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

Amanda Michaud
University of Western Ontario

David Wiczer*
Stony Brook University

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Abstract

In recent decades, Social Security Disability Insurance (SSDI) claims have risen rapidly. We evaluate the importance of changing macroeconomic conditions in shaping this trend. Our quantitative framework considers that economic conditions interact with individuals' health status in their decisions to apply for SSDI. Crucially, these factors are correlated through the nature of work: multiple sectors differentially expose workers to health and economic risks. Decomposing factors driving SSDI growth in a calibrated model, we find the secular deterioration of economic conditions contributed an average of 14% of new awards per year, particularly concentrated before 2000 when the contribution was 24%. Total exits from the labor force amount to a 6.3 percentage point increase in non-employment and the share of which are non-employed for reasons other than disability falls from 75% to 44%.

*E-mail: amichau9@uwo.ca 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 Hugo Benitez-Silva, Mariacristina De Nardi, Soojin Kim, Sagiri Kitao, Yue Li, Hamish Low, Timothy Moore, Luigi Pistaferri, Steven Stern, James Zilliak ; and participants at Barcelona GSE, BLS, Census, Colby College, FRB-Cleveland, FRB-NY, FRB-St. Louis, GRIIPS-Keio, IUPUI, NBER, Purdue, SED, Temple, University of Alberta, University of Kentucky, University of Melbourne, & University of Virginia.

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 .[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 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

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

[2]Our own analysis provided in the online appendix. See also Liebman (2015) for a similar analysis and conclusion.

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: workers' demographics and the economic shocks they face; as well as health outcomes. Therefore, it is not clear how to divide the blame for changes in the SSDI rolls between economic conditions and demographics. To what extent have individuals who are healthy enough to work when economic prospects are good decided to apply for disability when their prospects worsened? To what extent is it the opposite side of the coin: that poor economic prospects have come down mostly on those already in legitimate pain, but who had been 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.[3] 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

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

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 awards. To do so, we feed in changes in the age-occupation structure of the population as well as secular wage declines and business cycle fluctuations in job loss and finding rates each differentiated by occupation. Overall, the model's predicted flows onto DI in response to these shocks alone closely follows the data except for an over-prediction of awards in the late 1980's and under prediction in the early 2000s. The more than one percentage point rise in awards in the 1990s captured by the models is driven by the endogenous response to wage declines for occupations with high health risks even while mitigated by youthful demographics. The ageing of the baby-boom generation is the main contributor to the larger rise from the mid-2000's onwards also captured by the model. Cyclical fluctuations contribute quantitatively insignificantly. However, this result is tempered by the running theme of the paper: it matters which demographics experience these shocks.

Changing economic conditions interact with the SSDI program to increase non-employment by more than what is accounted for by the rise in disability beneficiaries. Rising applications account for 16% of the 6.3 percentage point increase in non-employment from 1984-2013 accounted for by the model and contributed more to the increase in non-employment for individuals in their 40's and those in occupations with high health risks. Applications are even more sensitive to wage trends than awards. Wage trends drive them to rise in both the 1990s and mid-2000's onwards, but rejections also rise during these periods.

Our structural model complements empirical studies analyzing whether economic conditions affect SSDI by evaluating the differential impact on individuals with different health and demographics. For example, we find an average elasticity of applications to secular wage declines of about 20%. This is lower than empirical estimates which consider shocks that disproportionately affect certain demographics such as declines in coal or oil prices. We also find that fraudulent applications of workers in good health are more responsive to job loss than secular wage declines relative to applications of workers in poor health.

One feature of the rise in awards not accounted for by the model is the rise in new awards with vocational considerations from 25% in late 1980's to almost 60% after 2010. These vocational considerations include education and age, as well as scope to consider regional or industrial economic prospects. The structural model includes a vocational component of the screening process that determines the probability an application is successful conditional on economic circumstance and age in addition to health. It's parameters are calibrated to best replicate empirical studies on award probabilities conditional on age and to match the average vocational award share over the period. Even so, we find the model predicts almost no arise in new awards with vocational considerations. This result is suggestive that there is room for de facto changes in how these rules of the screening process are applied, whereas they are held fixed in our model.[4]

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.

[4]It is already known that the discretion of judges in appeals impacts awards, so much so that random assignment of judges is used as a source of exogenous variation in studies like French and Song (2014).

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.[5] 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.[6] 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.[7] Whereas these papers

[5]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.

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

[7]The conclusion of **?**pista) highlights one of our relative contributions: " A second restriction is in terms of the stochastic process for work limitations, which we take to be exogenous. The probability of receiving a negative shock to the ability to work is likely to be partly under the individual's control, through occupation choice and other decisions on the job."

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.

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.[8] 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.[9] 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.

[8]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.

[9]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)

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 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.[10] We use data from the Current Population Survey to measure employment within an occupation and data from the Panel Study of Income Dynamics to link individuals' life-time occupational exposure and health outcomes.[11] We measure occupational exposure by an individual's longest held occupation.[12] Our measure of health risk is the proportion of individuals in a given life-time occupation who report a "severe work limitation" by age 60.[13]

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

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

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

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

Figure 1 shows the correlation of health and long-run employment growth by occupation.[14] Figure 2 shows the correlation of health and labor income growth.[15] 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 1). Similarly, not all safe occupations are expanding. The safest occupation, clerical 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 2) 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 3 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

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

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

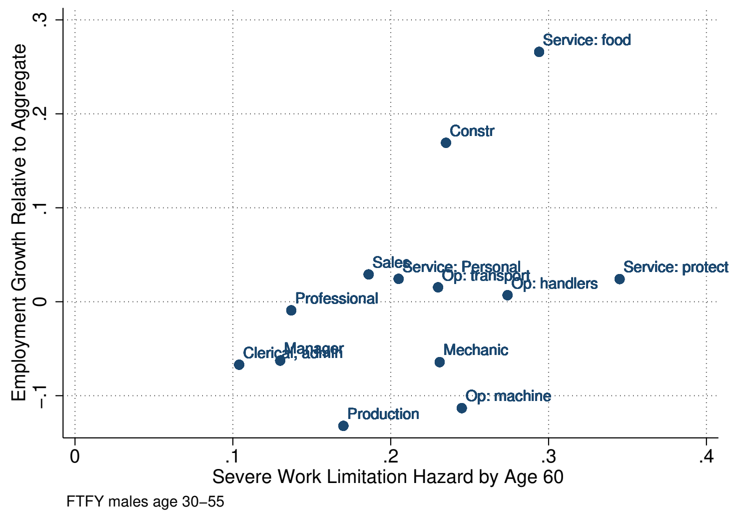


Figure 1: The correlation between health and long-run job growth.

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".[16] 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. Claims made by uninsured workers are rejected in the first stage. To be insured, a worker must have

[16]See extended appendix for a glossary of key administrative terms and a simplified vocational grid.

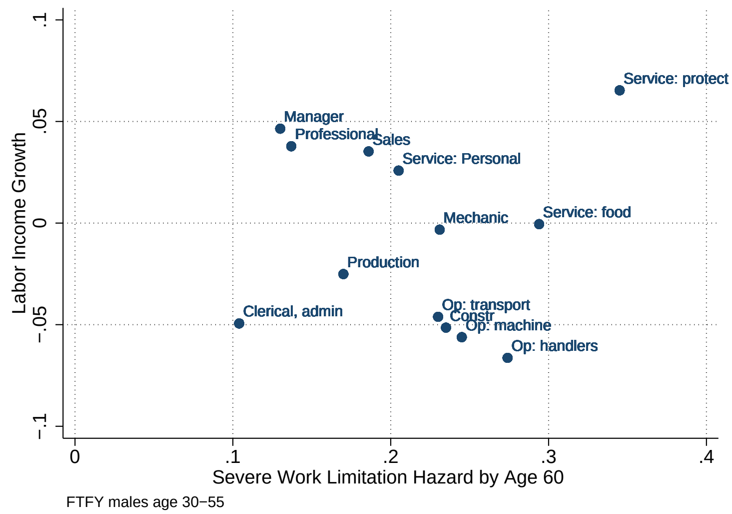


Figure 2: The correlation between health and long-run wage growth.

accumulated a sufficient number of SSA work credits.[17] 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

[17] 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.

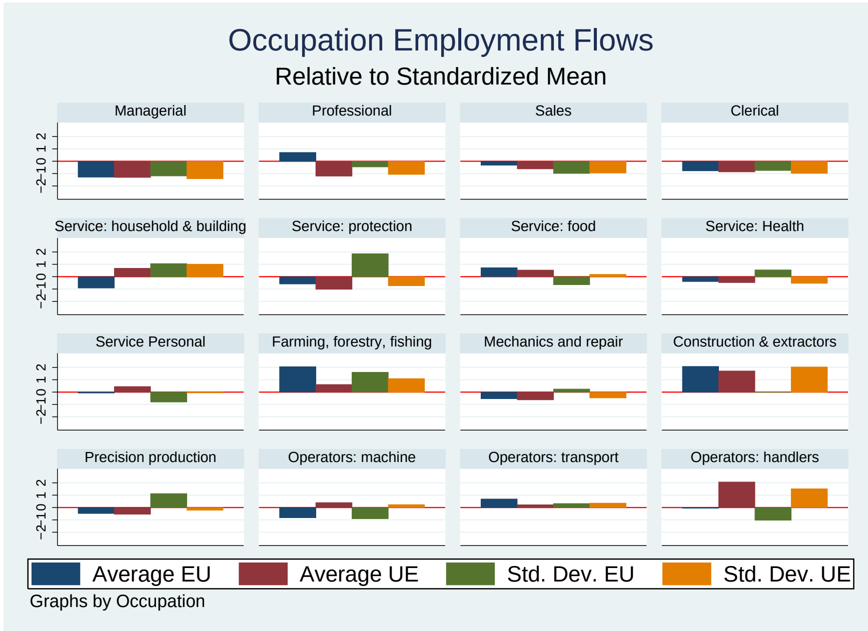


Figure 3: Variation in average and cyclical employment flows by occupation.

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 adaptability. First, age and education are considered according to a vocational grid. 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.

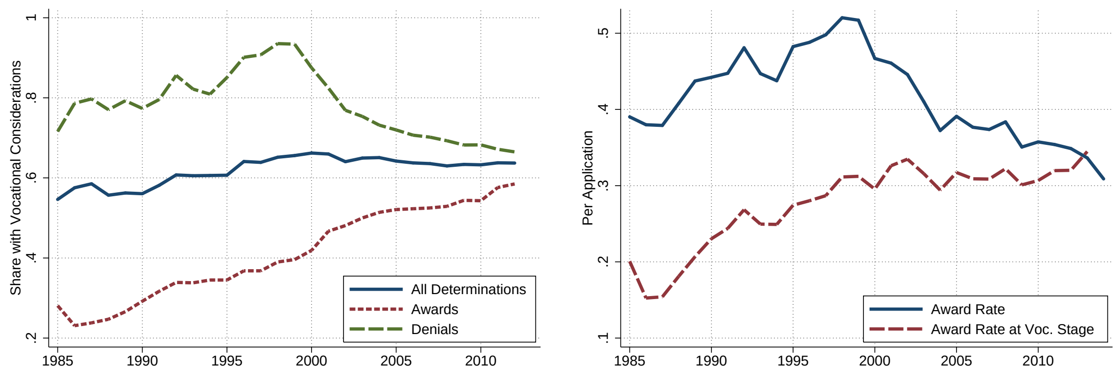


Figure 4: Role of Vocational Considerations in SSDI Trends)

Figures 4 and 19 show 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.

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.

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.

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 $d = 1$.

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[18] In line with the US systems, these transfers depend on an index of agents' prior earnings: e. This index is updated when an agent works according to their current wage, age, and past earnings: $e' = H_\tau(w, e)$. Retirees 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.[19] An agent's SSDI application is accepted with probability $\xi(d, \tau, z)$. The SSDI decision criteria include health status in addition to age and economic status, and so we model these aspects as well. An agent who is accepted as a beneficiary must permanently leave the labor force and will collect SSDI benefits until they age into retirement and switch to SSI.

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

Exogenous Employment Transitions Occupations differ in exogenous job destruction rates and exogenous rates at which unemployed workers find job opportunities. The business

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

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

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.

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

Agents' Decisions We define the problems agents face, recursively, yielding a set of value functions: working agent $V^W_{j,\tau}(\alpha, a, e, d; z, y)$, unemployed $V^U_{j,\tau}(\alpha, a, e, d; z, y)$, long-term unemployed $V^N_{j,\tau}(\alpha, a, e, d; z, y)$, disability beneficiary $V^D_{j,\tau}(a, e, d)$, and retiree $V^R_{j,\tau}(a, e, d)$. To economize on notation, we suppress the fact that value functions are also indexed by agents' 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 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 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.

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

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:

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

An Unemployed Agent's Problem An agent who chooses unemployment faces only the consumption-savings choice. As he makes this choice, he considers that, with probability 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.

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

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.

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

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.[20] Finally, observe the long-term unemployed receives a flow of real income b, which can be considered a combination of home production and broader social transfers (food stamps, TANF, etc).

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

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

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

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

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' out-

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

comes calculated from microdata, and features of the Macroeconomy most relevant for the analyses we conduct.[21]

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 age groups die randomly by a probability following their health-specific death rate.[22]

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:

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

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

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

We choose $\theta = -0.448$ and $\eta = -0.185$ as in Low et al. (2015).[23] 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.[24] We set $\gamma = 1.5$, within the standard range of risk-aversion.[25] The interest and discount rate are set to 1.6% and 2.5%, also in keeping with Low et al. (2015) and consistent with wealth in the PSID and SCF.

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.[26] 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.[27] Second, the applicant must have been non-employed for five months prior to application and not have earnings exceeding a low

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

[24]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.

[25]Low et al. (2015) show results for $\gamma = 1.5, 3$ with 1.5 as their baseline. Kitao (2014) uses $\gamma = 2$.

[26]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.

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

threshold of substantial gainful activity.[28] 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. [29] This figure 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.[30] 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 un-

[28] \$1090/month in 2015.

[29] We include the requirement for younger workers under the assumption that gaps in their work history are provided by factors outside the model such as education. Not including the requirement for older workers is not a pivotal assumption given that we focus on males. Authors' calculations from SSA earnings credit files show that between 93% and 95% of men age 50-59 meet the work requirements between 1980 and 2005. However, eligibility displays both trends (a decline from 1980 to 2000) and procyclicality. Eligibility of women in the same demographic rose from 77% in 1980 to 90% in 2005. (Graphs available upon request).

[30] 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.

employment 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.[31] Research examining this issue has found that SSDI screening produces high levels of both false positives and false negatives.[32] 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.[33] 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

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

[32]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.

[33]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.

with administrative data on SSDI outcomes, and observed aggregates to estimate an SSA "decision rule," ξ. $\xi(d,\tau,z)$ takes the form:

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

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.[34] We assume that the vocational acceptance probability is linear in $\frac{\bar{z}-z_{jt}}{\bar{z}-\underline{z}}$), given a health d. Here, $\bar{z},\underline{z}$ are the max and min of the realizations of z_{jt} so that we are normalizing the occupation productivity shock within its support. [35] The vocational acceptance probability of workers over 55 is an additional 12.4 percentage points higher consistent with both the marginal effect 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, $\zeta_{V,0}$ and $\zeta_{V,2}$, where $\zeta_V(d=1)=\zeta_{V,0}$ and $\zeta_V(d>1)=\zeta_{V,2}$ Thus, we have parameters $\{\zeta_j\}_{j=0}^2,\zeta_\tau,\zeta_{V,0},\zeta_{V,2}$ to summarize the SSA decision rule. ζ_j are determined outside of the model, but $\zeta_{V,0},\zeta_{V,2}$ 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

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

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

the 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:[36]

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

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.[37] 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

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

[37]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.

increase.[38]

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

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.[39] 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.[40]

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

[38]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 ($\tau = 2$).

[39]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.

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

a termination for economic reasons (job destruction) because of low productivity.[41] These workers would be eligible for UI.[42] 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.[43] An additional 7% receive worker's comp and 7% receive SSI. Other transfers come from informal networks. Since we are not interested in program interactions and reform (as opposed to Kitao (2014) and Low et al. (2015)), we model all other transfers as a fixed payment for the non-employed. We chose the size of this transfer to be 30% of the median earnings in the model, consistent with the typical poverty threshold for a single household.[44][45]

[41]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.

[42]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.

[43]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.

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

[45]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

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 5 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. Statistics summarizing how these things vary across occupations are shown in Table 6.

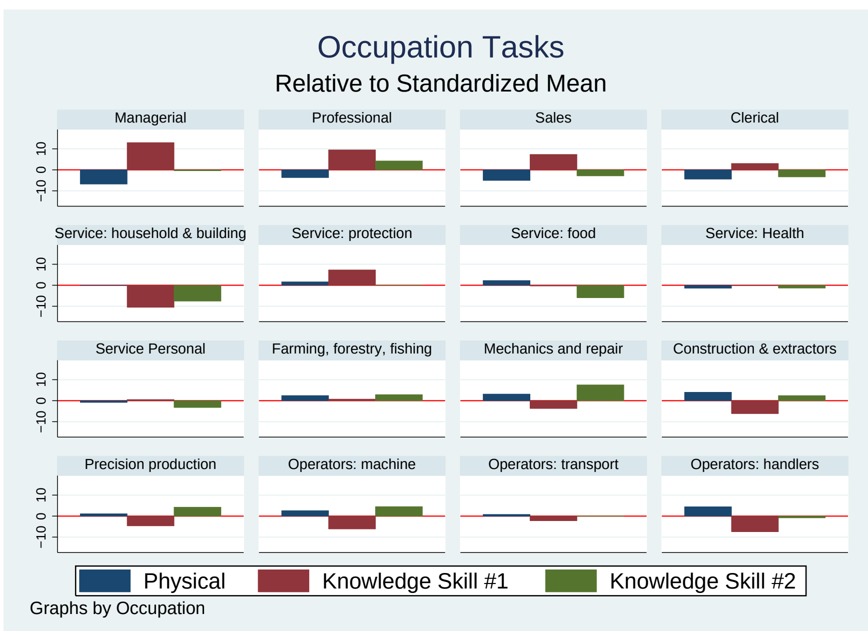


Figure 5: Variation in task intensity across occupations.

pensions, houses, etc). Therefore, we do not include asset testing 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.[46] 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:

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

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.[47] 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

[46] 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.

[47] 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.

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.[48]

Table 1: Wage Equation Estimation

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

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

Results of the first-step probit for employment are summarized in Table 1 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

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

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.[49] Our results in Table 1 indicate that both moderate and severe work limitations significantly lower wages by 0.26 and 0.97 log points, respectively.[50]

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.

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

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.[51] The final term is an interaction of the time-cubic with the

[49] As shown in Table 1, the coefficient on the Mills ratio is positive in the wage regression, confirming our conjecture that selection biases wages upwards. The average truncation effect is 0.25 log points or 9.4% of the mean log wage (2.66) in 1999 dollars.

[50] 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 1.

[51] 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.

Onet task triple.

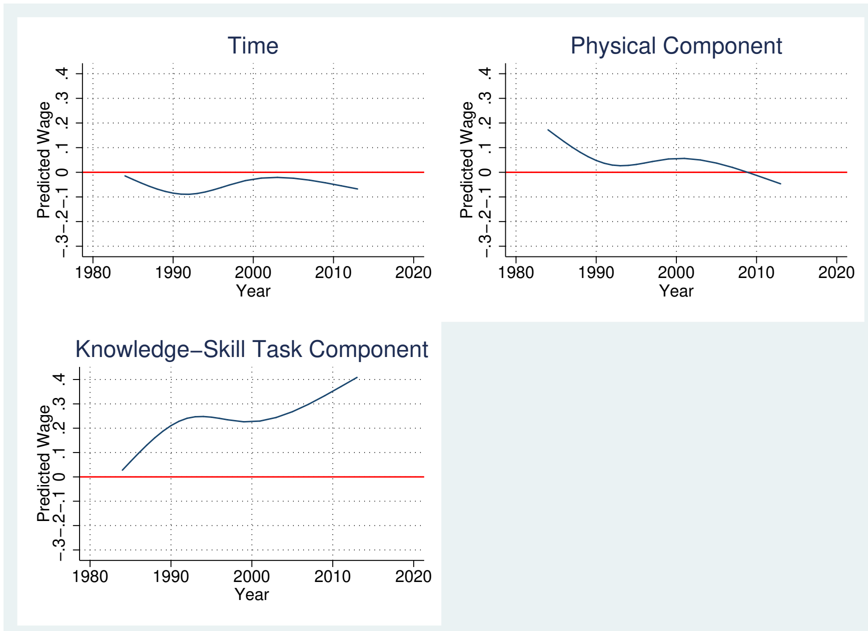


Figure 6: Predicted change in time and occupational task-skill component of wages.

The decomposition of occupational wages into the "price" paid to each task-skill along with the year trend components can be seen in Figure 6. 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. Figure 7 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-

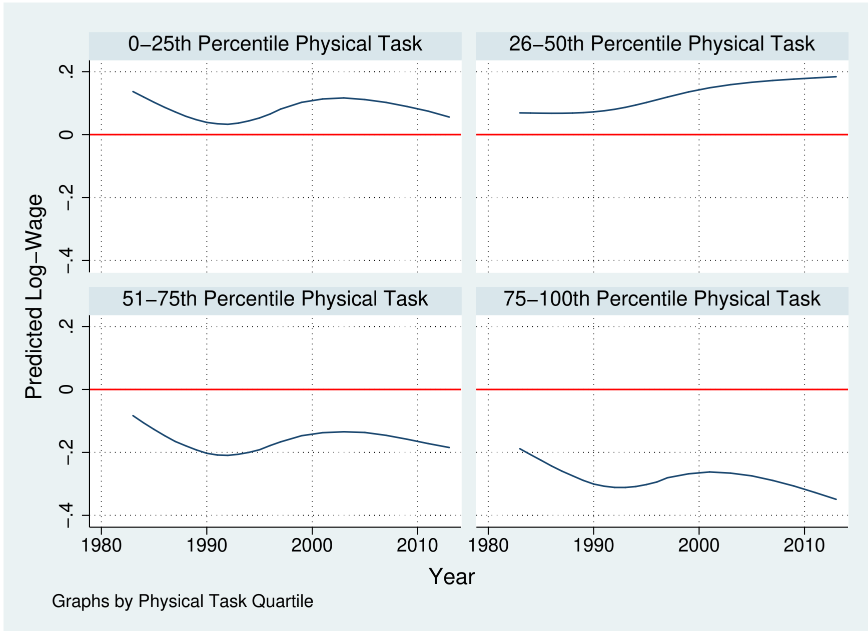


Figure 7: Predicted change in time and occupational task-skill component of wages.

ment. We use the CPS in the 1984-2013 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.

Because actual transition rates into and out of unemployment are endogenous, we cannot directly feed them into the first column and first row of the α process. Instead we will calibrate two parameters that scale the separation and finding rates. The job finding rate is the complementary probability of the first element of π_α, which we parameterize as

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

The first term λ_0 must be adjusted to get the average flows correct while λ_y adjusts for the cycle and λ_j for the occupation effect. Separation rates, the first column of each row r after the first are given by

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

Again, the first term ι_0 must be adjusted to capture the average flows while ι_y adjusts for the cycle and ι_j for the occupation effect.

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.[52] 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

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

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 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.

Model Fit. Table 2 shows the model's fit to targeted moments. The labor market design we use is unique to our model. Justification it is a good quantitative theory of labor markets is warranted. The share of employment to unemployment flows that are exogenous in the model are not too far from the flows reported as involuntary in the PSID: 51% and 36%, respectively. The share of long-term unemployed ($>$ 25 weeks) among the unemployed manages to perfectly match: 48% in both model and data. In the following section we discuss the model's fit to the non-targeted moments with regards to who goes on DI.

6 Results from the Quantitative Model

6.1 Determinants of The Disability Option

In this section, we explore how the model predicts economic and health shocks contribute to the decision to apply for DI and whether benefits are awarded in the cross-section.[53] To quantify, at the individual level, how shocks translate to outcomes, we begin by analyzing the

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

Parameter	Value	Moment	Target	Model	Source
ν	0.05	1984-86 DI Awards	0.0337	0.0337	Social Security Administration (2013)
$\zeta_{V,0}$	0.02	$d = 0$ DI Awards		0.20	PSID
$\zeta_{V,2}$	0.14	Voc DI Awards	0.25	0.25	Social Security Administration (2013)
ζ_{τ}	0.25	Adv Age DI Awards	0.25	0.25	
F_0	0.20	$d = 1$ LFP difference	-0.20	-0.20	PSID
F_2	0.61	$d = 1$ LFP difference	-0.65	-0.65	PSID
λ_0	2.40	Unemp Duration	3	3	CPS
ι_0	1.35	Unemp Rt	0.055	0.055	CPS
ζ_T	13.5	Application Duration			Autor et al. (2015)
θ	-0.448	Preference for health			Low et al. (2015)
η	-0.185	Preference for leisure			Low et al. (2015)
γ	1.5	Risk Aversion/IES			Low et al. (2015)
β	0.9979	Time Preference	2.5%		Low et al. (2015)
R	1.0013	Return on Savings	1.6%		Low et al. (2015)
$\{\lambda_{j,y}\}$		Occupational finding rates			CPS
$\{\iota_{j,y}\}$		Occupational separation rates			CPS

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

elasticities of individuals' DI application and award propensity with respect to three sources of adverse economic prospects: a long-run decline in wages; an incidence of involuntary job loss; and the effect of a recession. We estimate a simple probit model, with the three variables of interest and a cubic of time. We measure both dependent variables out of the working-age population, counting an award as anyone receiving SSDI 18 months after the reference period and an application is measured as the cross section of anyone submitting an application. Table 3 summarizes the results for the full model simulation of our period of study, 1984-2012.

The magnitude of these elasticities differ from the empirical literature for several reasons. First, the model estimates consider the response of the entire population to a shock. This is a different interpretation than empirical strategies to measure the response to wage decline which focus on the populations most vulnerable to SSDI uptake: lower income workers in occupations with high health risks. For example, Black et al. (2002) and Charles et al. (2017)

	Model		Empirical Literature
	Individuals' Applications	New Awards	
Wage Trend	-0.20	-0.15	(-0.29,-0.4)
Exogenous Job Loss	0.06	0.00	(0.17, 0.34)
Unemployment Rate	0.01	0.00	n/a
$d > 0$			
Wage Trend	-1.23	-0.77	
Exogenous Job Loss	0.15	0.01	
Unemployment Rate	0.07	-0.01	
$d = 0$			
Wage Trend	-0.18	-0.13	
Exogenous Job Loss	0.14	0.00	
Unemployment Rate	0.01	-0.01	

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

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).

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, 6%. There are two factors feeding this discrepancy. First, the incidence of non-employment is independently distributed across individuals in the model whereas 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 whereas job loss can be cleanly separated in the model. That is, what they measure as job loss mixes what we call wage trend and job loss, because job loss and the declining price of some skills is entangled in the data. Finally, we find a very small effect from recessions on application or uptake at the individual level. Empirical papers study instead the response of aggregate applications to aggregate unemployment rates and offer no analogy to our model statistic. However, qualitatively consisten with our findings, Mueller et al. (2016) finds no response of SSDI applications to unemployment insurance benefit expiration during the Great Recession.

Table 3 also shows simulated applications are more responsive than awards to economic shocks. This is a straightforward result of the screening process in which awards are more responsive to poor health shocks. The fact that the award response to job loss or recessions falls to zero suggests that healthier applicants apply in response to thehocks. This is partly because wage trend shocks hit less healthy applicants more: A 1% decrease in the wage trend brings a 5% increase the in the probability of a health problem, $d > 0$, among those older than 45.

Applications also respond to unemployment by more than awards because the application decision of healthy people is more responsive to job loss and recession shocks relative to wage trend shocks. To better understand this mechanism, we can run the same estimation as but split the sample into those with $d = 0$ and those with $d > 0$ and condition on age greater than 45, who are most likely to go onto disability. Notice that the good health and bad health groups have nearly the same application elasticity with respect to job loss, 14% against 15% respectively. Exogenous separations, however, do not increase the likelihood of being awarded SSDI. On the other hand, those in bad health are very responsive, both in terms of application and award, to wage trend pressures while those in good health are much less responsive.

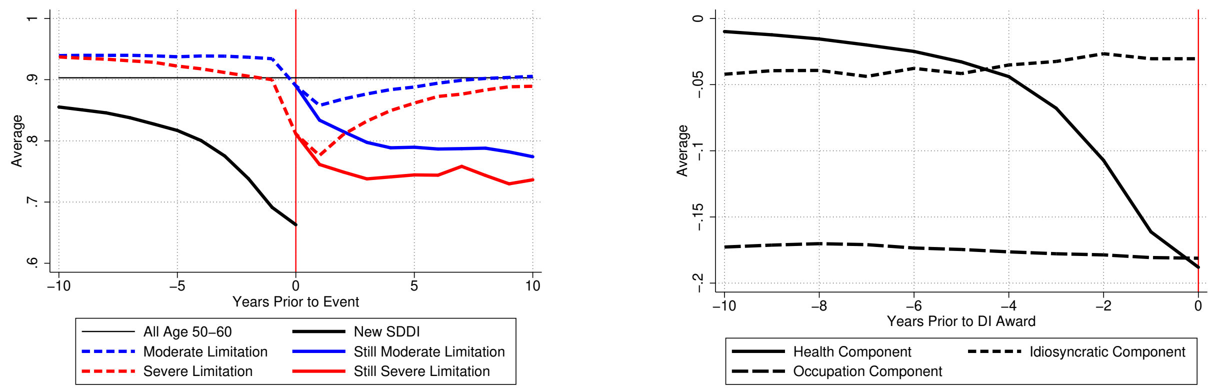
6.2 Composition of Applications and Awards

In both model and data, a salient feature of SSDI recipients is that many experience persistently poor economic outcomes for many years prior to their application. To analyze these dynamics in the model generated data, panel (a) of Figure 9(b) shows that individuals going onto DI had wages (or shadow wages) 6% lower than the average 50-60 year old ten years prior to their award. This gap increases to more than a 25% penalty in the year of the award.[54] 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 individuals who receive a disability award have persistently lower wages than individuals who acquire a moderate or severe limitation. This reveals a selection effect: not all individuals with severe limitations go on DI and those do have lower wages throughout their lives than individuals with comparable health problems. Panel (b) of Figure 9(b) shows that the wage dynamics for an individual going on DI are primarily driven by the wage impact of poor health, but the persistent low level of their wages in general is due to their occupation.

Panel (a) of Figure 9 shows that individuals receiving DI awards have comparable levels of employment to the average 50-60 year old until 4 years prior to their DI award. This three year drop is partially a consequence of needing to be non-employed while applying for DI and also reflects the waiting time, through appeals if necessary, between application and award. Observe also that the employment rates of those who recover from a work limitation take time to recover. In the model, this is driven by the wage scar following non-employment relevant for those individuals who quit their jobs for health reasons or to apply for DI.

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

Figure 8



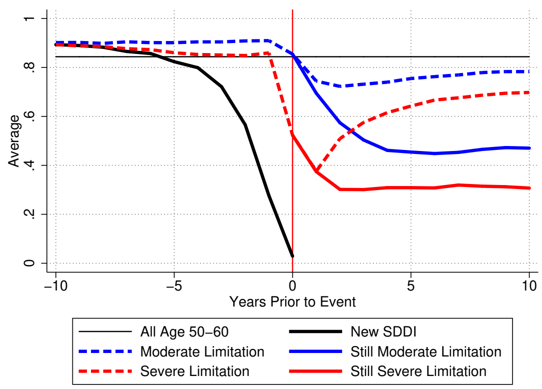
(a) Wage Paths Prior to Event

(b) Wage Path Components Prior to DI Award

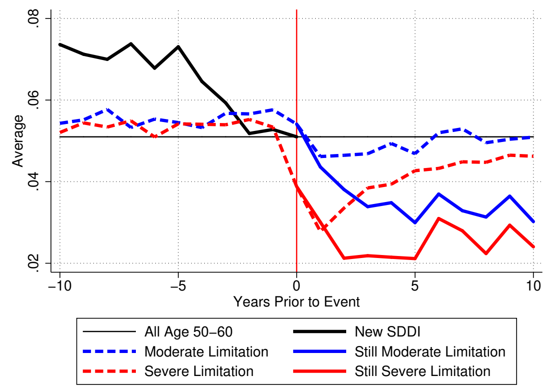
Recall, our calibrated income process included an high risk of low earnings after a job-loss and these wage scars are apparent in Panel (a) of Figure 9(b). Panel (b) of Figure 9 shows that those going on DI experience up to an 40% higher incidence of involuntary job loss than the average 50-60 year old. 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 non-employment.

How do these economic incentives manifest themselves in the composition of individuals with new SSDI awards? Table 4 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 distinguished particularly by having low labor income during the periods they were employed in the 5 years prior to their award. More than two-thirds see their labor earnings (or wage in the

Figure 9



(a) Employment



(b) Involuntary Job Loss

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.[55] The bottom two rows show that those going on SSDI are more likely to have a moderate or severe work limitation, a bit more so in the model than in the data.

Digging further, we would like to see if those going onto SSDI are unique in being affected by a confluence of poor health and poor economic prospects. Figures 10(c)-11(a) display heat maps of the model population, split between those entering DI next year and the average population aged 50-60. These figures emphasize differences in the joint distribution of economic and health risks and their realizations across the two groups. Figure 10(c) shows that individuals going on SSDI come disproportionately from occupations with both high health risks and declining wage trends. The distribution of new DI awards is more biased on the wage trend margin, but these individuals are represented in the entire distribution

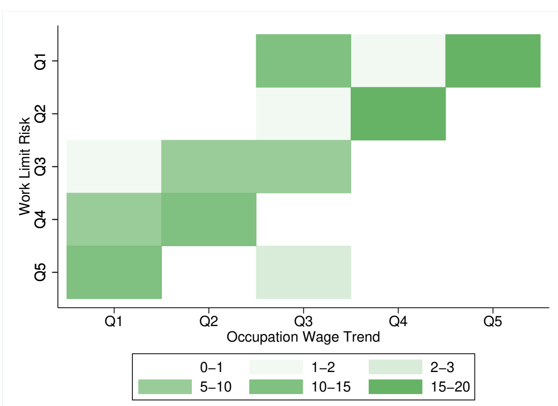
[55]The incidence of involuntary unemployment is over-predicted in the model. This is because, empirically, involuntary separations are serially correlated at the individual level (see Michaud (2018)). Replicating this feature would require an additional state variable and so we must exclude it, but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

Table 4: Types of individuals going on DI

	Model		Data	
Share	New DI	Reference Pop	New DI	Reference Pop
Labor income <20-percentile in last 5 years	69.9%	30.9 %	77.8% (3.7)	21.9% (0.8)
Involuntary unemployment in last 5 years	24.6%	18.8%	4.3% (1.0)	5.5% (0.4)
Severe Work Limitation	57.2%	5.1%	68.5% (7.1)	8.3% (0.5)
Moderate Work Limitation	36.6%	5.9%	12.0% (4.8)	9.6% (0.5)

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

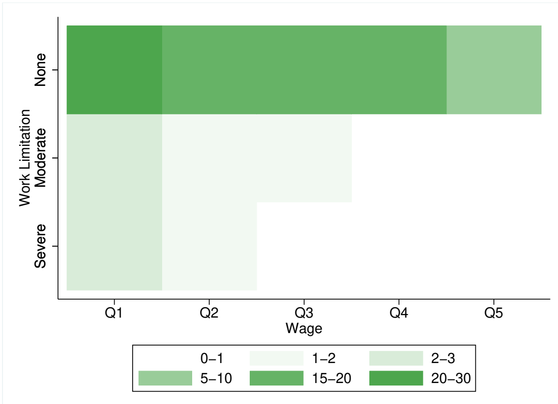
of occupational risk. Figure 11(a) compares the distribution of individuals across current states. It reiterates the importance of considering both the health and economic margins, jointly. It also shows that many older workers have relatively low wages during the decades we consider, putting them at risk of applying for DI even if they are in good health.



(c) All Age 50-60

(d) New DI Award

Figure 10: Occupation health risk and occupation wage trend quintile



(a) All Age 50-60

(b) New DI Award

Figure 11: Current health status and current wage quintile

6.3 What Drives Aggregate Trends in SSDI?

In this section, we use the model to try to understand the external changes driving 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.[56] 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.[57] We also expose agents to occupational job finding and job loss rates calculated from the data. Agents' decision rules include an expectation of exogenous switching between recessionary periods and normal times each with the average rates during these times given by λ_y, ι_y.

Figure 12 shows the model's success in matching the rise in new awards of SSDI over

[56] 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.

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

the period since 1984. We focus on the pattern in new awards rather than the stock of SSDI recipients because because the stock is relatively slow moving and would hide some of the successes and failures of the model. There are two notable successes. The model can account for most of the rise in the share of new awards to DI in the early 1990s and mid 2000s and also predicts the flattening out in the late 1990s. The place where the model falls short is in the first rise in the early 2000s, where it is late in predicting the rise. 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.

Figure 12: New Awards: Model vs. Data.

How does the type of individuals flowing onto DI change over time? Figure 13 shows changes in the age and health composition of applicants over time and how it translates to new awards. Qualitatively, these are the patterns one might expect: Applicants become younger and healthier when some occupations' wages are stagnating in the 1990's and during the Great Recession. However, applicants in good health are mostly rejected during the screening process while the composition by age changes less between application and award.

The model features fewer new awards to individuals without a work limitation than the PSID data: 5% versus 20%; and so it may be wise to avoid conclusions about the efficacy of the actual SSDI screening process.

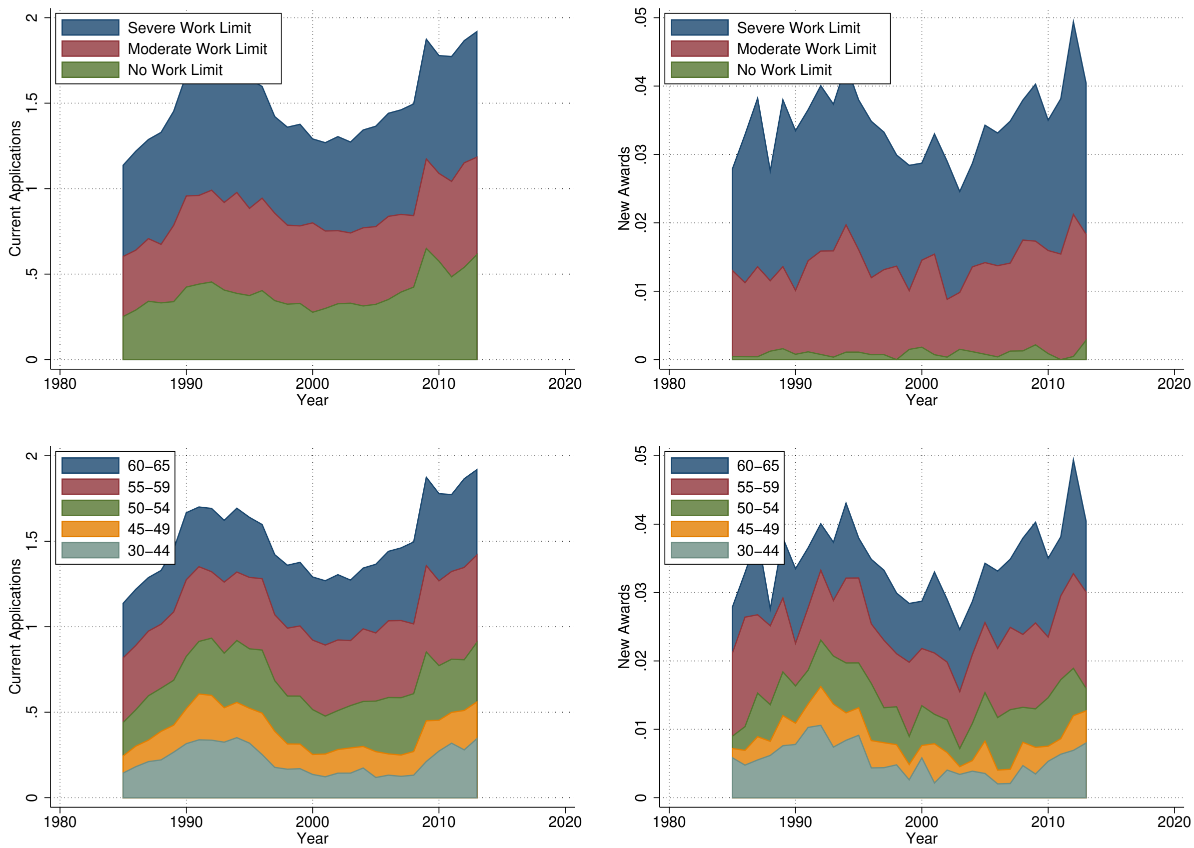


Figure 13: Demographic Composition of Applications and Awards

The model allows us to isolate and decompose the impact of individual factors that played into the rise in SSDI. Figure 14 shows the contribution to applications arising from each trend: age demographics, occupational composition, and wage trends. These outside factors interact with each other, for instance older workers may be more susceptible to apply for SSDI given a set of shocks than younger workers. Hence, we use a Shapley-Owen decomposition: for each trend, we compute the implied contribution by compare counter-factual simulations with it on or off. This contribution is computed for every permutation of all of the other trends being on or off and we report the average.

The two most important factors are demographics and wage trends, with the former accounting for about 4% of the total number of applications and the latter with 13% each year. During the 1990s, the baby boom generation lowered predicted SSDI awards before driving almost the entirety of the increase after 2000. The wage trend is overall the most important component to awards, but most of its effect is early in the period. In particular, prior to 2000, wage trends accounted for 24% of new awards, but after they contribute only 3%. Demographics, on the other hand, have a negative contribution prior to 2000 but 13% of new awards after. There is a small uptick in the number of awards around the Great Recession, 2009-2011, due to business cycles. However, most of the time, the model gives very little role for business cycles or changes in occupational composition.

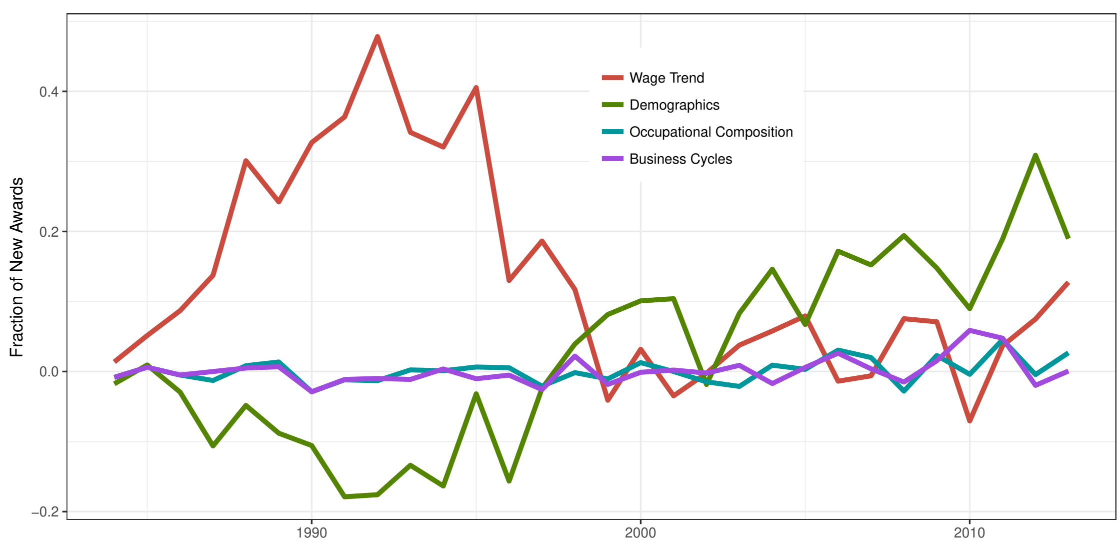
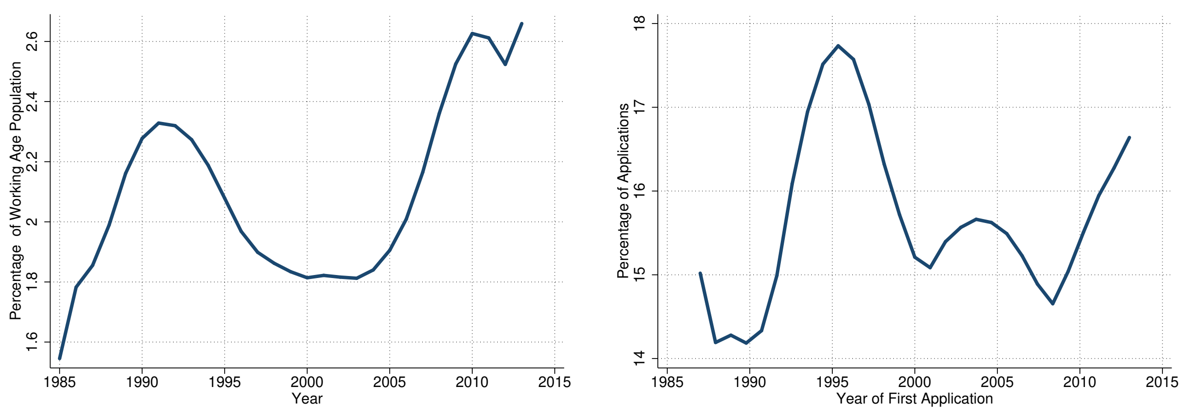


Figure 14: Decomposed contributions to new SSDI awards

Looking at the rise in the rate of disability, we can perform the same Shapley-Owen decomposition. Again, wage trends and demographics are far the most important factors, but demographics are most important to the stock of SSDI. Of the 2.1 percentage point rise in SSDI predicted by the model, 58% comes from the demographic changes and 33% comes from wage trends. The reason for the larger role of demographic changes is that it makes the average age of entry younger, whereas wage trends make the average age of entry older. Again, occupational composition and business cycles have a minimal effect on the model's predicted rise in SSDI, accounting for 3.8% and 4.5% of the model's total rise in SSDI.

We now consider how changes in the application rate and how applicants are screened in the awards process contribute to changes in the awards rate. Figure 15 displays applications in the model. Applications are dated by the first year the agent began to apply given they did not apply in the prior 12 months.[58] Therefore, they provide a better sense of the timing of when agents chose the DI option.



(a) Applications

(b) Denials

Figure 15: Applications and denials per working age person by date of first application.

Changes in the denial rate per application fill in the quantitative discrepancy between

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

the application and award rates Figures 15(a) and 12). Denials are defined as continually applying for 14 months without receiving an award and are dated by the date of first application.[59] To compare the level denials to data, SSA data pooled over gender show a denial rate averaging about 22% during this time period. However, they include technical denials such as applying when ineligible or not completing forms. These account for 30% of all denials in the data. Since we do not include these types of applications in the model, the comparable statistic in the SSA data is a denial rate of about 15.5% which is not far from our model prediction.

For the most part, increases in denials follow increases in applications and is consistent with the results in the prior section that applicants become younger and more healthy during such surges. Notice that applications surged in both the 1990s and Great Recession, but the former accompanied a larger rise in denials. This suggests that the pool of applicants deteriorated more in the first period than latter.

Decomposing the forces contributing to applications, we see exactly why the applicant pool deteriorated more in the 1990s SSDI boom than in the mid to late 2000's. The Shapely-Owen decomposition for the application rate is shown in Figure 16. Notice that wage trends now have a much more pronounced effect throughout the simulation, particularly in driving the early 1990s increase in applications. Aging still contributes towards the end, but is less pronounced than Figure 14 because these older workers are less likely to be denied. This is happening because health is correlated with aging and vocational awards also become more lenient, hence applications are much more likely to lead to awards at higher ages.

Looking at other forces driving applications, there are small spikes from business cycles at each recession: the early 1990s, 2000's and Great Recession. These are larger than

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

the spikes we saw in the awards decomposition (Figure 14) because recessions cause more marginal applicants to joint the pool. None of these spikes, however, account for more than a few percent of the new applications. Most of the time business cycles contribute negatively to applications because during expansions awards are somewhat subdued. Changes to the occupational composition is also reducing applications but only very minimally.

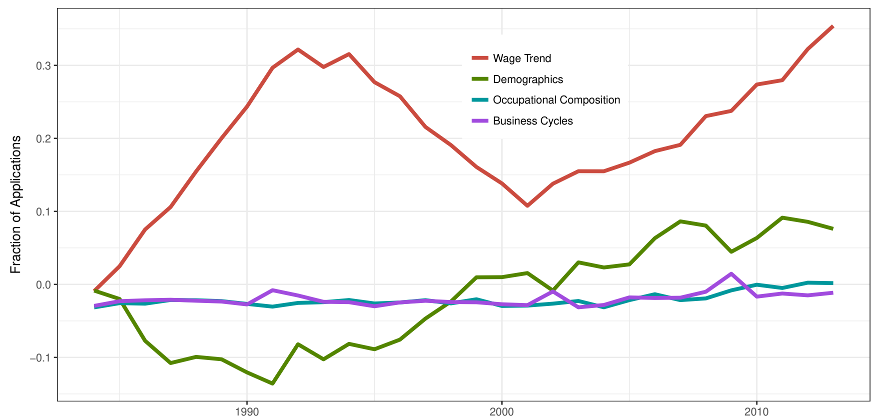


Figure 16: Applications: Shapley-Owen Model Decomposition.

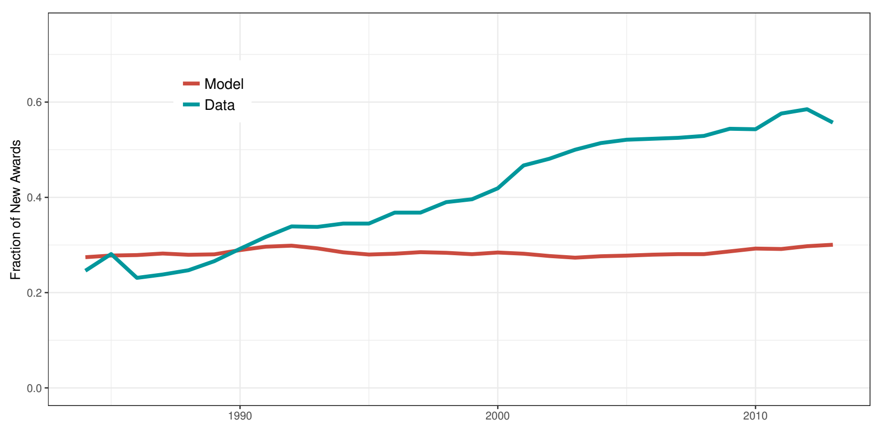


Figure 17: New Awards: Fraction with Vocational Considerations

To further understand the driving forces, the model was careful to incorporate how the occupational composition is exposes workers to joint health and economic risks. The Shapely-

Owen decomposition was used explicitly because shocks interact: declining wages in some occupations affect relatively unsafe occupations more, especially among the old who tend to be less healthy. We can try to understand the role of this crucial correlation by drawing health shocks independent of occupation, but otherwise keeping everything else the same, including the overall health risks. The result is about 5% fewer awards, distributed evenly throughout the simulation period. This makes the correlation between occupations and health risks more important than business cycles, but less important to driving awards than deomgraphics since 2000.

Data from the SSA show awards with vocational considerations have driven almost all of the rise in new awards since 1984. Figure 17 shows how many of the current beneficiaries had vocational considerations factored into their award in our model. Though difficult to see because of the scale of the graph, vocational awards generally rise by about 5 percentage points and, along with applications in general slump after the 1990s rise. Although the model predicts a slight rise in vocational awards, it is not the main driver of the overall trend as it is in the data. 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 applying this grid can generate a rise in awards but not vocational ones, suggests that these rules may not have been implemented in a consistent way across time and/or space. Indeed, this hypothesis is consistent with other work exploiting the variation in award leniency across locations in their research design (French and Song (2014)) and has been a focus of internal reforms in the Social Security Administration. The model is, however, successful cross-sectionally, as Figure 4 shows the model's predictions were consistent with our conjecture: vocational awards grew more in occupations with high health risks due to the correlation of economic and health risks at the occupation level.

7 Impact on Employment and Welfare

7.1 Contribution to employment trends

A typical question in the literature is the impact of the SSDI program on employment and labor force participation. The employment to population ratio for working age men fell by 6.4 points over our period of study (1984-2012). The model exactly predicts this rise although this was not a targeted statistic. We now examine how the demographic and economic trends as well as business cycles we fed in to the model generate non-employment when social security disability is an option.

Our model has an advantage in addressing this question over existing administrative and survey data because we can observe the individuals who are non-employed because they are either in the application process or waiting to be eligible to apply. Figure 10(c) shows individuals in this situation are comprise 1.6-2.6% of the working age population. This is a sizeable. The stock of current beneficiaries rose from around 2% in the 1980s to almost 5% by 2010 meaning current applications amounted to two-thirds of the stock of beneficiaries in the 1980's falling to about one-half by 2010. Omitting this group would understate the employment impact of SSDI by 30-40%.

Applicants, or those waiting to apply, also comprise a large and rising share of the total non-employed in our model. In 1985, those unemployed for reasons other than disability accounted for three-quarters of the non-employed. By 2010, this share fell to 44%. Concurrently, applicants/beneficiaries shares rose from 10/15% to 20/36%, respectively. Indeed, by 2012, the share of the working age population on SSDI was equal to the working-age population non-employed for reasons other than disability.

	Total	By Age					By Occ Health Risk			
		30-44	45-49	50-54	55-59	60-65	Q1	Q2	Q3	Q4
Δ Non-Employed	+ 6.3	+ 1.9	+ 3.0	+ 4.2	+ 4.7	+ 9.2	+ 0.9	+ 5.1	+ 5.1	+ 8.7
% Δ on DI	93.5	94.2	76.7	93.5	132.6	1.04	118.4	78.2	111.4	94.2
% Δ applying for DI	18.4	27.8	24.9	12.9	-4.7	4.6	26.8	16.1	12.1	21.8
% Δ other	-11.9	-22.0	-1.6	-6.4	-45.4	-5.0	-45.2	5.6	-23.5	-16.0

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

The disability option contributed differentially to the disparate non-employment trends of different demographic group. Starting with the first column in

7.2 Welfare value

Our structural model allows us to compute the value of the disability option to each individual at each state. Important to note is that this is a partial equilibrium notion; because the goods market does not clear, we are not incorporating the costs of the SSDI program, e.g. higher taxes. However, the model allows us to see heterogeneity in the value of SSDI across age and occupation and across cohorts.

To compute the value of the SSDI option to an individual at a given state, we compute the model without the ability to apply for disability, as if $\nu \to \infty$. This yields a counter-factual value function, V_{CF} at any state and from which we can compute welfare in consumption terms, $\frac{V}{V_{CF}}^{1/(1-\gamma)} - 1$. For each worker in our simulation who is not already on SSDI, we store this welfare gain. This measure requires several caveats, chiefly that we are evaluating both the true and counter-factual value functions using the true policy functions, a', m and labor supply, that are chosen by individuals with access to SSDI, however, V_{CF} is computed as if that option were unavailable. Hence, this measure should be understood as an instantaneous value of SSDI starting from a particular point in an agent's history.

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

These differences across health turn out to be crucial to understand who values SSDI. In Figure 18 we compute a moving average of welfare gain across wage trend, z, splitting the sample between $d = 0$ and $d > 0$. Notice that for any given wage trend $d > 0$ gain more from SSDI. When $z = 0$, they get about 80% more gain, 1.46% against 0.80%. As we see lower realizations of z, the program generally becomes more valuable, but especially for those in poor health who are more likely to receive an award. For $z < -0.4$, if $d > 0$ they value SSDI about 125% more than those in good health with $d = 0$. At the other extreme, when times are good and z is relatively high, neither health group places much value on SSDI at all.

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

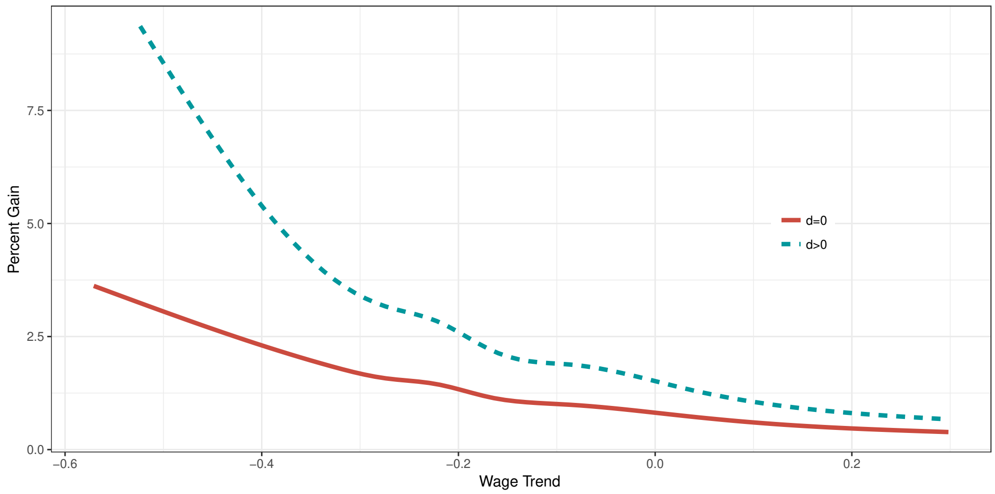


Figure 18: Welfare gain across wage trend levels and by health

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.

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

We further used the model to assess the impact of changing demographics and economic conditions on non-employment when disability is an option. The contribution of disability goes beyond new beneficiaries. It also includes people entering non-employment in order to apply or appeal for SSDI benefits as well as those rejected applicants who have lost attachment to the labor force over the several years of applications and appeals. The model replicates almost the entire rise in male non-employment from 1984-2012: 6.3 percentage points and SSDI plays an important role. The share of non-employed who are not on nor wishing to apply for disability falls from 75% to 44%.

The analysis is limited by a couple of short comings. First, women are omitted from the study. Female eligibility grew significantly over this time period while male eligibility declined reflecting different fundamental labor force participation trends. Most new awards to women are for mental and emotional conditions whereas musculoskeletal is the predominant diagnosis of males. Since female trends in SSDI awards are sufficiently distinct from male trends, we concluded that the demographic group merits its own study and excluded them from this paper. Second, the model predicted too few new awards to individuals in good health (type one error) and was unable to replicate the rise in awards with vocational considerations from 25% in the 1980's to almost 60% after 2010. We believe these problems are related and arise from a common source. We used a consistent and time invariant vocational-grid award probability set to replicate elasticities from internal audit studies and to match the average share of vocational awards over our study period. De facto changes in how these rules operate over time or inconsistencies in how they operate across space could generate a rise in vocational awards alongside rising awards to individuals in good health. Analysis of additional data from the Social Security Agency to answer questions about the variability in the awards process, and particularly in the vocational grid, is a promising avenue for future research and would complement this paper.

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9 Figures

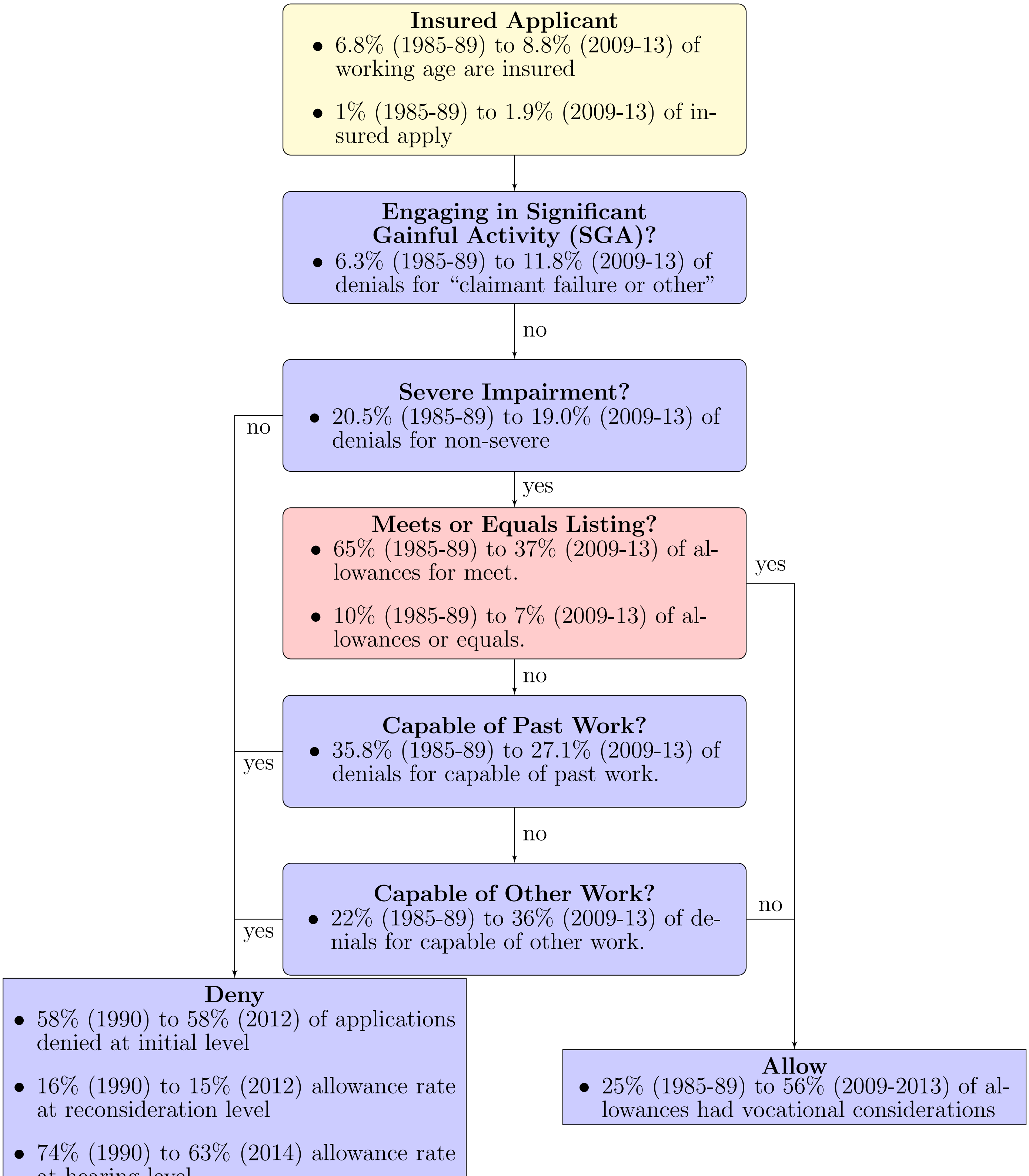

Figure 19: Initial decision process. Allowances from the red step “Meets or Equals the Listing” do not consider ability to work, all other steps do.

Table 6: 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.

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

† $p < 0.10$, * $p < 0.05$, ** $p < 0.01$