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

Amanda Michaud David Wiczer*

Indiana University Stony Brook University

This Version: May 21, 2018

Most Recent Version.

(Preliminary. Please do not cite)

Abstract

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

*E-mail: ammichau@indiana.edu or david.wiczer@stonybrook.edu.

Michaud thanks FRB of Atlanta & FRB of Kansas City for hospitality and support for this project. For comments, we thank Mariacristina De Nardi, Sagiri Kitao, Yue Li, Hamish Low, Timothy Moore, Luigi Pistaferri, James Zilliak ; and participants at Barcelona GSE 2016, BLS, Census, Colby College, FRB-Cleveland, FRB-NY, FRB-St. Louis, GRIIPS-Keio, IUPUI, NBER, Purdue, SED 2017, Temple, U Alberta, UKentucky, UMelbourne, & UVA.

1 Introduction

The number of U.S. Social Security Disability Insurance (SSDI) beneficiaries has risen consistently for the past 30 year years, nearly without abatement. In 1985 there were 3,907,169 individuals receiving SSDI benefits, 2.2% of the labor force. By 2015 beneficiaries swelled to total 10,931,092, 6.6% percent of the labor force[1]. This expansion was not a consequence of changes in program rules; the last major overhaul was completed in the early 1980s. Nor is it easily accounted for by broad demographic factors: expanded eligibility for benefits resulting from increased female participation and the aging of the baby-boom cohort contribute to less than a third of the rise (See Figure 6).[2]

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

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

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

[2]Predicted changes are constructed as the weighted sum of predicted new awards across 14 age cross gender demographic cells. Predicted new awards at the demographic cell level are the product of share of insured workers times new awards per insured worker. We hold all these rates and the weight of each cell to the 1985-89 average and introduce the actual time series changes cumulatively: first changing the share of insured in each cell and then add to this the total demographic share (weights) on each cell. Details explained in the appendix

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

We put structure around individuals' SSDI application decisions to provide insight into the forces shaping them. We develop a quantitative framework in which individuals face correlated economic and health risks as they age. We discipline the quantitative predictions of this structure using individual-level microdata over the period in which SSDI was rising most steeply. Our key insight is that occupations bundle tasks differently, and as a result impose differential heath and economic risks across individuals. This allows us to infer from individuals' lifetime occupational histories a portion of the health risks they have faced and the economic risks associated with their vocational skill set. We connect these risks to worker's labor-force participation decisions. Variation across workers with different occupations reveals how realized health and economic status—along with future prospectives for them—affect the labor supply decision. It also suggests that changing occupational demographics impact aggregate outcomes. We calibrate parameters of our model such that the behavior of agents replicates moments summarizing the patterns of individuals' behaviors that we document. We then use the model to predict how changes in the occupational and demographic structure along with differential exposure to economic risk contributed to the rise in SSDI applications.

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

A second difficulty, another reason to use a structural model, is that SSDI acceptance rules explicitly consider individual characteristics besides health. These so called "vocational considerations" include education and age, as well as scope to consider regional or industrial economic prospects. The implication is that SSDI acceptance probabilities differ even for individuals of the same health. Data show the percentage of new SSDI awards in which the grounds for acceptance included vocational considerations, not just health, has increased from 25% in late 1980's to almost 60% after 2010. It is not clear whether the rising importance of vocational considerations stems from increasing de facto leniency of the awards process or a change in the demographics of who is applying. In our structural model, we will estimate a static decision rule, our version of the so-called "vocational grid," that determines the probability an application is successful conditional on health, economic circumstance and age. From this we learn how the vocational rules affect incentives to apply and then can ask whether the trend in vocational awards can be accounted for by changing demographics and economic conditions. If not, we conclude there is room for de facto changes in the institutions themselves.

All the forces we discussed: demographic change, differential health exposure, economic trends, business cycles, and program rules are important to address whether the increase in SSDI was a one-off confluence of particular factors or whether high enrollment will be sustained in the future. However, these counterfactuals are not obvious from inspection of data given the rich interaction of these forces. Our main results use the model for this decomposition. Overall, the model accounts for about three-quarters of the rise in flows onto SSDI. Within that decline, 22% can be accounted for by the dynamics of observed real wages and 32% from the disproportionate concentration of health risks in certain demographics. In thinking about the future, we find that the elasticity of SSDI with respect to a uniform real wage decline is 28% and with respect to a uniform increase in unemployment risk is 10%. cyclical cyclical fluctuations contribute quantitatively insignificantly. However, this result is tempered by the running theme of the paper: it matters which demographics experience these shocks.

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

2 Literature

Topically, our paper belongs to a literature studying the incentives and circumstances determining whether individuals apply for Social Disability Insurance. The methodology employed by this literature is divided between reduced form strategies and quantitative analyses of structural models.[3] We employ the latter methodology, but conduct exercises explicitly designed to relate our approach to findings in the empirical literature.

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

We maintain key ingredients from these works, but abstract from other ingredients in order to accommodate innovations necessary to answer the specific question we are after. Our new features include: sectors with differential health and economic risks; a variety of economic risks including cyclical job finding and displacement rates, long-run wage decline/growth, and heterogeneous idiosyncratic wage risk; and a realistic SSDI acceptance criteria that includes vocational considerations.

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

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

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

3 Motivation

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

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

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

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

3.1 Occupations Provide Correlation in Health and Economic Risks.

To motivate our analysis, we link health and economic risks to 16 broad occupational categories. The time period we consider in 1980-2014, with data collected at an annual frequency.[6] 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.[7] We measure occupational exposure by an individual's longest held occupation.[8] Our measure of health risk is the proportion of individuals in a given life-time occupation who report a "severe work limitation" by age 60.[9]

Figure 7 shows the correlation of health and long-run employment growth by occupation.[10] Figure 8 shows the correlation of health and labor income growth.[11] Both graphs show ample variation in outcomes amongst both occupations with low and high health risks. Large occupations with high risks such as Production and Machine Operators are in decline, but smaller occupations also having high health risks, such as Food Services, are growing, (Figure 7). Similarly, not all safe occupations are expanding. The safest occupation, cler-

[6]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.

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

[8]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.

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

[10]Employment is defined as full-time ($\geq$ 30 hours in the reference week) and full year ($\geq$ 50 weeks/year).

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

ical work, is in substantial decline relative to trend. Differences in SSDI claim behavior across these occupations will inform the relative importance of long-run decline in Economic prospects and how much the incidence of Economic decline affects those with high health risk more than those with low health risks. Labor income (Figure 8) also shows substantial variation across the health risk spectrum. In particular, labor income decline is not necessarily isolated to occupations with lower employment growth relative to trend. Transportation is a notable example. This variation is useful in informing the importance of labor income apart from employment.

Figure 9 provides an alternative view on employment risk. Instead of long-run movements in the occupational structure of the US economy, these graphs show both average and cyclical rates of flow for individual workers between employment and unemployment. The average is a measure of churn that is also interpreted as average job/unemployment duration. For example, Managers have low Employment to Unemployment (EU) flows indicating long job duration, but also have low Unemployment to Employment (UE) flows indicating long unemployment duration. Construction is on the other end of the spectrum with high churn: unstable jobs, but fast job finding from unemployment. The standard deviation shows how much these hazards change over the business cycle. Occupations such as services and production show high cyclical rates of job loss whereas construction workers and handlers have instead a slow down in exit from unemployment. We will incorporate this rich variation in job hazards to provide a more nuanced understanding of the business cycle than can be ascertained by considering variation in unemployment rates alone.

3.2 SSDI Award Criteria Consider both Health and Vocation.

The SSDI award criteria directly distorts the incentive to apply for SSDI across demographics, particularly through explicit rules called "vocational considerations", (key SSA terms defined in 3). Vocational considerations are the last step in the four-stage sequential decision process the Social Security Administration uses to determine whether or not to award a disability claim (see 10). Claims made by uninsured workers are rejected in the first stage. To be insured, a worker must have accumulated a sufficient number of SSA work credits.[12] Claims made by insured workers currently engaged in substantial gainful activity are rejected in the second stage. In 2016, the threshold for substantial gainful activity was having earnings greater than $1,130 per month. Health is considered at the third stage. Claims are accepted at this stage if the applicant provides proof of a severe medical condition expected to last for at least one year or result in death, that meets or is equivalent to a condition the SSA's listing of impairments.

Claims that pass the first two stages and are *not* accepted at the third stage move on to the final stage in which vocational factors are considered. First, the residual functioning capacity (RFC) of the applicant is evaluated in order to identify the types of work the individual is capable of in spite of their disability. If it is deemed the applicant is capable of performing their recent past work, their application will be denied. Otherwise, it will be considered whether the applicant has the vocational skills to adapt to new work feasible given their (RFC). Crucially, from here forward health is no longer considered in the accept/reject conditions. The set of possibilities is explicitly narrowed by expected vocational

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

adaptability. First, age and education are considered according to a vocational grid (see 4). The grid defines explicit age categories at 18-44, 45-49, "approaching advanced age" at 50-54, and "advanced age" at 55+. Rules dictate that older applicants are limited in vocational adaptability and should be more likely to receive an award compared to younger applicants with similar RFC. Education is evaluated along three dimensions: formal education, literacy, and ability to communicate in English. Similarly older applicants, those with limited education are also ruled to be less able to adapt to new vocations and more likely to get an award. Second, an individual's past work experience is considered. Specifically, it is evaluated whether skills they used in the past are easily transferable to other occupations. After the set of occupations to which the applicant can be expected to adapt are narrowed by RFC and vocational considerations, the SSA can only reject the claim if it can provide evidence that job openings in significant numbers in such occupations. Otherwise the claim will be awarded.

Figure 12 shows the role of the Vocational stage in SSDI claim outcomes has changed in important ways over the past decades. In the late 1980's 80% of denials were based upon the decision that work suited to the applicants residual functioning capacity was available. This share rose to 90% in the 1990s before falling to less than 70% in the 2010s. Moreover, the share of awards based upon the decision that suitable work was *not* available rose monotonically from 25% in the 1980s to 60% after 2010. Yet the share of all decisions, awards and denials, with vocational considerations only rose 10 points. This implies that a larger/smaller portion of denials/awards are taking place at the medical stage. What is not clear is whether these trends are indicative of the award rate at the vocational stage reacting to changing economic conditions or whether economic conditions changed the demographics of the types of workers who file SSDI claims. Likely, it is both. This motivates our inclusion of separate medical and vocational award stages in our model so that we may disentangling the two for a deeper understanding of how much and why economic conditions are important for SSDI claims.

4 The Model

The model features overlapping generations of agents that spend a portion of their lives with the option of participating in labor markets and a portion of their lives in retirement. At birth, agents are assigned a life-time occupation that affects wage, employment and disability risks. Over the life course 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.

4.1 Demographics

The model is populated by agents of various ages $\tau \in \{0, 1, 2...T\}$. Agents age sequentially; at each age τ they progress to $\tau + 1$ with probability ϕ_τ. Agents of age τ and health status d die with probability $\phi_\tau^{death}(d)$ and are replaced by an equal measure of new-born agents of age $\tau = 0$. Agents begin life employed in an occupation $j \in \{1, 2...J\}$. They then draw a permanent δ^i related to their personal health deterioration risk. The characteristic δ^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 φ. Otherwise, they choose whether to go back to work or remain unemployed in the following period. Long-term unemployed chose whether to apply for SSDI or search for a job. Agents of age $\tau = T$ are retired. Retired agents and agents receiving SSDI cannot work; they consume from their savings a and social security retirement payment $SSI(e)$ or disability payment $SSI(e, F)$, where e is a measure of their prior labor market earnings and F is an indicator for whether the agent retired at the Social Security threshold of full-retirement age.

4.2 Income

Wages are exogenous. They depend on agents' idiosyncratic component α, their current age τ 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, α 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 α evolves stochastically, according to a process π_α.

4.3 Disability

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

4.4 Social Transfer Programs: Unemployment, Disability, & Retirement

Non-employed agents receive exogenous social transfers, $UI(e)$,$SSDI(e)$, and $SSI(e, F)$, according to their state: unemployed, disability beneficiary, or retired, respectively[13] In line with the US systems, these transfers depend on an index of agents' prior earnings: e. This index is updated when an agent works according to their current wage, age, and past earnings: $e' = H_\tau(w, e)$. Retirees automatically receive old age insurance $SSI(e, F)$. Newly unemployed agents receive $UI(e)$ until, with Poisson probability φ, 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 ν.[14] 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

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

[14] 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.

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.

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: $SSI(e, F = 0) = 0.8 * SSDI(e, F = 1)$.

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

4.6 Preferences

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

4.7 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' type i. We proceed backwards with the terminal value of retirement, then the irreversible disability beneficiary, and finally the unemployed, long-term unemployed, and working agent as well as the choice between work and unemployment.

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

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

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

A Disability Beneficiary's Problem A disability beneficiary's problem is also boring. Agents' disability extent and earning index do not change, but they do continue to age and face differential mortality given their disability d. The only choice agents make is a consumption versus savings decision given their asset holdings and SSDI income. This problem repeats until the agent exogenously ages into retirement $\tau = T$. Of the individual state, d, e are constant and earnings components α, β are no longer relevant.

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

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

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

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

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

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

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

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

Application for SSDI benefits is a discrete choice: $m = 1$ if the agent applies and is zero otherwise. If the SSDI application is accepted (with probability ξ_d), the agent becomes a disability beneficiary for the rest of life until retirement. If the application is not accepted, the agent remains long-term unemployed: $\mathbf{E}[V^N_{j\tau'}(\alpha', e', d', a'; z', y')]$. If the agent does not apply, there is a probability ρ he or she will have the opportunity to work again next period: $\mathbf{E}[V_{j\tau'}(\alpha', e', d', a'; z', y')]$; and with probability $(1 - \rho)$ remains unemployed. Long-term unemployed cannot search for a job, they may only apply for DI.[15] Finally, observe the long-term unemployed receives a flow of real income b, which can be considered a combination of home production and broader social transfers (food stamps, TANF, etc).

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

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

$$V_{j\tau}^{W}(\alpha, e, d, a; z, y) = \max_{c,a} u^{W}(c, d) + \beta \sum_{\tau} \phi(\tau, \tau')E[V_{j\tau'}(\alpha', d', e', a'; z', y')]$$

$$c + a' \leq w_{j\tau}(d, z) + Ra \;:\; a' \geq 0$$

$$e' = H_{\tau}(e) \quad z' = \mathcal{Z}(z)$$

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.[16]

5.1 Externally Set Parameters- Preferences and Demographics

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

Demographics Individuals age through 5 age groups: 30-44, 45-49, 50-54, 55-59, 60-65 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

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

age groups die randomly by a probability following their health-specific death rate.[17]

Agents are assigned a "life-time" 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 their occupation probablistically to match the distribution among this group.

Preferences Preferences follow Low et al. (2015), in which workers value consumption, 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 et al. (2015).[18] This implies disability and work both increase the marginal utility of consumption. In other words, disabled individuals must have higher general consumption expenditure to maintain the same utility. Quantitatively, this implicitly captures the higher health expenditures of those in poor health which we do not model explicitly.[19] We set $\gamma = 2$, within the standard range of risk-aversion. [20] We choose the interest rate such that the wealth level of the 55-62 age group is equal to four times the economy average as is targeted in Kitao (2014) to match the corresponding statistic from the Survey of Consumer Finance.

[17] Population demographics calculated using linear interpolation on decennial census data. Health specific death hazards for each age group are calculated from PSID data.

[18] See Low et al. (2015) for details on how consumption data is used to identify these parameters using consumption data.

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

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

5.2 Social Insurance Institutions

Social Security Disability Acceptance Screening The Social Disability Insurance (DI) program in our model is designed to replicate realistic features of the US Social Security Disability Insurance (SSDI) program.[21] The SSDI program provides partial earnings replacement to covered individuals unable to work because of a health-related work limitation. Award of insurance payment upon the onset of disability is subject to meeting several sequential criteria. First, the individual must be eligible: they must meet an work requirement on prior earnings and file an application.[22] Second, the applicant must have been non-employed for five months prior to application and not have earnings exceeding a low threshold of substantial gainful activity.[23] Third, the applicant must demonstrate a physical or mental impairment resulting in the 'inability to engage in substantial gainful activity" and is expected to last for one year or terminate in death. Fourth, it must be deemed that the applicant can neither perform the job they did previously nor can they be "expected to adjust to other work that exists in the national economy".

With regard to the first criteria, we consider 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. [24] This figure

[21] The program underwent major changes in the late 1970's and early 1980's. There have been no major changes since the 1984 reforms. As such, our analysis begins at 1984.

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

[23] $1090/month in 2015.

[24] 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

is 83.4%. Agents incur a utility cost to submit an application. This cost is proportional to the expected gain from receiving disability benefits. In practice this cost includes physical and/or mental examination, a court hearing, and very often appeals.[25] In the model, this cost is a key parameter determining whether the marginal individuals apply for benefits. Therefore, this cost is calibrated jointly with other parameters discussed below, but most directly mapping to the new awards for disability in the beginning of the simulation.

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

The third criteria, that of a severe work limitation, is neither verifiable by the SSA with respect to applicants nor by the authors with respect to the PSID sample.[26] Research

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).

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

[26] The validity and interpretation of self-reported work–limitation is not uncontroversial. We, and other researchers, find that self-reported work limitation in the PSID is a strong predictor of observable outcomes

examining this issue has found that SSDI screening produces high levels of both false positives and false negatives.[27] Further, administrative acceptance criteria of the SSA consider more factors than work limitation status alone. The fourth vocational criteria: ability to do any type of work in the economy, brings age into play. The SSA considers older individuals to be less likely to be able to "adjust to other work" compared to younger individuals with the same work limitation.[28] As a result of these complexities, we do not set the acceptance probability of individuals' with severe limitations to one. Instead, we use estimates from Lahiri et al. (1995), who use the same health reports from survey data that we do merged with administrative data on SSDI outcomes, and observed aggregates to estimate an SSA "decision rule," ξ. $\xi(d, \tau, z)$ takes the form:

$$\xi(d, \tau, z) = 1 - (1 - \sum_j \zeta_j \mathbb{I} d = j)^{1/\zeta_{T1}} + 1 - (1 - e^{\zeta_\tau \mathbb{I} \tau \geq 55} \zeta_V(d) F^{-1}(z))^{1/\zeta_{T2}}$$

The dummies, ζ_j are the health-related acceptances and we take these directly from Lahiri et al. (1995) who show the increased likelihood of DI acceptance for applicants with each moderate and severe limitations.[29] We assume that the vocational acceptance probability is linear in $F^{-1}(z_{jt})$, the percentile of the occupation productivity shock within its global distribution, given a health d. [30] The vocational acceptance probability of workers over 55 is an additional 12.4 percentage points higher consistent with both the marginal effect

such as high medical spending and death. Therefore, we are comfortable with our assumption that self-reported work limitation implies lower marginal utility of consumption and lowers wages (as we documented), the two channels through which disability affects choices in our model.

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

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

[29] Because the base scale is indeterminate, we normalize $\zeta_0 = 0$.

[30] We set acceptance rates to be constant over the business cycle following Coe and Rutledge (2013), who document constant acceptance rates once correcting for demographics and types of limitations of applicants.

calculated by Coe and Rutledge (2013) in the data and the descriptive age considerations of the SSA policy. Finally, we adjust for the expected time an application will take, using the calculations from Autor et al. (2015), in ζ_{T1}, ζ_{T2}, where the vocational are decided at later stages and therefore take longer. Because d is ordinal, we do not want to make $\zeta(d)$ a continuous function in d. Instead we give it two values, ζ_V^1 and ζ_V^2, where $\zeta_V(d = 1) = \zeta_V^1$ and $\zeta_V(d > 1) = \zeta_V^2$ Thus, we have parameters $\{\zeta_j\}_{j=0}^2, \zeta_\tau, \zeta_V^1, , \zeta_V^2$ to summarize the SSA decision rule. ζ_j are determined outside of the model, but ζ_V^1, ζ_V^2 and ζ_τ must be determined to the the proper number of new awards given for vocational reasons and the correct effect from "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). 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.

We use an age-dependent recursive formulation to keep track of past earnings as follows.[32]

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

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

We compute the updated earnings index by weighting the previous index as though the individual is at the midpoint of the age group. For example, the age group 30-44 spans 15 years and the prior index is weighted by $1 - 1/(7.5 \times 12)$ or .988, consistent with the median individual in this age group, one in her 37.5th year (7.5th year of work). The index is only updated with the current month's wages for the last two age groups if it provides an increase.[33]

$$e' = \begin{cases} e \times (1 - \frac{1}{7.5\times12}) + w\frac{1}{7.5\times12} & e < \text{age 30-44} \\ e \times (1 - \frac{1}{17.5\times12}) + w\frac{1}{17.5\times12} & e < \text{age 45-49} \\ e \times (1 - \frac{1}{22.5\times12}) + w\frac{1}{22.5\times12} & e < \text{age 50-54} \\ \max\{e, e \times (1 - \frac{1}{27.5\times12}) + w\frac{1}{27.5\times12}\} & e < \text{age 55-59} \\ \max\{e, e \times (1 - \frac{1}{31.5\times12}) + w\frac{1}{32.5\times12}\} & e < \text{age 60-64} \end{cases}$$

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.[34] This is an important program feature to include in our model since SSDI pays benefits equal to the full retirement age rate. We calibrate the option for early retirement for our 61-65 by setting the arrival rate of the option for early retirement to equal $\frac{1}{5}$ to match the eligibility of ages 62-65. If an agent chooses early retirement, we adjust the law of motion for their AIME index e' to provide 80% of full retirement benefits.[35]

[33] Zeros are included in the AIME for individuals with less than 35 years of earnings. We adjust for this feature by scaling the AIME index of the two youngest age groups *if* the individual enters SSDI. The adjustment assumes the worker has worked since age 20 and is currently the median age within the age group. This implies $e' = \frac{17.5}{35}e|(SSDI == 1\&Age == 30 - 44)$ for the youngest group ($\tau = 1$) and $e' = \frac{30}{35}e|(SSDI == 1\&Age == 45 - 54)$ for the second to youngest age group ($\tau = 2$).

[34] For cohorts born prior to 1937, the full retirement age was 65 and those opting for early retirement starting at age 62 collected 80% of full retirement age benefit. The full-retirement age has been gradually increasing for subsequent cohorts reaching age 66 for the 1943 cohort and age 67 for the 1960 cohort.

[35] This is done properly using the inverse of the benefit function to take care of kinks: $SSDI(e') = 0.8 * SSDI(e)$.

Unemployment Insurance The US unemployment insurance program pays benefits to workers who are separated from their job by no fault of their own (ie: they did not quit and were not fired). We do not distinguish between different types of separation in our model. Workers chose "rest" unemployment when their wages fall below an acceptable threshold or if they decide to apply for SSDI. The drop in wage of the former group can be considered a termination for economic reasons (job destruction) because of low productivity.[36] These workers would be eligible for UI.[37] Unemployment benefits average 45% of workers' wage in the job they lost and a duration of 6 months. To conserve state variables, we impose a replacement rate of 45% of the earnings index of average lifetime earnings e, used also to calculate individuals' SSDI and SS retirement benefits. Unemployment benefits are only paid while individuals are in short-term of "rest" unemployment. We set the probability an individual is forced from rest to long-term unemployment to provide an expected duration of rest unemployment of 6 months, consistent with the average maximum duration of UI payments.

Other Social Welfare Schemes and Transfers Coe et al. (2013) document that SNAP benefits (food stamps) are an important source of consumption for SSDI applicants- more than 30% receive SNAP during the application process out of the 50% who are eligible.[38] An additional 7% receive worker's comp and 7% receive SSI. Other transfers come from informal networks. Since we are not interested in program interactions and reform (as opposed to

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

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

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

Kitao (2014) and Low et al. (2015)), we model all other transfers as a fixed payment for the non-employed. We chose the size of this transfer to be 30% of the median earnings in the model, consistent with the typical poverty threshold for a single household.[39][40]

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 task content of each occupation. We condense the 120 task measures into 3: the first principal component of the 19 physical tasks and the first and second principal components of the remaining Knowledge, Skill, and Ability tasks. Figure 11 summarizes the relative task intensities across occupation. The following paragraphs describe how we use these skill measures to calibrate health, wage, and employment risk in the model.

Wages- Age, Health, and Individual Effects We first perform a regression analysis to calibrate wages in the stationary version of the model. It requires establishing a relationship between age, health, and individual effects on wages.[41] The log-wage of an employed individual i (or shadow wages for an unemployed individual) aged τ, in occupation j, and with health d at time t is given by the expression:

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

[40]In reality, there is a threshold on liquid asset holdings below which individuals are eligible for SNAP benefits and other in-kind transfers. We have no analogy in the model since there is only one asset (ie: no pensions, houses, etc). Therefore, we do not include asset testing in the model.

[41]Later we run additional regressions to establish the relationship between time, occupation, and their interaction on wages. We do this in two steps because we use annual data for the first regression, which stop at 1997 in the PSID, but use the whole sample for the second regression up to 2014.

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

The error term, comprised of $\bar{\alpha^i}$ and α_t^i are an individual fixed effect and a time varying individual effect, respectively. 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 three O*NET task components summarizing the occupation: the first principal component of physical and the first and second components of knowledge-skill.[42] 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 *and* following period to capture selection on health. To capture selection on economic factors, we include one year and five year differences in log full-time, full-year national employment in the individual's age-education group.[43]

[42] 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.

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

Results of the first-step probit for employment are summarized in Table 6 and the full results are in the online appendix. They indicate 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 changes in aggregate employment are jointly-significant and positive on average with the five year change having a larger, more significant impact than the one year.

The second-step wage equation is a typical Mincer regression with the regressors specified in Equation 5.1. Consistent with the model assumption that individuals do not switch occupations, the occupation controls are the task components of the individual's longest-held occupation. We correct for selection by including the inverse Mills ratio from the first step selection equation.[44] Our results in Table 6 indicate that both moderate and severe work limitations significantly lower wages by 0.26 and 0.97 log points, respectively.[45]

The idiosyncratic component α_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.

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-skill tasks. We run the following regression to attribute wages to common time trends and to the task composition of occupations over time.

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

[44] As shown in Table 6, 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.

[45] Omitting the selection correction also biases the effect of poor health on wages significantly towards zero for severe limitations as shown in column three of Table 6.

The first regressor is a vector of demographic variables; the second $\mathbf{T_t}$ is a cubic in annual time; the third $\mathbf{O_i}$ is a triple including the first principle component of the O*NET physical tasks and the first and second principle component of the Onet knowledge-skill tasks in the individuals lifetime occupation.[46] The final term is an interaction of the time-cubic with the Onet task triple.

The decomposition of occupational wages into the "price" paid to each task-skill along with the year trend components can be seen in Figure 13. It shows that the first principle component of Knowledge-Skill tasks have been a driver of wage growth. However, different occupations have different mixes of these components. The prediction for wage trends in each occupation based on how the price paid to tasks used in that occupation changes overtime can be seen in Figure 14. Occupations with declining payments to the tasks they use include household and building services, construction and extraction, production occupations, and most operator occupations.

Figure 15 provides a more concise definition of occupation. It groups the 16 SOC codes into quartiles of 4 occupations each according to their physical task intensity. Clearly, the most physically intensive occupations have suffered the largest predicted wage declines. This is important for our analysis because we will show that the physical task intensity of an occupation is a strong predictor of both reported work limitations and disability receipt.

Job Finding and Job Loss Probabilities. Cyclical risk is delivered through time-varying job finding and separation rates. For each occupation and phase of the cycle, we calculate the job separation rate into unemployment and job finding rate from unemploy-

[46] 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.

ment. We use the CPS in the 1984-2010 sample period and use Elsby et al. (2009) to correct for monthly time aggregation. Because the CPS is a relatively short sample, we cannot compute the life-time occupation, and so we assign workers to the occupation from which the worker originated before the unemployment spell.

Health Risks The probability of a health transition between no-work limitation, moderate limitation, and severe are assumed to be both age and occupation dependent. We estimate the effects of age and occupation on health transitions are estimated using a linear probability model on observed health status 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. To address this issue, we use the strategy developed in Michaud and Wiczer (2014). Namely, we summarize the health risk component of an occupation by 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.[47] In both the implied and actual disability rates, there is significant variation and a very long-tail of health risk. Table 7 shows how this relates to the physical component of occupations. 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. Consistent with realized outcomes, production, construction/extraction, and some service occupations have the highest risks of adverse transitions. Their hazard rates can be double those of the safest occupations.

Because we will be simulating transition paths, we must ensure the distribution of health is stationary, otherwise agents may get sicker and more likely to go onto disability simply because of the estimated transition matrix. Therefore, we use the RAS-method to impose

[47] See appendix for further explanation and tests of instrument validity.

row and column constraints on the estimated Markov transition matrices. This minimizes the 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 health distribution.

6 Results from the Quantitative Model

6.1 The Disability Option

In this section, we evaluate how well the calibrated model captures the disability decision and explore the types of paths that lead people on to DI. We focus on aspects central to our study including the interaction of disability receipt with economic risk and leave validation of more standard statistics such as age to the online appendix. We begin by analyzing the elasticities of individuals' DI application decision 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 recession. While these elasticities are straightforward to compute in the model, we rely on results found in the microeconometrics literature for validation.[48] Black et al. (2002) and Charles et al. (2017) estimate the response of SSDI uptake to local earnings using, respectively, coal prices in the 1970's and 80s and oil and gas prices over 1970-2011 as exogenous shocks. The former finds an elasticity of -0.3 to -0.4 and the latter finds an elasticity of -0.293 (standard error of 0.069). The analogous elasticity in our model is within these ranges: (-0.28,-0.32) for individuals' applications. The new award elasticity is

[48]In the online appendix, we compare results from a logistic regression of flows onto DI in our model to the same regression in the PSID data.

lower, in part because of the administrative delays built into the model leading awards to rise more over several years. Section IV of Autor and Duggan (2003) studies the response of low-skilled workers' applications to adverse employment shocks using variation across U.S. states in industrial composition changes. They find an application elasticity of -0.17 to -0.34 in their baseline specification. Our model predicts a smaller elasticity, 8-9%. There are two factors feeding this discrepancy. First, the incidence of non-employment is independently distributed across individuals where as in the data it tends to be serially correlated at the individual level. Second, the design of Autor and Duggan (2003) is likely correlated with wage and earnings losses. Therefore it may be more accurate to sum the first two rows. Awards are higher because we are regressing the unemployment rate which takes more adverse conditions to move, not just the individual job loss which has a large component that is orthogonal with wages. Finally, we find a very small added response of an individual to a job loss if his or her occurs during a recession. Empirical papers study instead the response of aggregate applications to aggregate unemployment rates and offer no analogy to our model statistic. However, Mueller et al. (2016) finds no response of SSDI applications to unemployment insurance benefit extensions during the great recession. In the same spirit of these studies, table 1 provides the elasticity of applications and awards calculated from model generated data for the three economic shocks in our model.

	Model		Empirical Literature
	Individuals' Applications	New Awards	
Wages/Earnings	(-0.28, -0.32)	(-0.16,-0.19)	(-0.22,-0.4)
Job Loss	(0.08, 0.09)	(0.16, 0.39)	(0.17, 0.34)
Recession	(0.01, 0.05)	(0.01, 0.02),	n/a

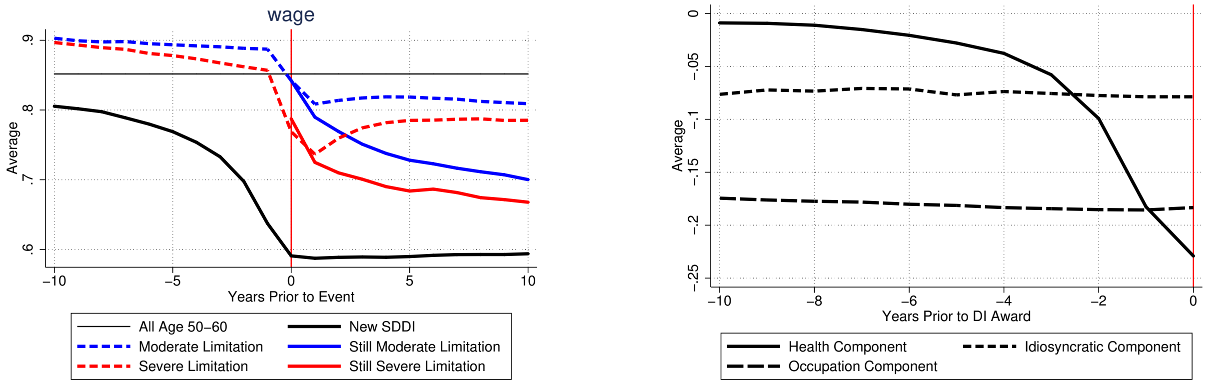
Table 1: Empirical and model elasticities with respect to adverse economic shocks.

The above elasticities relate to contemporaneous elasticity of individuals' applications decisions and aggregate awards to present economic outcomes. Another salient feature of SSDI recipients in the data is that many experience persistently poor economic outcomes for a long expanse of time prior to their application. We now analyze these dynamics in the model generated data. Panel (a) of Figure 2(a) 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 about a 30% penalty in the year of the award.[49] The dashed lines track individuals who suffer a severe or moderate work limitation at time zero. The solid lines after time zero follow only those who maintain this limitation where as the dashed additionally includes those whose recover. Observe that in the year an individual receives a disability award, they have about a 23% lower wage than the average person with a severe limitation. This is for two reasons. First is a composition effect: not all individuals with severe limitations go on DI and those do have lower wages than average. Second, in order to apply for DI, one must first spend time in long-term non-employment. Our model features the "scarring" effect of long-term unemployment apparent in the data and which we generate through a draw of a lower idiosyncratic wage employment. This mechanism is apparent in the permanently lower wages of the individuals who recover from their limitation after $t = 0$ (dashed lines). Panel (b) of Figure 2(b) shows that the wage dynamics for an individual going on DI are primarily driven by the wage impact of poor health.

Panel (a) of Figure 3(a) shows that while individuals going onto DI had a history of low wages they have comparable levels of employment to the average 50-60 year old until 3 years prior to their DI award. This three year drop is 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 even those who recover from

[49]These figures include the shadow wages: the wages non-employed individuals would earn if employed.

Figure 1



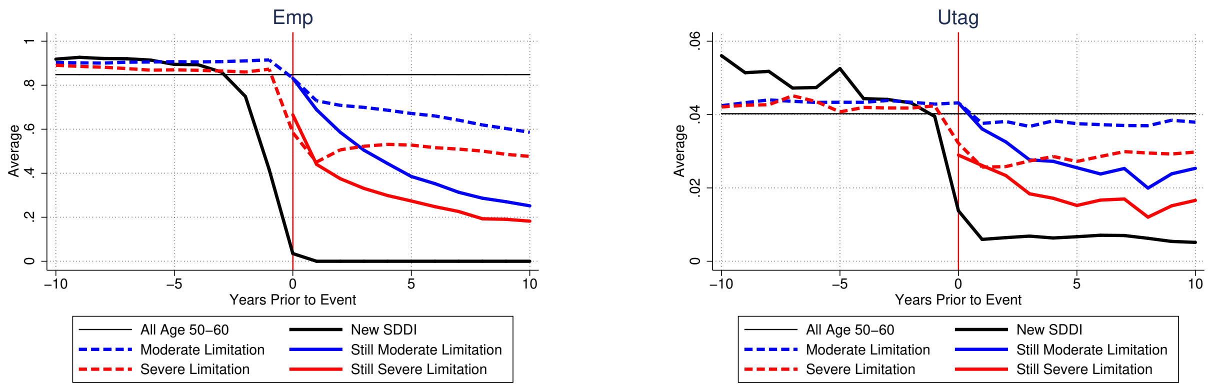
(a) Wage Paths Prior to Event

(b) Wage Path Components Prior to DI Award

a work limitation permanently have lower employment rates. In the model, this is driven by the wage scar following long-term non-employment during which these individuals were applying for DI prior to their recovery. Panel (b) of Figure 3(a) shows that those going on DI experience a 20% higher incidence of involuntary job loss than the average 50-60 year old. 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. This can apply to job losses several year prior through the wage scar impact of long-term non-employment.

How do these economic incentives manifest themselves in the composition of individuals with new SSDI awards? Table 2 compares the percent of new DI beneficiaries with each of several characteristics in each the model simulation to the PSID data, as further validation of non-targeted statistics. The first two rows depict two measures of poor realized economic outcomes. In the model, as in the data, individuals going onto SSDI are particularly distinguished by having low labor income during the periods they were employed full time in the 5

Figure 2



(a) Employment

(b) Involuntary Job Loss

years prior to their award. More than three-quarters see their labor earnings (or wage in the model) fall to the bottom 20% of the reference population aged 45-60 in that year. In both the model and in the data, the two groups are not different in their incidence of involuntary unemployment.[50] The middle two rows show that those going on SSDI are more likely to be in poor health, a bit more so in the model than in the data.

Digging further, we would like to see if those going onto SSDI are unique in being affected by a confluence of poor health and poor economic prospects. Figures 3(c)-4(a) display heat maps of the model population, split into those entering DI next year and the average population aged 50-60. These figures illuminate differences in the joint distribution of economic and health risks and their realizations across the groups. Figure 3(c) shows that individuals going on SSDI come disproportionably from occupations with both high health risks and secularly declining wages. The distribution of new DI awards is more biased on the wage

[50]The incidence of involuntary unemployment is over-predicted in the model. This is because a salient feature of the data is serial correlation in involuntary separations at the individual level (see Michaud (2018)). Replicating this feature would require an additional state variable and so we must exclude it, but this choice does not seem to drive up DI applications as the statistic is similar across those going on DI and the reference group.

Table 2: 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	79.2%	26.6%	77.8% (3.7)	21.9% (0.8)
Involuntary unemployment in last 5 years	14.6%	16.4%	4.3% (1.0)	5.5% (0.4)
Severe Work Limitation	87.0%	5.1%	68.5% (7.1)	8.3% (0.5)
Moderate Work Limitation	6.9%	5.8%	12.0% (4.8)	9.6% (0.5)

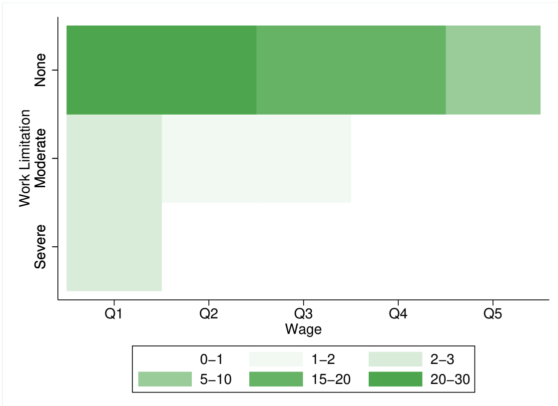
Prior x year spans begin one year prior to DI award. Reference population: age 45-60.
Standard errors in parentheses.

trend margin, but these individuals are represented in the entire distribution of occupational risk. Figure 4(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 the decades we consider, putting them at risk of applying for DI even if they are in good health.

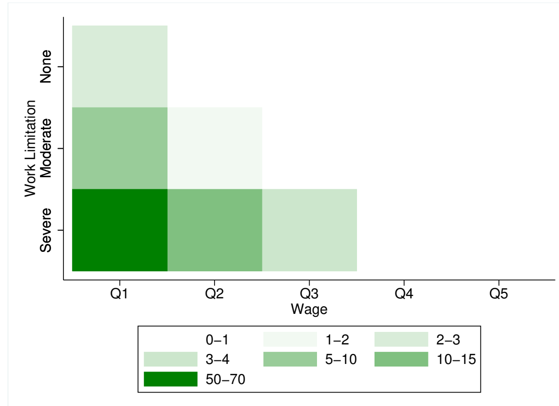
(c) All Age 50-60

(d) New DI

Figure 3: Occupation health risk and occupation wage trend quintile



(a) All Age 50-60



(b) New DI

Figure 4: Current health status and current wage quintile

6.2 Components of the Rise

In this section, we use the model to try to understand the drivers behind the rise in SSDI. To begin, we set the distribution of occupation, age, and health groups to match as closely as possible the US in 1980-1985.[51] In every subsequent period, we add and remove individuals as necessary to match exactly the age-occupation distribution of the United States workforce. 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 related to their occupation.[52] We also expose agents to occupational job finding and job loss rates calculated from the data. Agents' decision rules include an expectation of Markov switching between recessionary periods and normal times each with the average rates during these times.

Figure 16 shows the model's success in matching the rise is SSDI over the period since

[51] We cannot see the asset or AIME distributions in this period, though both will factor into the application decision. Instead, when we create agents at the beginning of the simulation, we will draw assets and AIME from ergodic distributions of these distributions.

[52] These shocks are unanticipated and estimated by a cubic spline on time, occupational task components, and their interactions as detailed in Section 5

1985. There are two notable successes. The model can account for most of the rise in the share of the population on DI and predicts the flattening out of the rising trend after 2010. The place where the model falls short is in generating the scope of the rise that occurred during the 1990s. Looking closely at the data from SSA, one sees that increases in admissions on mental/emotional conditions increased rapidly in the 1990s and then decreased through the 2000s. A focus on these factors could improve the model's fit with respect to the timing of the rise.

The model allows us to isolate the impact of individual factors that played into the rise in SSDI. Figure 17 shows the rise predicted with each trend fed into the model turned off individually: age demographics, occupational composition, and wage trends. The factor with the largest contribution is demographics, but with a nuanced timing. during the 1990s, the baby boom generation lowered predicted SSDI rolls before driving almost the entirety of the increase after 2000. The wage trend is the second most important component. The fall of wages at the bottom half of the distribution during the 1990s implied a significant rise in DI during this time followed by a sustained rise into the 2000's. Finally, the model predicts that occupational composition is moving towards occupations with a joint health and economic risks that are less likely to provoke workers to apply to DI.

Data from the SSA show awards with vocational considerations have driven almost all of the rise in new awards since 1985 (Figure 12). Figure 18 shows the implied trends for awards with vocational considerations as predicted by the model. Clearly, the theory presented cannot account for the rise in awards with vocational considerations. However, this should not be considered a failure of the theory. Instead, our experiment predicts what should occur if the defacto implementation of the vocational grid rules are held constant over time. The result that a rise in awards through this grid is not generated suggests that it may be the case that these rules have not 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 Trends

A typical question in the literature is the impact of the SSDI program on the employment to population ratio. We address this topic in two ways, first looking at the latent value of work for applicants in the model. Second, considering the elasticity of applications and employment with respect to changes in the award probability and in the replacement rate DI benefits provide.

Figure 5(a) shows that virtually all individuals newly awarded SSDI would have a higher value of working than non-employment in the prior year. This suggests that they are choosing non-employmentonly to apply for DI, as confirmed in Figure 5(b). This figure shows the value of applying dominates the value of working for several years prior to the award, even while the value of working dominates non-employment. Notice also that there are some individuals flowing onto DI that value employment more than application. How can this be since they must apply to receive DI? The answer is that they cannot find a job. Recall that individuals must be nonemployed for 6 months prior to application, consistent with the literature on declining exit rates for the long-term unemployed, we provide them with lower job finding rates. Figure 5(b) is also informative about the employment prospects of rejected applicants. The dashed blue and red lines after time zero show that even if an individual recovers to better health, there is a 10% or greater probability he will be inclined to continue to apply for

DI even three years later. This is again from the non-employment requirement to apply for DI. These individuals have a harder time finding a job and when they return to the market, they do so with a lower wage consistent with the data and literature on wage scarring.

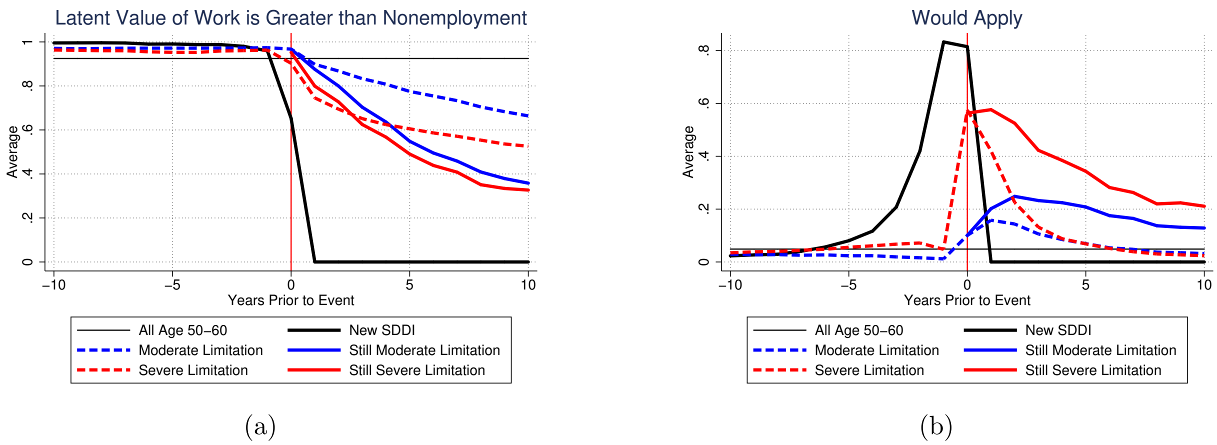


Figure 5: Latent Value of Work and DI Application

8 Conclusion

This paper quantitatively explored the rise in Social Security Disability Insurance over the last 30 years. Over this period, the fraction of working-age recipients tripled and the rate of new awards increased almost every year. Concurrently, the U.S. was experiencing pronounced changes in demographic, occupational and wage structure. Each factor individually affects the SSDI rate, but they also interact in decisions of households deciding whether to apply and in the determinations of the DDS office deciding to grant an award. To decompose their relative contributions, we created a structural model with occupation-specific health and economic shocks.

References

Autor, D. H., D. Dorn, and G. H. Hanson (2013): "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *American Economic Review*, 103, 2121–68.

Autor, D. H. and M. G. Duggan (2003): "The rise in the disability rolls and the decline in unemployment," *The Quarterly Journal of Economics*, 118, 157–206.

Autor, D. H., N. Maestas, K. J. Mullen, and A. Strand (2015): "Does Delay Cause Decay? The Effect of Administrative Decision Time on the Labor Force Participation and Earnings of Disability Applicants," NBER Working Papers 20840, National Bureau of Economic Research, Inc.

Benitez-Silva, H., M. Buchinsky, H. M. Chan, J. Rust, and S. Sheidvasser (1999): "An empirical analysis of the social security disability application, appeal, and award process," *Labour Economics*, 6, 147–178.

Benitez-Silva, H., M. Buchinsky, and J. Rust (2004): "How large are the classification errors in the social security disability award process?" Tech. rep., National Bureau of Economic Research.

Black, D., K. Daniel, and S. Sanders (2002): "The impact of economic conditions on participation in disability programs: Evidence from the coal boom and bust," *American Economic Review*, 92, 27–50.

Bound, J., S. Lindner, and T. Waidmann (2014): "Reconciling findings on the employment effect of disability insurance," *IZA Journal of Labor Policy*, 3, 11.

Charles, K. K., Y. Li, and M. Stephens Jr (2017): "Disability Benefit Take-Up and Local Labor Market Conditions," *Review of Economics and Statistics*.

Chen, S. and W. Van der Klaauw (2008): "The work disincentive effects of the disability insurance program in the 1990s," *Journal of Econometrics*, 142, 757–784.

Coe, N. B., S. Lindner, K. Wong, and A. Y. Wu (2013): "How Do the Disabled Cope While Waiting for SSDI?" Tech. rep., Center for Retirement Research.

Coe, N. B. and M. S. Rutledge (2013): "Why Did Disability Allowance Rates Rise in the Great Recession?" Tech. Rep. 13-11, Center for Retirement Research, Boston College.

Duggan, M. and D. Autor (2006): "The growth in the social security disability rolls: a fiscal crisis unfolding," Tech. Rep. 12436, National Bureau of Economic Research.

Elsby, M. W., R. Michaels, and G. Solon (2009): "The ins and outs of cyclical unemployment," *American Economic Journal: Macroeconomics*, 1, 84–110.

French, E. and J. Song (2014): "The effect of disability insurance receipt on labor supply," *American Economic Journal: Economic Policy*, 6, 291–337.

Kitao, S. (2014): "A life-cycle model of unemployment and disability insurance," *Journal of Monetary Economics*, 68, 1–18.

Lahiri, K., D. R. Vaughan, and B. Wixon (1995): "Modeling SSA's sequential disability determination process using matched SIPP data," *Soc. Sec. Bull.*, 58, 3.

Low, H., C. Meghir, and L. Pistaferri (2015): "Disability Insurance and the Dynamics of the Incentive-Insurance Tradeoff," *American Economic Review*.

MICHAUD, A. M. (2018): "A quantitative theory of information, worker flows, and wage dispersion," *American Economic Journal: Macroeconomics*, 10, 154–83.

MICHAUD, A. M. AND D. WICZER (2014): "Occupational hazards and social disability insurance," Working Papers 2014-24, Federal Reserve Bank of St. Louis.

MUELLER, A. I., J. ROTHSTEIN, AND T. M. VON WACHTER (2016): "Unemployment Insurance and Disability Insurance in the Great Recession," *Journal of Labor Economics*, 34, S445 – S475.

RUTLEDGE, M. S. (2011): "The impact of Unemployment Insurance extensions on Disability Insurance application and allowance rates," *Boston College Center for Retirement Research Working Paper*.

VON WACHTER, T., J. SONG, AND J. MANCHESTER (2011): "Trends in employment and earnings of allowed and rejected applicants to the social security disability insurance program," *The American Economic Review*, 3308–3329.

9 Figures

Table 3: SSA Decision Process Details

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

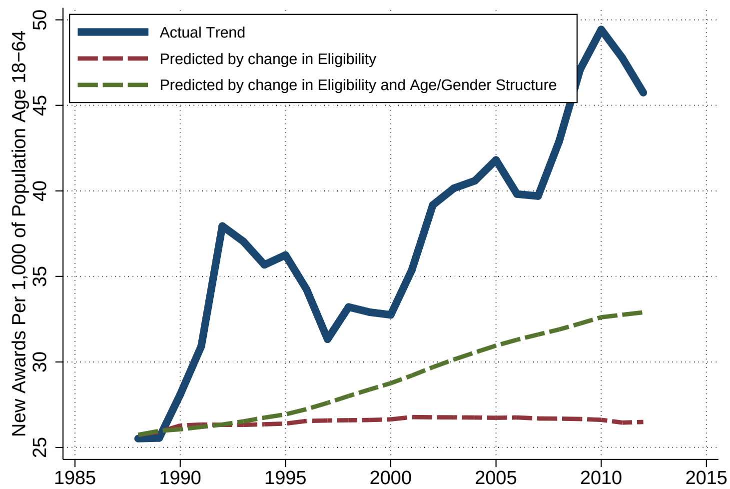


Figure 6: New Awards as predicted by Changing Demographics. (See extended appendix for details)

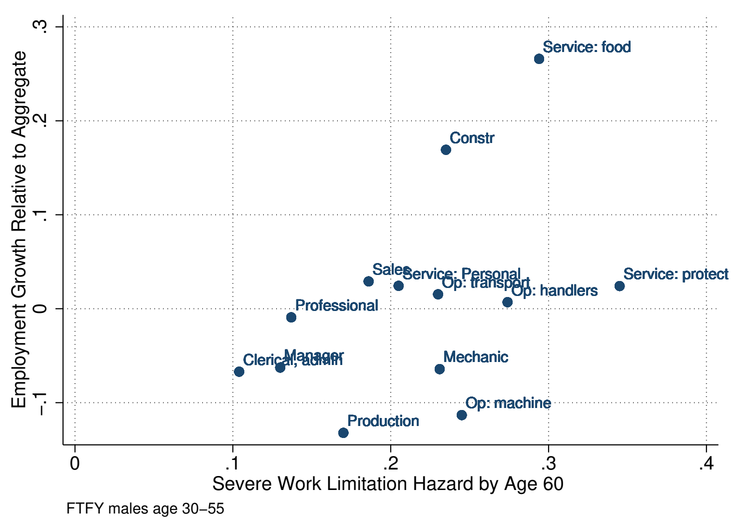


Figure 7: The correlation between health and long-run job growth.

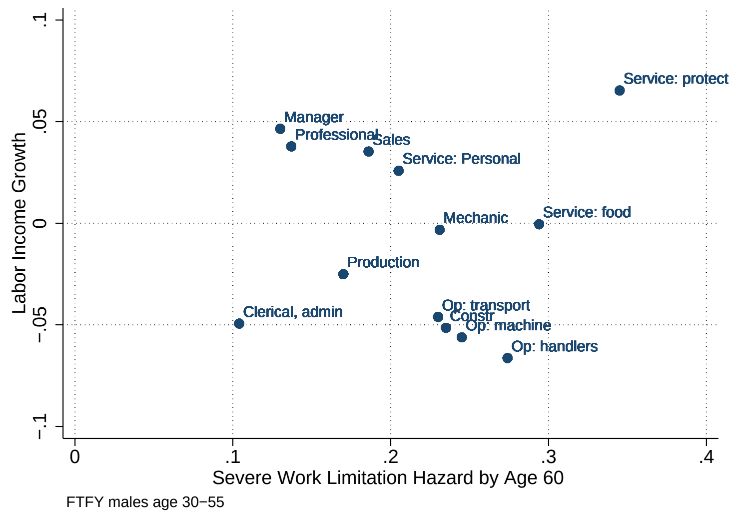


Figure 8: The correlation between health and long-run wage growth.

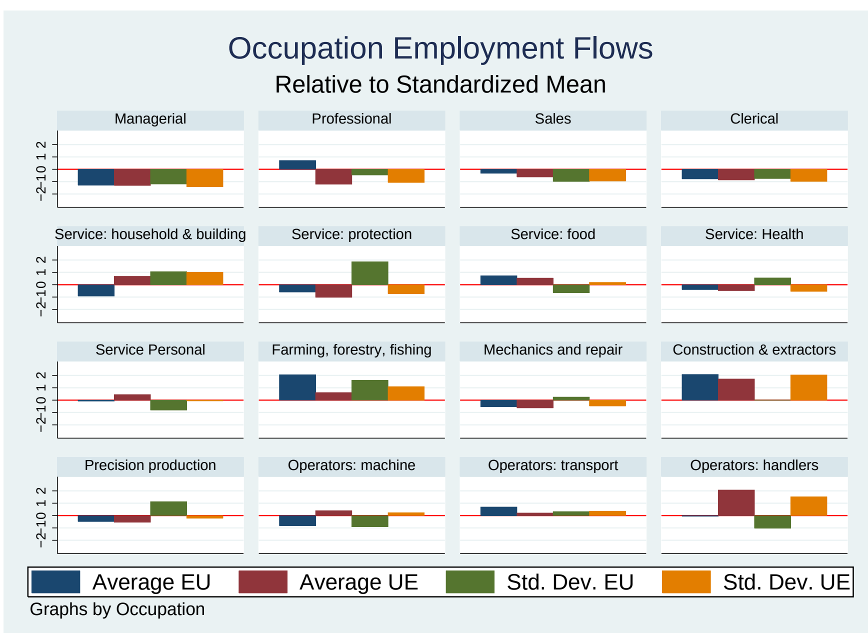


Figure 9: Variation in average and cyclical employment flows by occupation.

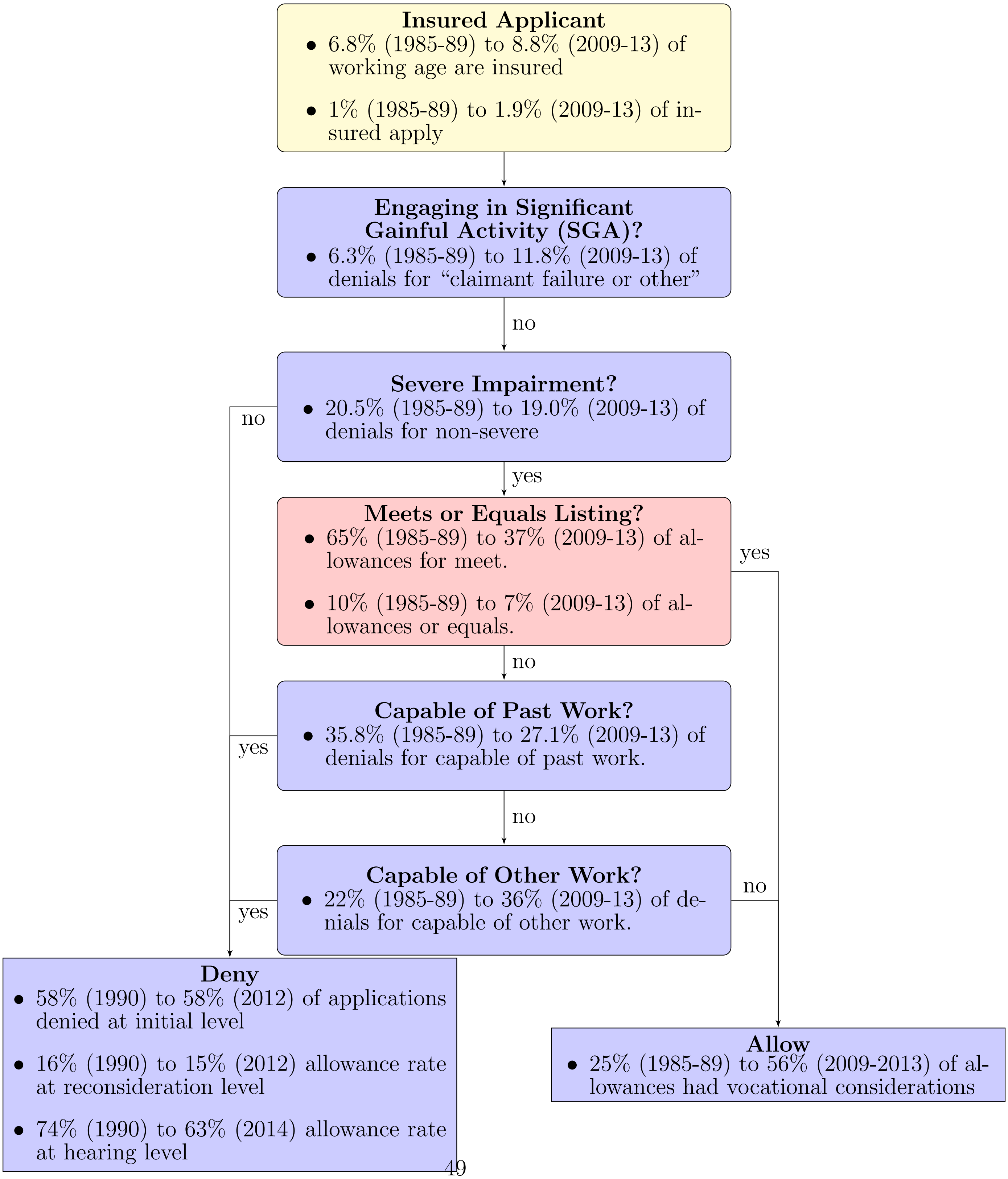


Figure 10: Initial decision process. Allowances from the red step "Meets or Equals the Listing" do not consider ability to work, all other steps do.

Table 4: Condensed Vocational Grid- Capability for Unskilled, Sedentary Work

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

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

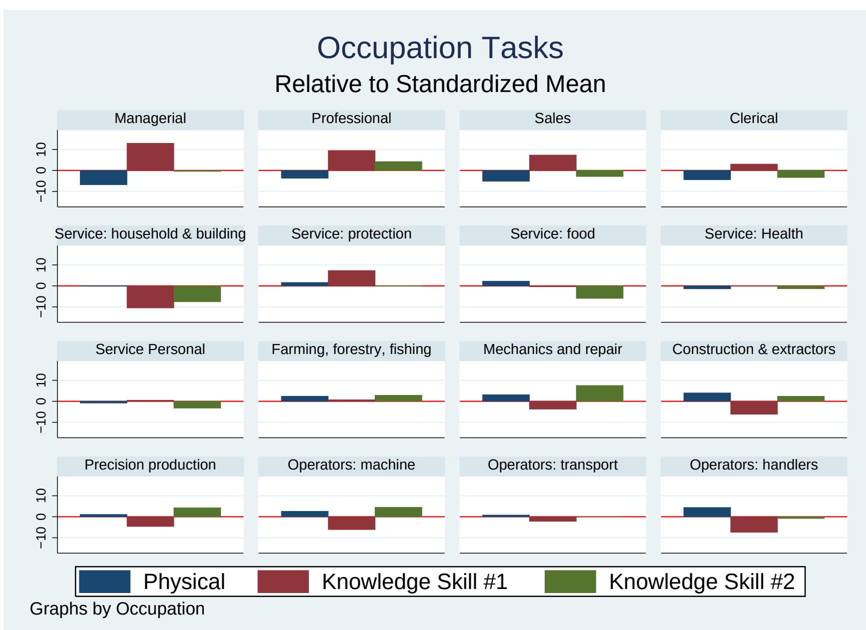


Figure 11: Variation in task intensity across occupations.

Table 5: Occupational Characteristics and Risks

	O*NET Tasks			Health		Flows				Wages	
SOC	Physical	Know 1	Know 2	Any	Severe	μEU	$\sigma(EU)$	μ UE	$\sigma(UE)$	$\mu(ln(w))$	$\mu(ln(w_{t+5}) - ln(w_{t-5})$
1	-6.79	12.96	-0.45	0.09	0.05	-1.29	-1.19	-1.31	-1.42	2.94	0.02
2	-3.71	9.50	4.22	0.10	0.05	0.71	-0.46	-1.21	-1.07	2.95	0.00
3	-5.05	7.33	-2.89	0.10	0.05	-0.32	-0.99	-0.62	-0.95	2.67	0.00
4	-4.43	3.02	-3.37	0.10	0.05	-0.78	-0.75	-0.86	-0.98	2.78	-0.03
5	-0.11	-10.51	-7.55	0.11	0.06	-0.92	1.06	0.68	1.01	2.27	-0.07
6	1.63	7.30	-0.13	0.11	0.05	-0.59	1.86	-1.02	-0.73	2.77	0.09
7	2.25	-0.35	-5.96	0.11	0.05	0.72	-0.65	0.54	0.19	2.38	0.06
8	-1.41	-0.19	-1.36	0.09	0.04	-0.40	0.55	-0.48	-0.54	2.53	-0.03
9	-0.84	0.52	-3.26	0.11	0.06	-0.08	-0.80	0.45	-0.06	2.32	0.00
10	2.43	0.74	2.87	0.12	0.06	2.06	1.60	0.61	1.09	2.04	0.02
11	3.14	-3.73	7.52	0.10	0.05	-0.54	0.25	-0.63	-0.47	2.82	-0.05
12	4.00	-6.18	2.42	0.12	0.05	2.08	0.01	1.71	2.04	2.75	-0.03
13	1.11	-4.64	4.25	0.12	0.06	-0.48	1.13	-0.54	-0.21	2.83	-0.07
14	2.59	-6.13	4.51	0.10	0.05	-0.82	-0.90	0.40	0.23	2.66	-0.06
15	0.80	-2.21	-0.00	0.11	0.05	0.69	0.32	0.21	0.36	2.61	-0.02
16	4.40	-7.43	-0.84	0.12	0.06	-0.04	-1.02	2.07	1.51	2.49	-0.02

O*NET Tasks: first PCA of Physical and first and second PCAs of Knowledge-Skill, standardized statistic.
Health: Estimated work limitation hazard at age 60.
Flows: Standardized statistic of employment to unemployment (EU) and unemployment to employment (UE) hazards
Wages.

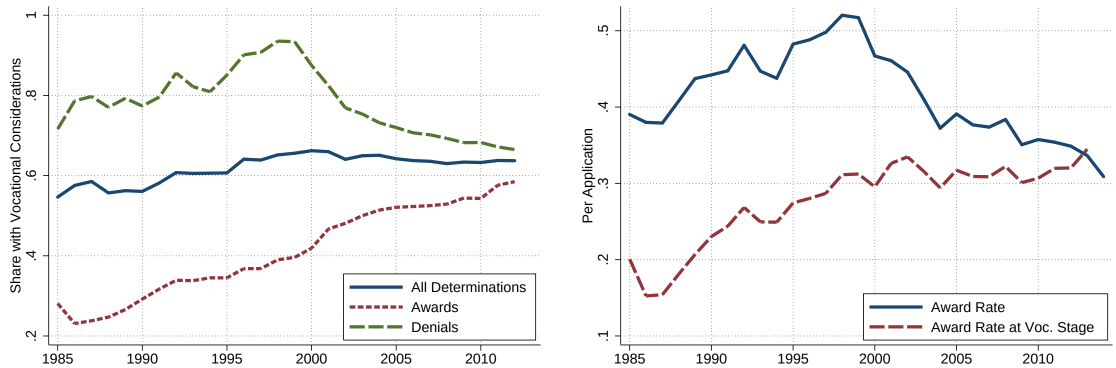


Figure 12: Role of Vocational Considerations in SSDI Trends)

Table 6: 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

Standard errors in parentheses.
**Denotes statistical significance at the 1%level.
*Denotes statistical significance at the 5%level.
† *Denotes statistical significance at the 10%level.
Probit results reported as Marginal Effects
See appendix for additional controls in each regression.

Table 7: Health Transition Hazard (Linear Probability)

	0-1	0-2	0-d	1-0	1-2	1-d	2-0	2-1	2-d
Occ-Physical	0.0031 **	0.0015 **		0.0247 †	0.0162 †		0.0044	-0.0282 †	
	(0.0007)	(0.0004)		(0.0142)	(0.0098)		(0.0118)	(0.0169)	
Age 46-55	0.0049 *	0.0013	0.0019 **	-0.0981 **	0.0300	0.0012	-0.1135 **	-0.0960 *	0.0027
	(0.0019)	(0.0010)	(0.0007)	(0.0371)	(0.0239)	(0.0050)	(0.0412)	(0.0484)	(0.0102)
Age 56-60	0.0095 **	0.0023	0.0093 **	-0.0586	0.0585 †	0.0118	-0.1417 **	-0.1057 *	0.0136
	(0.0031)	(0.0016)	(0.0020)	(0.0483)	(0.0342)	(0.0107)	(0.0383)	(0.0484)	(0.0118)
Age 60-64	0.0234 **	0.0086 **	0.0087 **	-0.1144 **	0.1696 **	0.0038	-0.1358 **	-0.1075 *	0.0321 †
	(0.0043)	(0.0026)	(0.0021)	(0.0408)	(0.0364)	(0.0067)	(0.0384)	(0.0491)	(0.0176)
Age 65+	0.0000	0.0000	0.0274 **	0.0000	0.0000	0.0464 **	0.0000	0.0000	0.1003 **
	(.)	(.)	(0.0026)	(.)	(.)	(0.0097)	(.)	(.)	(0.0139)
Constant	0.0123 **	0.0039 **	0.0009 **	0.3940 **	0.0912 **	0.0038	0.2182 **	0.3096 **	0.0076
	(0.0008)	(0.0005)	(0.0002)	(0.0221)	(0.0126)	(0.0027)	(0.0312)	(0.0356)	(0.0055)
Observations	42027	42027	49586	1352	1352	2261	850	850	1950

Standard errors in parentheses
† $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

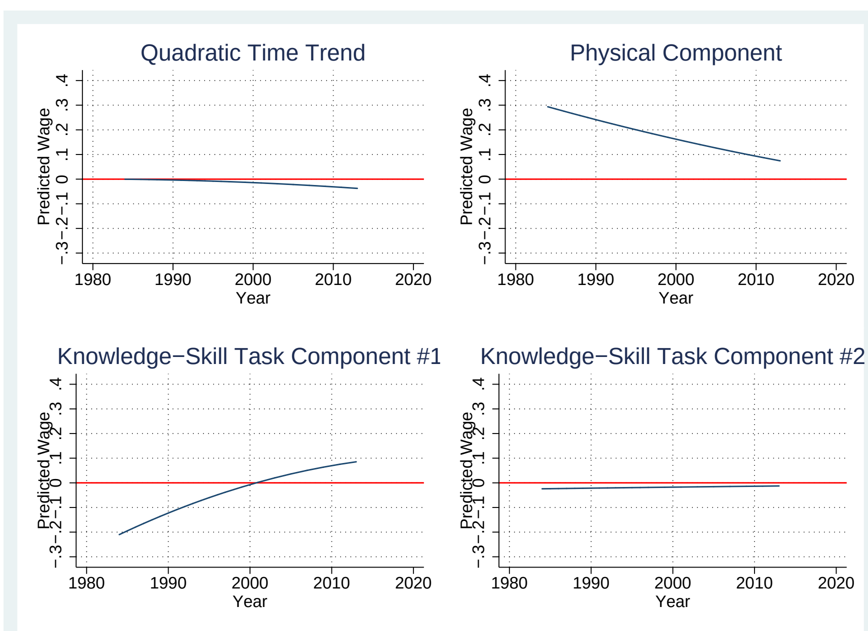


Figure 13: Predicted change in time and occupational task-skill component of wages.

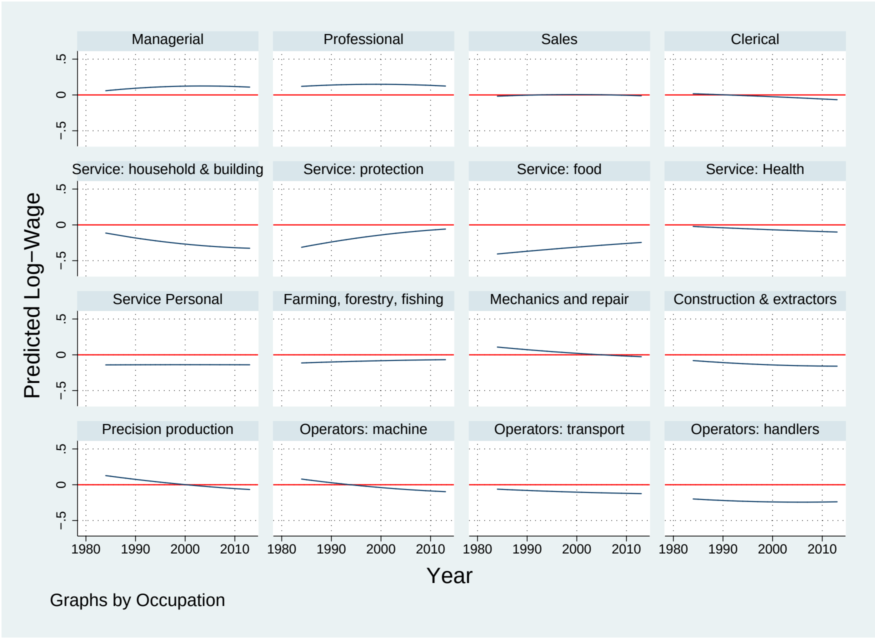


Figure 14: Predicted change in time and occupational task-skill component of wages.

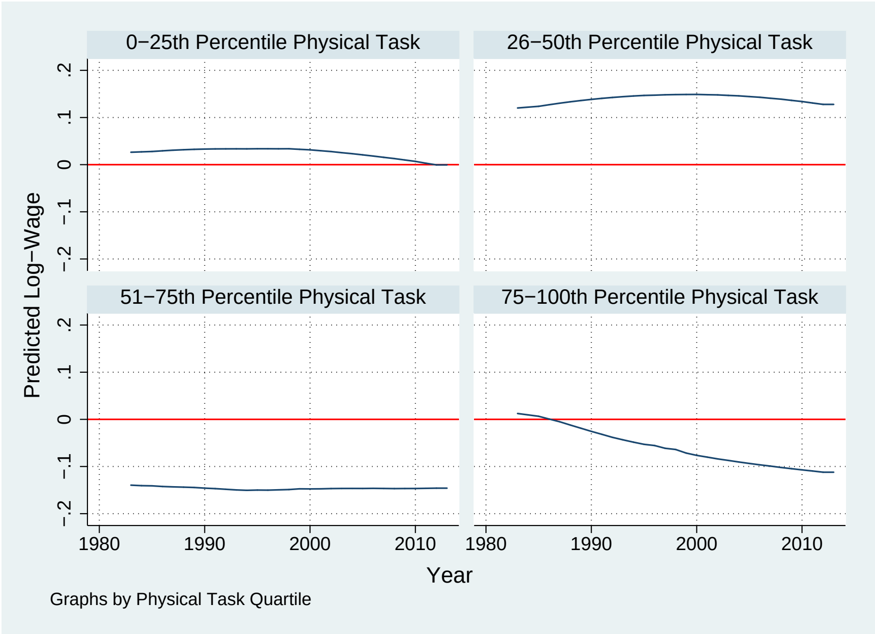


Figure 15: Predicted change in time and occupational task-skill component of wages.

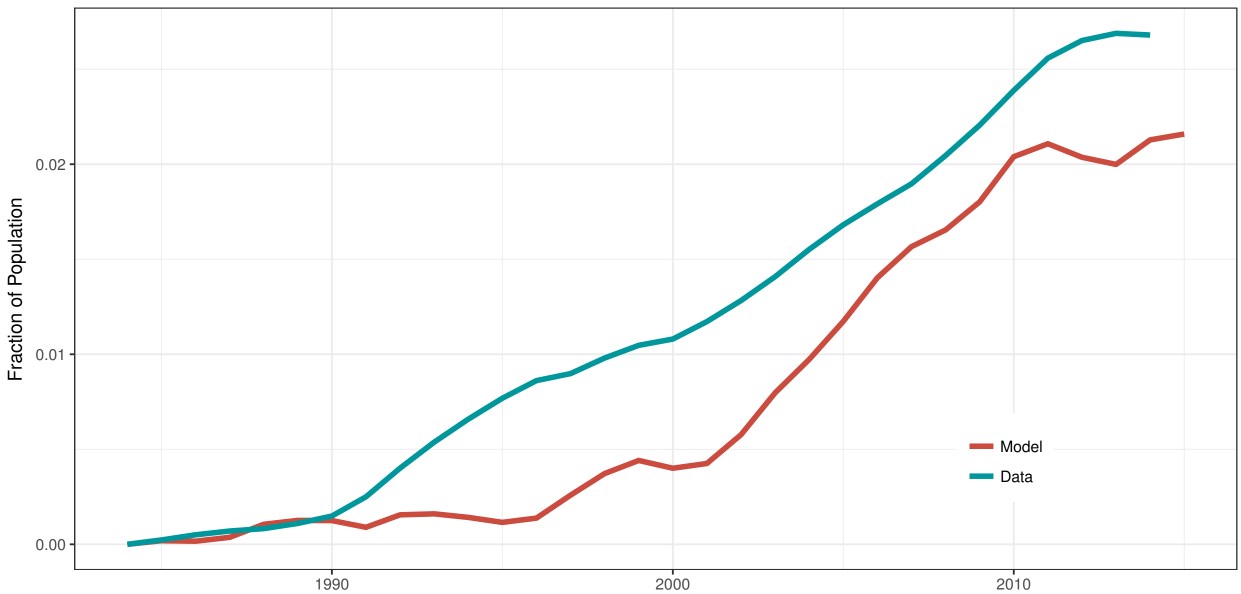


Figure 16: The fraction of 25-64 on SSDI

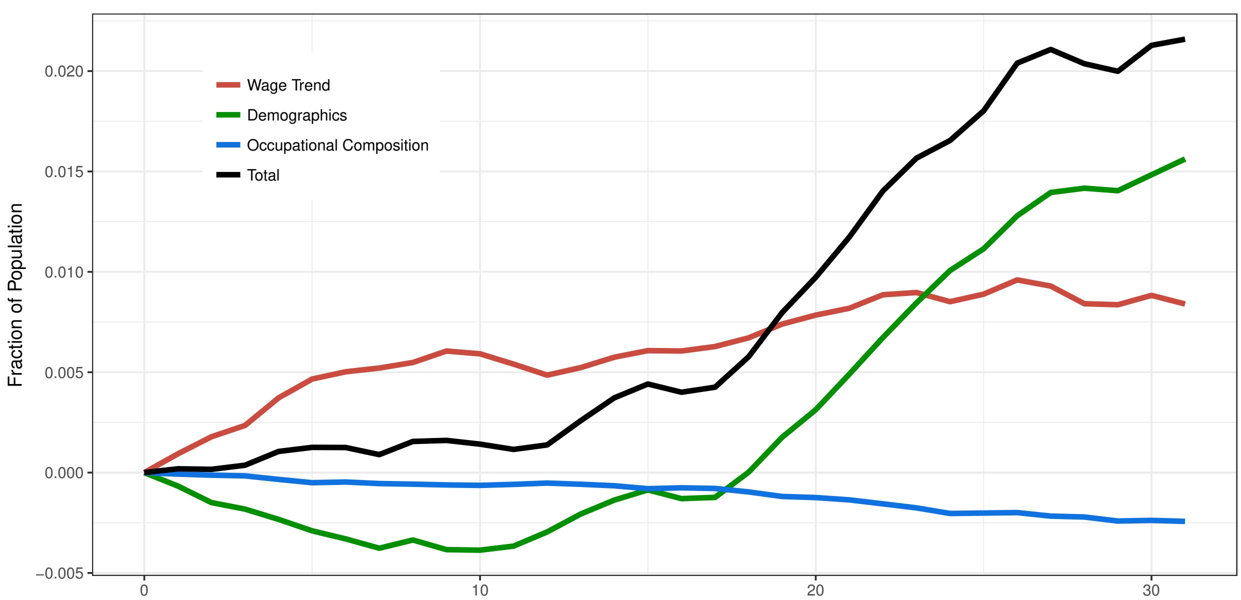


Figure 17: The fraction of 25-64 on SSDI

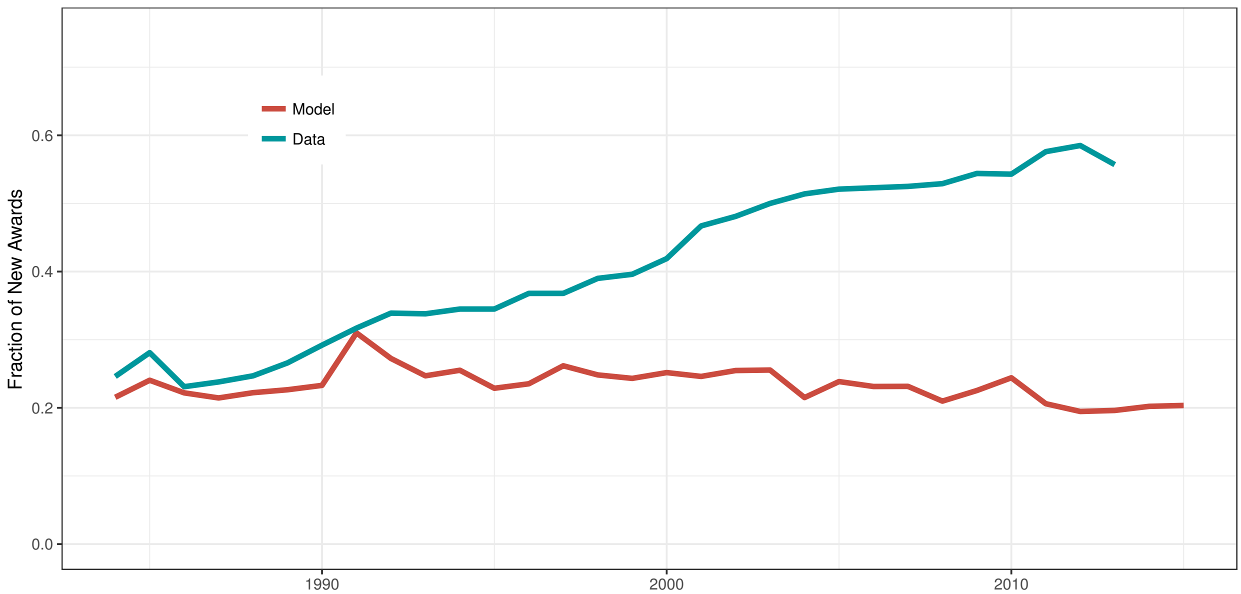


Figure 18: The fraction of 25-64 on SSDI