factoring in slow wage recovery after a job loss. For this same logic, we find a very small effect from recessions on application or uptake at the individual level. Empirical papers study the response of aggregate applications to aggregate unemployment rates and offer no analogy to our model statistic. However, qualitatively consistent with our findings, Mueller et al. (2016) finds no response of SSDI applications to unemployment insurance benefit expiration during the Great Recession.

Table 3 also shows simulated applications are more responsive than awards to economic shocks. This is a straightforward result of the screening process in which awards are more responsive to poor health shocks. The fact that the award response to job loss or recessions falls to zero is accounted for by healthier applicants applying in response to these shocks. This is not true for wage trends partially because wage trend shocks hit less healthy applicants more often: a five-percent increase the in the probability of a work limitation after age 45 is correlated with a one-percent decrease in the wage trend. To better understand the differential responses by health, we run the same estimation for individuals aged 45-65 split into those with ($d > 0$) and without ($d = 0$) a work limitation. We find the groups with and without a work limitation have nearly the same application elasticity with respect to job loss and nearly identical likelihoods of being awarded SSDI if they apply after a job loss. The response to wage trends, however, differs greatly across health groups as those in good health are much less responsive both in applications and awards.

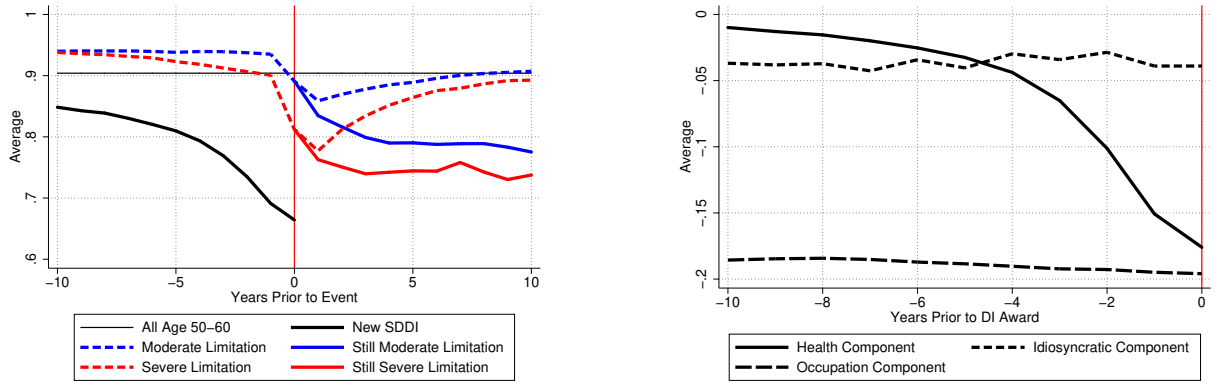
## 6.2 Composition of Applications and Awards

In both model and data, a salient feature of SSDI recipients is that many years of poor economic outcomes often precede an application. To analyze these dynamics in the model generated data, panel (a) of Figure 4 shows that individuals going onto DI had wages (or shadow wages) 6% lower than the average 50-60 year old ten years prior to their award. This gap increases to more than a 25% penalty in the year of the award.[40] Comparison with the dashed lines tracking individuals who suffer a severe or moderate work limitation at time zero reveals individuals who receive a disability award also have persistently lower wages than even individuals who acquire a moderate or severe limitation. This reveals a selection effect: not all individuals with severe limitations go on DI and those do have lower wages throughout their lives than individuals with comparable health

[40]These figures include the shadow wages: the wages non-employed individuals would earn if employed. Comparable figures for actual wages in the PSID in the online appendix.

problems. Panel (b) of Figure 4 shows that the wage dynamics for an individual going on DI are primarily driven by the wage impact of poor health, but the persistent low level of their wages in general is due to their lifetime occupation.

Figure 4




(a) Wage Paths Prior to Event

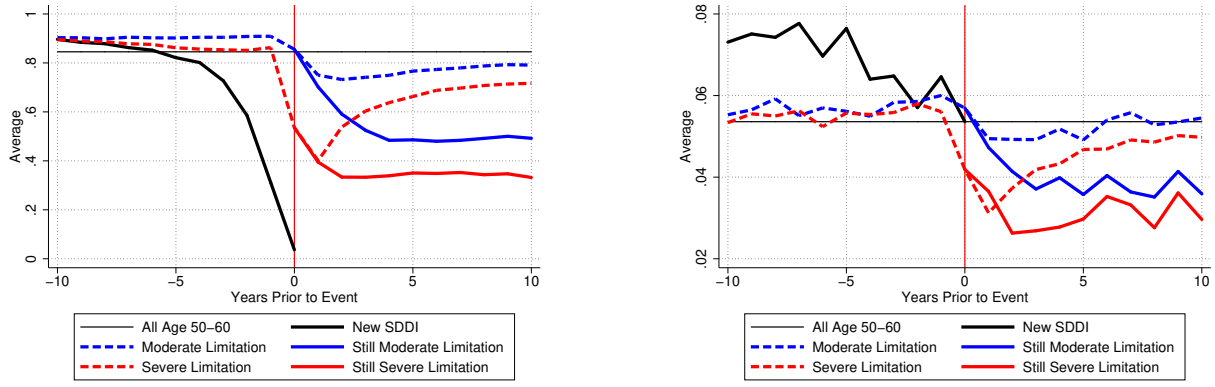
(b) Wage Path Components Prior to DI Award

Panel (a) of Figure 5 shows that individuals receiving DI awards have comparable levels of employment to the average 50-60 year old until 4 years prior to their DI award. This three year drop is partially a consequence of needing to be non-employed while applying for DI and also reflects the waiting time, through appeals if necessary, between application and award. Observe also that the employment rates of those who recover from a work limitation take time to recover. In the model, this is driven by the wage scar following non-employment relevant for those individuals who quit their jobs for health reasons or to apply for DI. These wage scars are apparent in Panel (a) of Figure 4. Panel (b) of Figure 5 shows that those going on DI experience up to an 36% higher incidence of involuntary job loss than the average 50-60 year old five years or more prior to their award.[41] Both composition and selection channels operate here as well. First, occupations differ in involuntary job loss risk and health risk, and these are positively correlated both with each other. Second, an involuntary job loss increases the likelihood an individual applies for DI for several years in the future through the persistent wage scar.

Table 4 shows how these economic incentives manifest themselves in the composition of individuals with new SSDI awards. In the model, as in the data, individuals going onto SSDI are

[41]The incidence of involuntary job loss falls within the 5 years immediately prior to the award because individuals applying for SSDI must drop out of the labor force and so are not subject to involuntary job loss.

Figure 5




(a) Employment

(b) Involuntary Job Loss

distinguished by having persistently low labor income prior to their award. About two-thirds have earnings in the bottom 20% of the reference population aged 45-60 in that year. In the model, those going on DI have a slightly higher risk of involuntary unemployment than the reference group whereas in the data the two hazards are not statistically different.[42] The bottom two rows show that those going on SSDI are more likely to have a moderate or severe work limitation, a bit more so in the model than in the data.

Digging further, we would like to see if those going onto SSDI are uniquely unlucky by being exposed to both poor health risks and and poor economic prospects. Figures 6(c)-7(a) display heat maps of the model population, split between those entering DI next year and the average population aged 50-60. These figures emphasize differences in the joint distribution of economic and health risks and their realizations across the two groups. Figure 6(c) shows that individuals going on SSDI come disproportionately from occupations with both high health risks and declining wage trends. The distribution of new DI awards is more biased on the wage trend margin, but these individuals are represented in the entire distribution of occupational risk. Figure 7(a) compares the distribution of individuals across current states. It reiterates the importance of considering both the health and economic margins, jointly. It also shows that many older workers have relatively low wages during

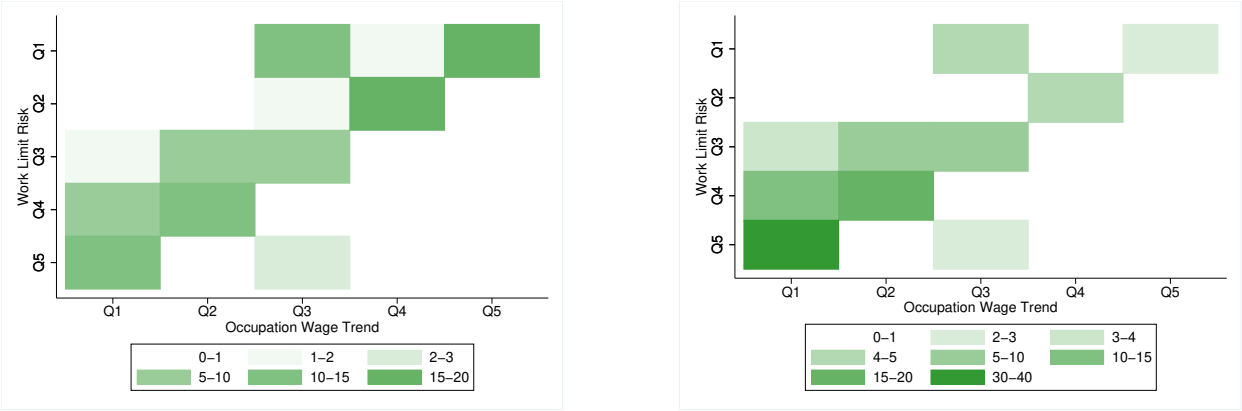
[42]The incidence of involuntary unemployment is over-predicted in the model. This is because, empirically, involuntary separations are serially correlated at the individual level (see Michaud (2018)). Replicating this feature would require an additional state variable, and our modeling choice does not seem to drive up DI applications as the statistic is similar across those going on DI and the reference group.

Table 4: Types of individuals going on DI

| | Model | | Data | |
|---|---|---|---|---|
| Share | New DI | Reference Pop | New DI | Reference Pop |
| Labor income <20-percentile in last 5 years | 66.2% | 28.4 % | 77.8% (3.7) | 21.9% (0.8) |
| Involuntary unemployment in last 5 years | 6.8% | 5.6% | 4.3% (1.0) | 5.5% (0.4) |
| Severe Work Limitation | 53.0% | 5.1% | 68.5% (7.1) | 8.3% (0.5) |
| Moderate Work Limitation | 35.3% | 5.9% | 12.0% (4.8) | 9.6% (0.5) |

Prior $x$ year spans begin one year prior to DI award. Reference population: age 45-60.
Standard errors in parentheses.

the decades we consider, putting them at particular risk of applying for DI regardless of health.



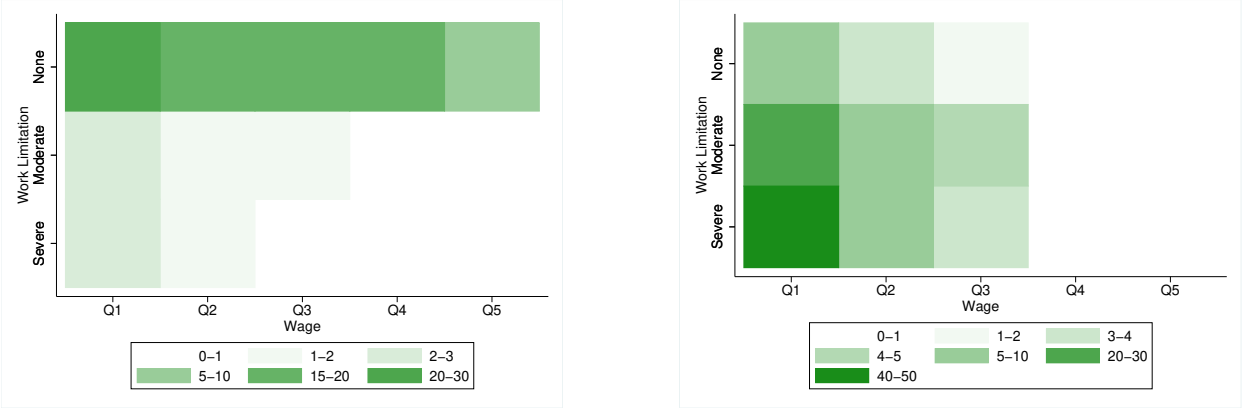

(c) All Age 50-60

(d) New DI Award

Figure 6: Population distribution over occupation health risk and occupation wage trend quintile

## 6.3 What Drives Aggregate Trends in SSDI?

In this section, we use the model to quantify the contribution of external changes—wage trends, demographic shifts, occupational composition trends and business cycles—to the rise in SSDI. To begin, we set the distribution of occupation, age, and health groups to match as closely as




(a) All Age 50-60

(b) New DI Award

Figure 7: Population distribution over current health status and current wage quintile

possible the US in 1980-1985.[43] In every subsequent period, we add individuals as necessary to match exactly the age-occupation distribution of the United States. This ensures that we have the right number of workers exposed to the occupation-specific risks throughout the transition. In each period of the transition, we expose these agents to wage trend shocks associated with their occupation, $z$, as detailed in Section 5. We also expose agents to occupational job finding and job loss rates calculated from the data. Agents' decision rules include an expectation of exogenous switching between recessionary periods and normal times each with the average rates during these times given by $\lambda_y, \iota_y$.

Figure 8 shows the model's success in matching the rise in new awards of SSDI over the period since 1984. In what follows, we focus on the pattern in new awards rather than the stock of all SSDI recipients, the latter essentially integrates the former over time and thus hides some of the successes and failures of the model. The model can account for most of the rise in the share of new awards to DI in the early 1990s and mid 2000s and also predicts the flattening out in the late 1990s. However, it misses the timing and magnitude of the rise in the 2000's through 2010.

Figure 9 shows changes in the age and health composition of applicants over time and how it translates to new awards. Qualitatively, these are the patterns one might expect: applicants become younger and healthier when some occupations' wages are stagnating in the 1990s and during the

[43] 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 the ergodic distribution of these variables.

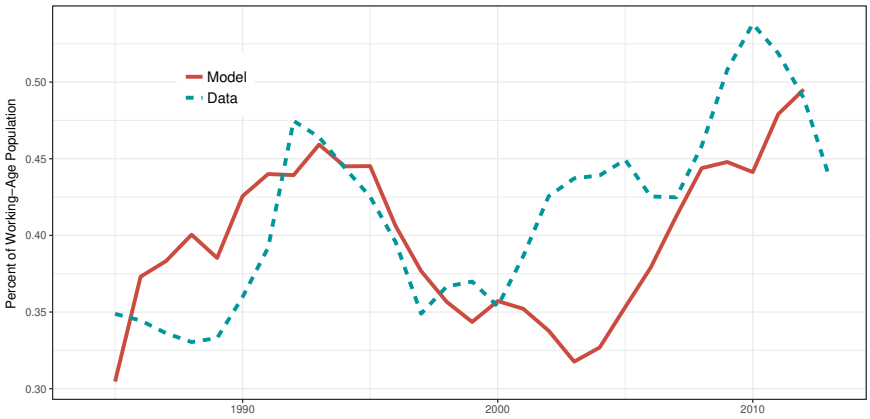



Figure 8: New Awards: Model vs. Data.

Great Recession. However, applicants in good health are mostly rejected during the screening process while the composition by age changes less between application and award.[44]

Figure 10 provides a Shapley-Owen decomposition in which we decompose the differential impact of each age demographics, occupational composition, and wage trends on new awards.[45] For each driving force, we compute the implied contribution by comparing counter-factual simulations including this force or turning off its realizations. To turn off realizations of the wage-trends, we include the aggregate wage trends but remove all of the occupation-specific components. To turn off the demographic and occupational composition changes we add workers in each period to keep the same demographic structure as in the first period and assign them occupations matching the incumbents' distribution. To turn off realizations of the business cycle, we hold it fixed in the expansion state. The Shapley-Owen contribution for a shock we report the average contribution when it is turned on, where we averaging over every permutation of the other shocks being on and off.

The two most important factors driving new awards are demographics and wage trends. The former accounts for about 3% of the total number of awards and the latter for 16% each year. The wage trend is overall the most important component to awards,but its impact is mostly concen-

[44]The model features fewer new awards to individuals without a work limitation than the PSID data: 10% versus 20%; and so it may be wise to avoid conclusions about the efficacy of the actual SSDI screening process.

[45]Decomposing the contribution of each trend is not as simple as turning each trend off one at a time because they interact with each other. For instance older workers may be more susceptible to apply for SSDI given a set of shocks than younger workers and we have more older workers in the economy over time.

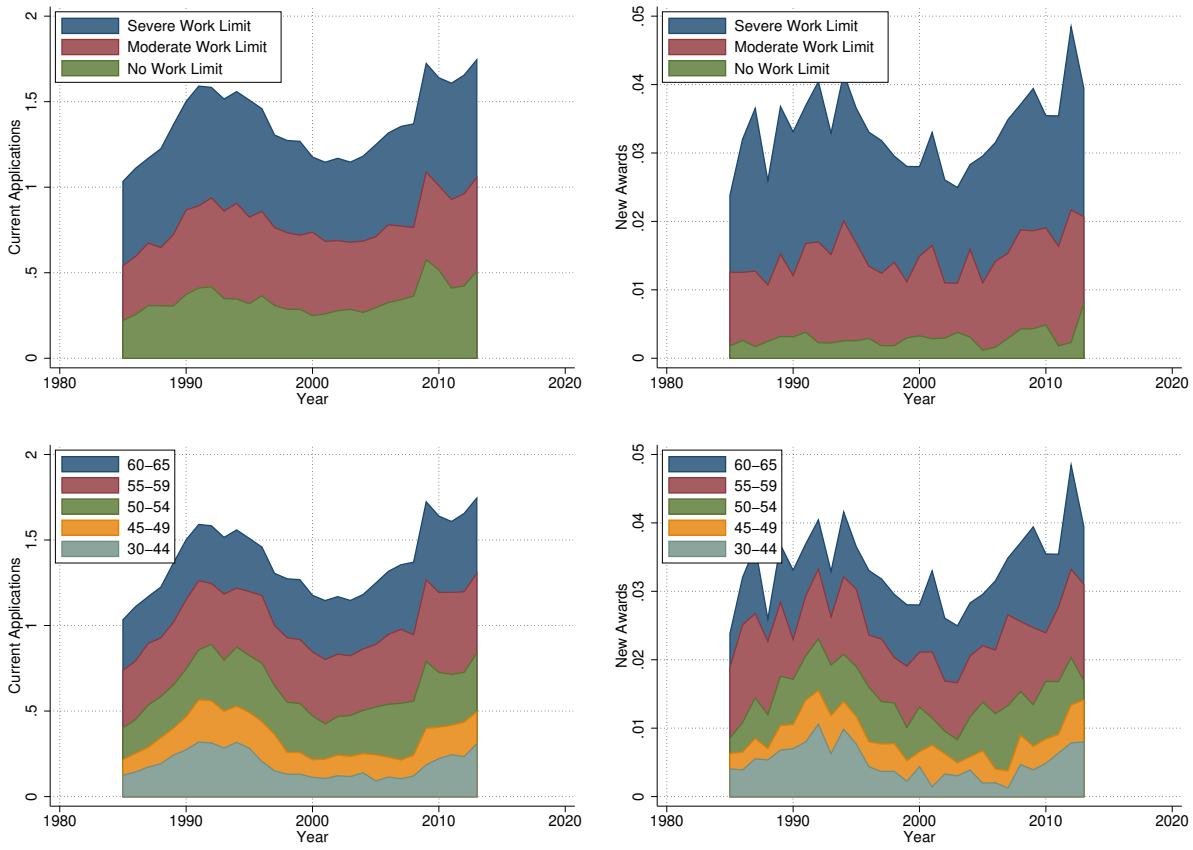



Figure 9: Demographic Composition of Applications and Awards

trated in the late 1980s through the mid 1990s. Prior to 2000, wage trends accounted for 24% of new awards, but after they contribute only 4%. Demographics, on the other hand, have a negative contribution prior to 2000 but account for 13% of new awards from 2000-2013 as the baby boom generation ages into its peak SSDI years. Business cycles contribute small upticks in the number of awards around the 2001 recession and the Great Recession, 2009-2011. However, most of the time, the model gives very little role for business cycles or changes in occupational composition.

Figure 11 displays how applications and rejections differentially contribute to new awards in the model. Applications are dated by the first year the agent began to apply given they did not apply in the prior 12 months.[46] Therefore, they provide a better sense of the timing of when agents

[46]We lack an empirical comparison for applications and outcomes because we do not have SSA data on these statistics that are disaggregated to men only.

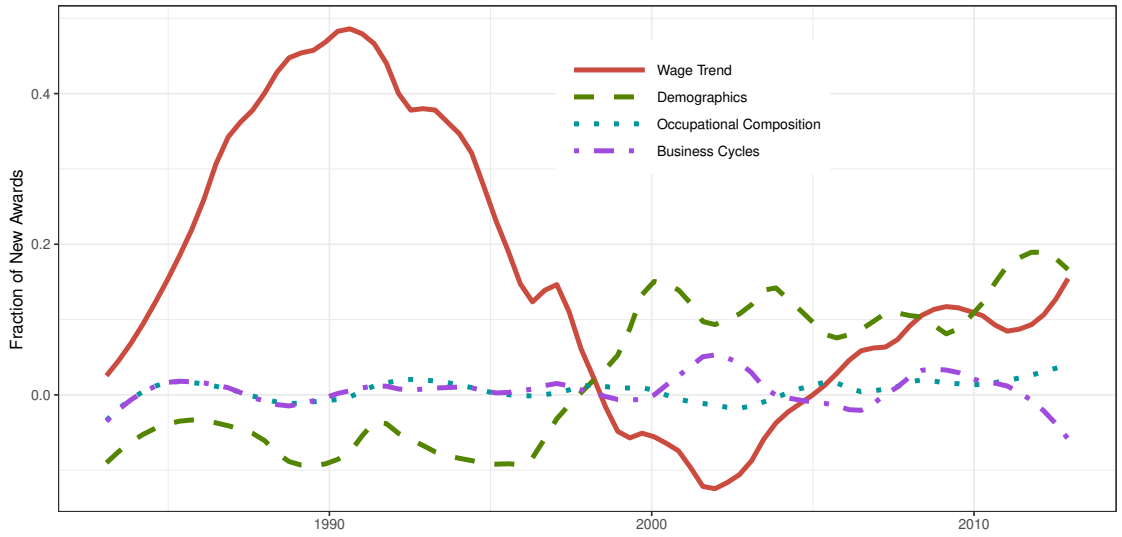


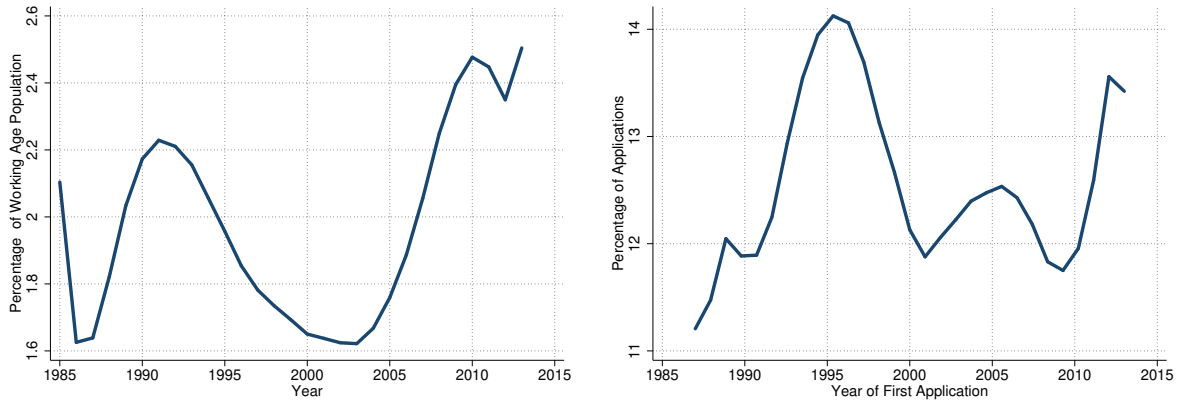

Figure 10: Decomposed contributions to new SSDI awards

chose the DI option. Indeed, they move more concurrently with secular wage declines in the early 1990s and the onset of the Great Recession than awards do. Denials are defined as continually applying for 14 months without receiving an award and are dated by the date of first application.[47] The denial rate in the SSA data pooled over gender during this time period is about 22%. However, the SSA data includes technical denials such as applying when ineligible or not completing forms. These account for 30% of all denials in the data. Once we correct for these denials on applications absent from the model, the model provides a good fit to the comparable SSA denial rate of about 15.5%. This is reassuring since denials were not directly targeted in the calibration.

Changes in the denial rate per application help fill in the quantitative discrepancy between the application and award rates (Figures 11(a) and 8). For the most part, increases in denials follow increases in applications and are consistent with the results in the prior section that applicants become younger and more healthy during such surges. Notice that applications surged in both the 1990s and Great Recession, but the former accompanied a larger rise in denials. This suggests that the pool of applicants deteriorated more in the first period than latter largely due to the presence of the older Baby Boomers in the pool of applicants during the latter period.

Figure 12 shows the Shapely-Owen decomposition for the application rate. Wage trends have a

[47] This follows the estimates in Autor et al. (2015) for the median duration of an application of 13.5 months.




(a) Applications

(b) Denials

Figure 11: Applications and denials per working age person by date of first application.

much more pronounced effect throughout the simulation than when we looked at awards. They are still driving the rise in the late-1980s to early-1990s increase in applications, but are proportionally larger in the post-2000 period. Overall, these wage-trends contribute 13% of applications and 6% after 2000, almost twice their contribution to awards in that period. Aging still contributes towards the end, but is less pronounced than Figure 10 because these older workers are less likely to be denied: they tend to be in worse health. Looking at other forces driving applications, there are small spikes from business cycles at each recession: the early 1990s, 2000's and Great Recession. These are slightly larger than the spikes we saw in the awards decomposition (Figure 10) because recessions cause more marginal applicants to joint the pool. Most of the time business cycles contribute negatively to applications because during expansions awards are somewhat subdued.

A main point in this paper was that occupations expose workers to correlated health and economic risks. We can try to understand the role of this crucial correlation in driving new awards through a counterfactual alternative calibration in which health shocks are drawn independently from occupation but everything else, including the overall health risks, is kept the same. The result is about 5% fewer awards, distributed evenly throughout the simulation period. This makes the correlation between occupations and health risks more important than business cycles in driving awards, but less important than demographics.

A distinct phenomenon the model cannot replicate is the rise in awards with vocational considerations that provide almost all of the rise in new awards since 1984. Figure 13 shows how many of

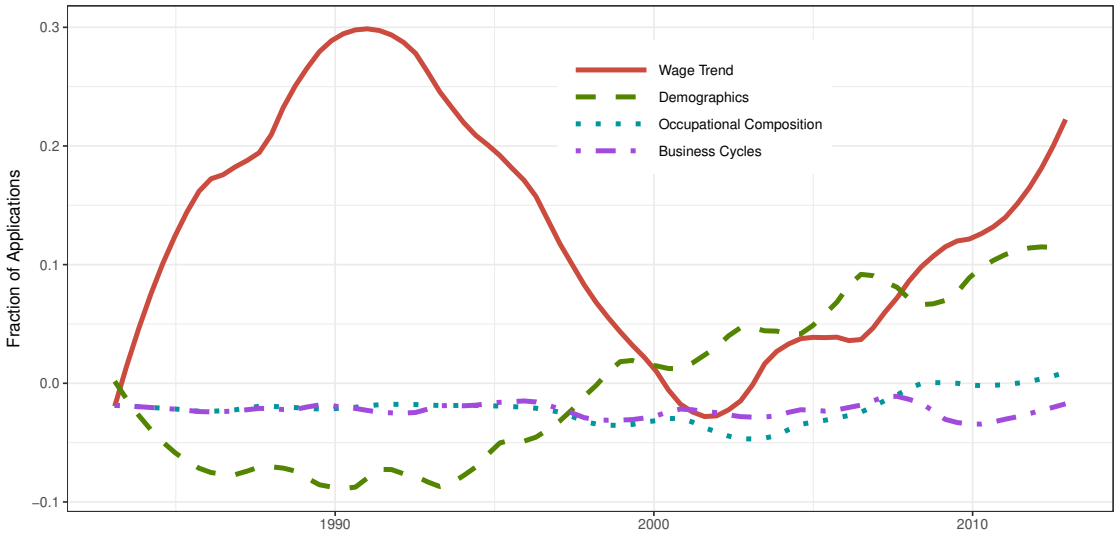



Figure 12: Applications: Shapley-Owen Model Decomposition.

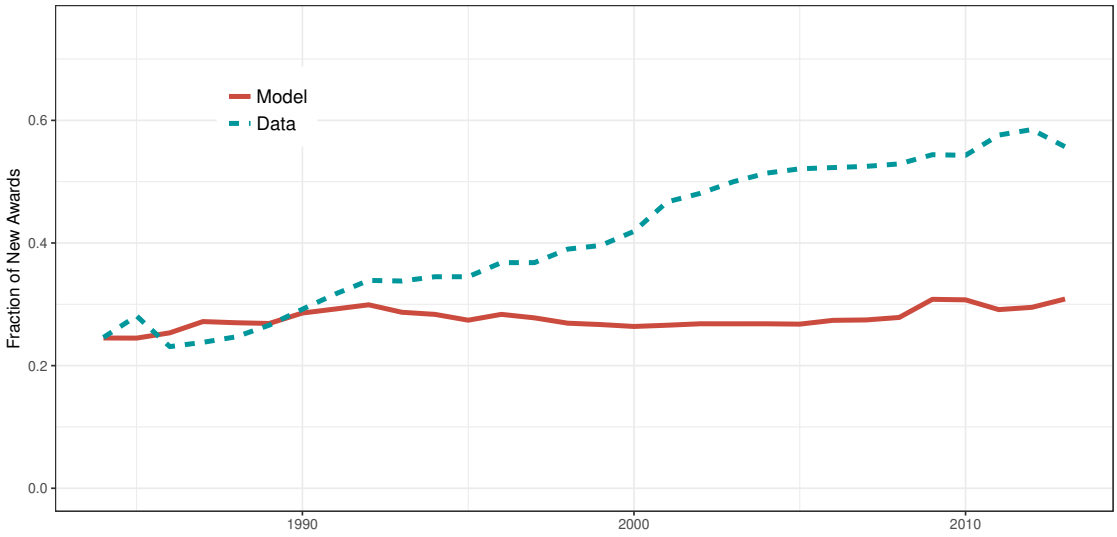



Figure 13: New Awards: Fraction with Vocational Considerations

the current beneficiaries had vocational considerations factored into their award in our model. We match the initial period exactly, as it was a calibration target. Thereafter, vocational awards rise by about 6 percentage points and follow a similar pattern to applications in general—rising through the early 1990s, slumping and then rising again. This is far less than the tripling share of awards

with vocational consideration seen in SSA data. However, our simulation's moderate rise compared to the data should not be considered a failure of the theory. Our experiment predicts what would occur if the defacto implementation of the vocational grid rules are held constant over time. The discrepancy with the data could be because, in actuality, the rules may not have been implemented in a consistent way across time and/or space. Indeed, this hypothesis is consistent with other work exploiting the variation in award leniency across locations in their research design (French and Song (2014)) and has been a focus of internal reforms in the Social Security Administration.

# 7 Impact on Employment and Welfare

## 7.1 Contribution to employment trends

A typical question in the literature is the impact of the SSDI program on employment and labor force participation. The employment to population ratio for working age men fell by 6.4 points over our period of study (1984-2012). The model predicts a decline of 4.3%, three-quarters of which is provided by the increase in SSDI beneficiaries.[48] We now examine how the demographic and economic trends as well as business cycles we fed in to the model generate non-employment when social security disability is an option.

Our model has an advantage in addressing this question over existing administrative and survey data because we can observe the individuals who are non-employed because they are either in the application process, waiting to be eligible to apply, or whose applications have been rejected but are choosing not to work. Individuals in this situation comprise 1.6-2.5% of the working age population in the model simulation. This is a sizeable. The stock of current beneficiaries rose from around 2% in the 1980s to almost 5% by 2010, meaning current applications amounted to two-thirds of the stock of beneficiaries in the 1980's falling to about one-half by 2010. Omitting this group would understate the employment impact of SSDI by 30-40%. This group also accounts for a growing share of those in non-employment, increasing from 25% in 1985 to 66% by 2010. This signifies that disability insurance has become an increasingly attractive option for the non-employed through the various channels we have previously discussed.

The disability option contributed differentially to the disparate non-employment trends of dif-

[48] Other theories of increasing non-employment among low skilled men include a higher return to non-participation through channels we do not include in this paper (Aguiar et al. (2017), Wolcott (2017), Abraham and Kearney (2018), and others).

| | Total | By Age | | | | | By Occ Health Risk | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 30-44 | 45-49 | 50-54 | 55-59 | 60-65 | Q1 | Q2 | Q3 | Q4 |
| $\Delta$ Non-Employed | + 4.3 | + 1.7 | + 3.2 | + 4.7 | + 4.5 | + 8.9 | + 0.8 | + 5.2 | + 4.7 | + 8.4 |
| % $\Delta$ on DI | 75.1 | 71.8 | 60.7 | 81.8 | 137.9 | 107.3 | 84.6 | 70.0 | 94.0 | 80.0 |
| % $\Delta$ applying for DI | 18.4 | 28.0 | 20.1 | 12.8 | -2.2 | -2.1 | 28.5 | 13.4 | 17.5 | 18.8 |
| % $\Delta$ other | 6.5 | 0.2 | 19.2 | 6.2 | -35.7 | -5.2 | -13.1 | 16.6 | -11.5 | 1.2 |

Table 5: Change in non-employment 1985-2013 in basis points, decomposed into change in SSDI beneficiaries, SSDI applicants (including those waiting in non-employment to apply), and those non-employed for other reasons.

ferent demographic group. Starting with the first column in 5, we see that an increase in current SSDI beneficiaries/applicants each contributed 75% and 18%, respectively to the increase in non-employment in the model. Across age groups, the increase in current beneficiaries is most important for the rise in non-employment of older individuals, particularly those 55-59. An increase in those currently applying is relatively more important for younger individuals. The pattern across occupational health risk demographics is less clear. This is because the exposure to economic shocks and aging demographics is not perfectly correlated with health risks and the screening rules for awards further complicates these relationships. However, the magnitude of the increase in non-employment is consistent with the intuition of our model: older workers and those in the occupations with the highest health risks have the largest increase in non-employment of over 8 basis points each.

## 7.2 Welfare value

Our structural model allows us to compute the value of the disability option to any individual at any moment in time and thus understand both the overall and distribution of welfare gains from this program.[49] To compute the value of the SSDI option to an individual at a given state, we compute the model without the ability to apply for disability, as if $\nu \to \infty$. This yields a counterfactual value function, $V_{CF}$ at any state from which we can compute welfare in consumption terms, $\frac{V}{V_{CF}}^{1/(1-\gamma)} - 1$. For each worker in our simulation who is not already on SSDI, we store this welfare gain. This measure requires several caveats, chiefly that we are evaluating both the true and counter-factual value functions using the true policy functions, $a', m$ and labor supply, that

[49] As in Low and Pistaferri (2015), a limitation is that we are using a partial equilibrium notion; we are not incorporating the costs of the SSDI program, e.g. higher taxes. Ours is additionally a more stark counterfactual– completely eliminating the program. Still, this exercise provides insight into the heterogeneity in the benefits of SSDI across age, occupation and cohorts.

are chosen by individuals with access to SSDI, however, $V_{CF}$ is computed as if that option were unavailable. Hence, this measure should be understood as an instantaneous value of SSDI starting from a particular point in an agent's history.

While the average welfare gain is relatively low, about 1% of consumption, there is a very long tail of those who place very high value on the program.[50] Interestingly, the program's value is not monotonically increasing in age. In fact, as workers near retirement, SSDI becomes relatively less valuable because of the lengthy application process. This age trend however, masks heterogeneity by health: for healthy individuals SSDI is most valuable when they are young and the monotonically declines from there, whereas if $d > 0$ the program's value peaks around 55 and is always more valuable.

Differences across health turn out to be crucial to understand who values SSDI. Figure 14 shows that the program generally becomes more valuable at lower realizations of the wage trend $z$, but especially so for those with a work limitation ($d > 0$). At $z = 0$, those with a work limitation get about 80% more welfare gain than those without. At $z < -0.4$, they value SSDI about 125% more. At the other extreme, when times are good and $z$ is high, neither health group places much value on SSDI at all. This once again emphasizes that economic conditions affect the application behavior of *all* health groups.

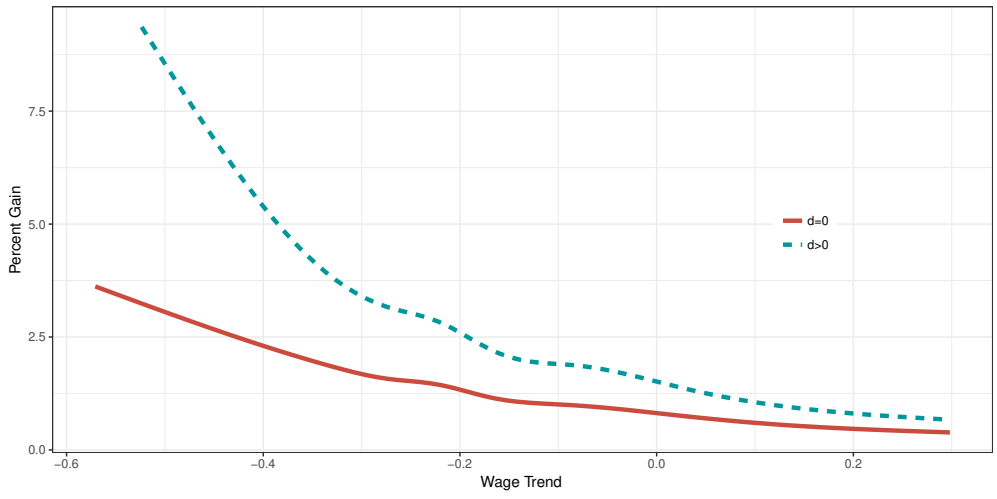



Figure 14: Welfare gain across wage trend levels and by health

[50]For comparison, Low and Pistaferri (2015) find a 30% reduction in SSDI benefits decreases welfare by less than a half of a percent on average, but by more than 1.5 percent for the lowest skilled workers.

# 8 Conclusion

This paper quantitatively explored the rise in Social Security Disability Insurance since the mid 1980s. Over this period, the fraction of working-age recipients tripled and the rate of new awards increased steadily. Concurrently, the U.S. was experiencing pronounced changes in its demographic, occupational and wage structure. Each long-term factor, along with regular business cycles, influenced applications both though direct incentives and also indirectly by impacting the likelihood a DDS office would grant an award. This paper studied the rise of SSDI with a rich model of household application choice and DDS decision rules incorporating these interactions.

Within a structural model we found that different factors drove SSDI trends over different periods. During the late 1980s and 1990s, the secular deterioration of economic conditions was particularly important. It accounted for 24% of the rise during this decade and only 3% after 2000. Demographic change, particularly driven by the aging of the Baby Boom cohort, mitigated SSDI awards prior to 2000 and then drove an increase in awards by 13% thereafter. While there was a small uptick in awards during the Great Recession, the business cycle itself has little impact in part due to its transitory nature and an effective screening process to reject those in good health.

We further used the model to assess the impact of changing demographics and economic conditions on non-employment when disability is an option. The contribution of disability goes beyond new beneficiaries. It also includes people entering non-employment in order to apply or appeal for SSDI benefits as well as those rejected applicants who have lost attachment to the labor force over the several years of applications and appeals. The model replicates two-thirds of the rise in non-employment of men without college education from 1984-2012: 4.3 percentage points, and SSDI plays an important role. The share of non-employed who are not on disability nor wishing to apply falls from 75% to 44%.

The analysis is limited by a couple of shortcomings. First, women are omitted from the study. Female eligibility grew significantly over this time period while male eligibility declined, which reflects different underlying labor force participation trends. Most new awards to women are for mental and emotional conditions whereas musculoskeletal is the predominant diagnosis of males. Since female trends in SSDI awards are sufficiently distinct from male trends, we concluded that the demographic group merits its own study and excluded them from this paper.

Second, the model predicted too few new awards to individuals in good health (type one error)

and was unable to replicate the rise in awards with vocational considerations from 25% in the 1980's to almost 60% after 2010. We believe these problems are related and arise from a common source. We used a consistent and time invariant vocational-grid award probability set to replicate elasticities from internal audit studies and to match the share of vocational awards during the initial years in our study period. De facto changes in how these rules operate over time or inconsistencies in how they operate across space could generate a rise in vocational awards alongside rising awards to individuals in good health.[51] Analysis of additional data from the Social Security Agency to answer questions about the variability in the awards process, and particularly in the vocational grid, is a promising avenue for future research and would complement this paper.

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# 9 Figures

Table 6: Occupational Characteristics and Risks

| | O*NET Tasks | | Health | | Flows | | | | Wages | |
|---|---|---|---|---|---|---|---|---|---|---|
| SOC | Physical | KSA | Any | Severe | $\mu$EU | $\sigma(EU)$ | $\mu$ UE | $\sigma(UE)$ | Level | Growth |
| 1. Managers | -6.79 | 12.96 | 0.09 | 0.05 | -1.29 | -1.19 | -1.31 | -1.42 | 2.94 | 0.02 |
| 2. Professional | -3.71 | 9.50 | 0.10 | 0.05 | 0.71 | -0.46 | -1.21 | -1.07 | 2.95 | 0.00 |
| 3. Sales | -5.05 | 7.33 | 0.10 | 0.05 | -0.32 | -0.99 | -0.62 | -0.95 | 2.67 | 0.00 |
| 4. Clerical | -4.43 | 3.02 | 0.10 | 0.05 | -0.78 | -0.75 | -0.86 | -0.98 | 2.78 | -0.03 |
| 5. Service: house/building | -0.11 | -10.51 | 0.11 | 0.06 | -0.92 | 1.06 | 0.68 | 1.01 | 2.27 | -0.07 |
| 6 Service: protect | 1.63 | 7.30 | 0.11 | 0.05 | -0.59 | 1.86 | -1.02 | -0.73 | 2.77 | 0.09 |
| 7.Service: food | 2.25 | -0.35 | 0.11 | 0.05 | 0.72 | -0.65 | 0.54 | 0.19 | 2.38 | 0.06 |
| 8. Service: health | -1.41 | -0.19 | 0.09 | 0.04 | -0.40 | 0.55 | -0.48 | -0.54 | 2.53 | -0.03 |
| 9. Service: personal | -0.84 | 0.52 | 0.11 | 0.06 | -0.08 | -0.80 | 0.45 | -0.06 | 2.32 | 0.00 |
| 10. Farm, Forest, Fish | 2.43 | 0.74 | 0.12 | 0.06 | 2.06 | 1.60 | 0.61 | 1.09 | 2.04 | 0.02 |
| 11. Machanics/repair | 3.14 | -3.73 | 0.10 | 0.05 | -0.54 | 0.25 | -0.63 | -0.47 | 2.82 | -0.05 |
| 12. Construction/extraction | 4.00 | -6.18 | 0.12 | 0.05 | 2.08 | 0.01 | 1.71 | 2.04 | 2.75 | -0.03 |
| 13. Precision Production | 1.11 | -4.64 | 0.12 | 0.06 | -0.48 | 1.13 | -0.54 | -0.21 | 2.83 | -0.07 |
| 14. Operators: machine | 2.59 | -6.13 | 0.10 | 0.05 | -0.82 | -0.90 | 0.40 | 0.23 | 2.66 | -0.06 |
| 15. Operators: transport | 0.80 | -2.21 | 0.11 | 0.05 | 0.69 | 0.32 | 0.21 | 0.36 | 2.61 | -0.02 |
| 16. Operators: handlers | 4.40 | -7.43 | 0.12 | 0.06 | -0.04 | -1.02 | 2.07 | 1.51 | 2.49 | -0.02 |

(a) O*NET Tasks: first PCA of Physical tasks and the first PCA of the Knowledge, Skill, and Ability (KSA) tasks, standardized statistic.
(b) Health: Estimated work limitation hazard at age 60.
(c) Flows: Standardized statistic of employment to unemployment (EU) and unemployment to employment (UE) hazards
(d) Wages: Level is mean log wage. Growth is the mean change in wages in 10yr rolling windows over 1984-2012