Explaining the Historical Rise and Recent Decline in Social Security Disability Insurance Enrollment

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March 2025

Abstract

After substantial growth in the 1990s and 2000s, enrollment in the U.S. Social Security Disability Insurance (SSDI) program has been declining since 2013. We present the first comprehensive statistical and causal analysis of the increase and decline in SSDI enrollment. Using a statistical decomposition combined with detailed administrative data, we find that nearly all of the decline in SSDI enrollment in the 2010s is attributable to declines in application rates (56%) and award rates (32%) within groups, rather than changes in composition across groups, financial eligibility, or exit. Older low-and-middle-skilled men drive the decline in SSDI applications, as do applicants with severe health conditions and applicants with mental conditions. In the causal analysis, we rule out several popular hypotheses for the decline in SSDI applications, including a discouragement effect of lower award rates at the appeals level, higher administrative burden of applying, and improved population health. We find that higher employment and potential earnings for individuals on the margin between working and applying for SSDI benefits is the most likely explanation for the decline in SSDI applications.

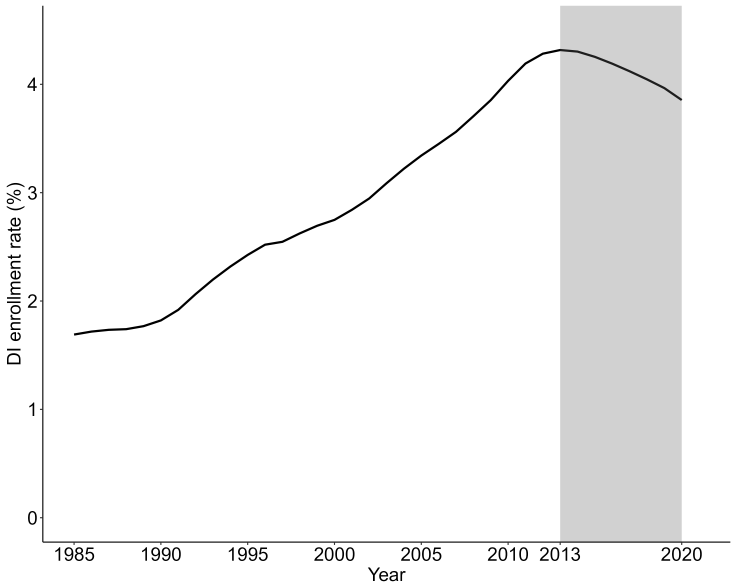
JEL-codes: J14, H31, I38. Key words: SSDI, disability, decomposition

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The growth of the U.S. Social Security Disability Insurance (SSDI) program in the 1990s and 2000s gained widespread attention from policymakers, researchers, and the public, fueling concerns about an impending fiscal crisis and about misaligned incentives for Americans who are potentially capable of working. The growth was attributed to a combination of aging and eligibility, more qualifying conditions, and high benefit levels relative to potential earnings from work for low-skilled workers (Autor and Duggan, 2003, 2006; Reno, 2011; Congressional Budget Office, 2012; Liebman, 2015).

Since 2013, however, the SSDI program has been shrinking, as shown in Figure 1. While other developed countries, including the United Kingdom, Australia, Sweden, and the Netherlands, have also experienced declines in disability enrollment, those declines can mostly be linked to policy reforms that were intended to curb enrollment (McVicar, Wilkins and Ziebarth, 2023). In contrast, there have been no explicit reforms in the U.S. to reduce SSDI enrollment. The reasons for the decline in SSDI, the future trajectory of the program, and the normative implications of the decline remain a mystery.[1]

Figure 1: SSDI enrollment has been falling since 2013



Notes: SSDI enrollment rate is number of SSDI recipients divided by population aged 18 to 66 years. Sources: Social Security Administration (2024) (Table 49), (Social Security Administration, 2023).

Several explanations for the decline have been suggested. Some explanations relate to economic and demographic changes in the 2010s: the economic recovery following the Great

[1]One specific policy reform was retraining of administrative law judges in the early 2010s, which led to lower award rates at the appeals level. However, this reform was not intended to curb enrollment, and, as we show, was not nearly large enough to account for the reduction in SSDI enrollment.

Recession, which could have increased work opportunities for people with disabilities; population aging, which could potentially increase exits from SSDI through retirement and death; lower labor force participation among men, which could potentially reduce financial eligibility for SSDI; the shift to less physically demanding jobs, which could potentially improve population health; and more access to other benefit programs. Other explanations point to SSA policies in the past two decades: lower award rates at the appeals level, attributed in part to the retraining of administrative law judges in the late 2000s; a potentially higher application burden if, e.g., application backlogs have grown; and the end of personal Social Security statement mailings in 2011. There are also factors that would be expected to work in the opposite direction of the decline, including the increase in the full retirement age, which would mechanically keep SSDI recipients on SSDI longer; increases in earnings inequality, which could increase demand for support programs; and population aging and the opioid crisis, which could have increased disability incidence.[2]

In this paper, we conduct a statistical and causal analysis to explain the historical increase in SSDI enrollment in the 1990s and 2000s and the subsequent decline in SSDI enrollment since 2013. We first develop a novel statistical decomposition method that allows us to take into account interactions across the many components of SSDI enrollment—composition, financial eligibility, application, award, and exit through various channels—and allocate these interaction terms flexibly to different components. Using this method we calculate a range of estimates for each component, each estimate representing a unique and plausible notion of the component's impact on DI stocks. Under realistic assumptions, the range of estimates we report nests the range generated by existing methods in the literature. Next, we take this decomposition method to individual-level administrative data from the Social Security Administration (SSA). This detailed administrative data allow us to account for composition changes across a rich set of population and applicant characteristics, construct financial eligibility for SSDI at the individual level, link SSDI applications to awards, and track exit through multiple channels. We apply our decomposition method first to the

[2]Work opportunities: Glenn and Goss (2018); Ruffing (2023), Center on Budget and Policy Priorities (2025); Liu and Quinby (2023). Population aging: Ruffing (2023), Center on Budget and Policy Priorities (2025); Liu and Quinby (2023); Mohamed, Burns and Cubanski (2024). Lower male LFP: Mohamed et al. (2024); vs Liu and Quinby (2023). Industry shift: Social Security Administration (2019); vs Liu and Quinby (2023). Other benefits: Glenn and Goss (2018); Ruffing (2023), Center on Budget and Policy Priorities (2025); vs Social Security Administration (2019). ALJs: Glenn and Goss (2018); Social Security Administration (2019); Ruffing (2023), Center on Budget and Policy Priorities (2025); Liu and Quinby (2023); Mohamed et al. (2024). Application cost: Glenn and Goss (2018); Ruffing (2023), Center on Budget and Policy Priorities (2025); vs Liu and Quinby (2023). Mailings: Ruffing (2023), Center on Budget and Policy Priorities (2025), Armour (2018); Mohamed et al. (2024). FRA: Social Security Administration (2019). Inequality: Social Security Administration (2019). Population health: Liu and Quinby (2023). Opioid crisis: Maestas, Sherry and Strand (2024).

increase in SSDI enrollment in the 1990s and 2000s (building on Liebman 2015), and then to the decrease in SSDI enrollment in the 2010s. Finally, we conduct a causal analysis using several data sources and empirical methods to investigate potential causes of the SSDI decline and determine which is most consistent with the data.

We first apply the statistical decomposition to the historical increase in SSDI enrollment in the 1990s and 2000s. We find, consistent with Liebman (2015) and other analyses, that the increase is attributable to a combination of higher entry onto SSDI (49%), lower exit from SSDI (31%), and composition changes (25%).[3] Our data and method allow us to expand on previous findings in a number of ways. Within SSDI entry, applications account for the largest share of the increase, but increases in award and eligibility also play a role. Most of the decrease in exits reflects lower exit through death, but a nontrivial share comes from lower exit through retirement (due to increases in the full retirement age). Low-skilled women (of all ages) overwhelmingly drive the increase in applications, and to a lesser extent the increase in awards. Mental and musculoskeletal conditions represent most of the increase in applications and awards, consistent with the expansion in medical eligibility of these conditions (Autor and Duggan, 2003, 2006).

We next apply the statistical decomposition to the decline in SSDI enrollment in the 2010s. We find that virtually all of the decline can be attributed to declines in entry onto SSDI within observable subgroups, rather than changes in composition across subgroups or increases in exit.[4] Most of that decline in SSDI entry (55%) is attributable to lower application rates, but lower award rates also contribute (30%); changes in financial eligibility contribute little to the decline in entry. In contrast to the historical increase in SSDI, the decline in SSDI applications is driven disproportionately by older low-to-middle-skilled men. We also find that the decline in SSDI applications is driven by potential applicants with mid- to high-severity conditions, while those with low-severity conditions continue to apply at similar rates. The decline in applications is also driven disproportionately by potential applicants with mental conditions, while those with musculoskeletal conditions contribute less.

The decline in awards is perhaps less surprising than the decline in applications given previously documented, policy-driven declines in award rates at the appeals level (Hoynes, Maestas and Strand, 2024). In contrast to the decline in applications, the decline in awards is driven disproportionately by older low-to-middle-skilled women. The decline in awards is largest for applicants with mental conditions and endocrine conditions (who also contribute

[3]These numbers add up to more than 100% because the interaction between across-group composition and within-group SSDI rates is negative.

[4]We end our analysis in 2019 in order to focus on the secular decline in SSDI enrollment and avoid the exceptional circumstances of the COVID-19 pandemic.

substantially to the decline in applications), and for applicants with musculoskeletal conditions (who contribute less to the decline in applications). Not surprisingly, applicants with the least severe conditions contribute the most to the decline in awards.

Since applications play the largest role in the decline in SSDI enrollment, we evaluate several possible causes of the decline in applications using a number of data sources and empirical strategies. For each hypothesis, we determine two things: whether the parameter (e.g., probability of award) has changed over the relevant time period in a direction that would be expected to reduce SSDI applications, and if so, the elasticity of SSDI applications with respect to that parameter. We rule out several explanations with a reasonable degree of confidence. With respect to the probability of award, we find that although the probability of award has declined during this time period (specifically at the appeals level due to policy changes), the elasticity of applications with respect to this probability is close to zero. With respect to the hassle cost of applying, we find that Social Security field office closings and changes in legal representative fees could explain a small fraction of the decline but not a significant share. Other measures of hassle costs—like wait times and processing times—actually fell during this time period. We also find no evidence for improvements in population health—if anything, population health has worsened. With respect to other benefit programs, there were no significant expansions of SNAP, TANF, or unemployment insurance during this time period. Other studies have found no effect on SSDI applications from expansions in health insurance under the Affordable Care Act. We also determine, by identifying veterans in our data, that the rapid growth of Veterans Disability Compensation in the 2010s cannot explain the SSDI decline.

The evidence is most consistent with an increase in employment and potential earnings among people on the margin between applying for SSDI benefits and working. Earnings and employment among older low-to-middle skilled men, the group that drives the application decline, reached historic highs in the late 2010s relative to previous birth cohorts. In the spirit of Autor and Duggan (2003), we calculate SSDI replacement rates—the SSDI benefit amount that someone would receive if on SSDI relative to potential earnings from work—and find that replacement rates are at historic lows for recent cohorts of low-to-middle skilled men. This is for two reasons: their potential earnings are higher than previous cohorts, and their hypothetical SSDI benefit amount is lower due to employment declines during the Great Recession.

We conduct two exercises to test whether, within the population of low-to-middle-skilled men, the same subgroups that drive the decline in SSDI applications also experience increases in employment and earnings. First, we estimate changes in the joint likelihood of employment and SSDI application. We find that the likelihood of applying and not working has fallen and

the likelihood of not applying and working has increased (while the likelihood of not applying and not working has decreased). This suggests that the shift out of applications has come from people who are working. Second, our estimates from SIPP-SSA linked data reproduce the same earnings and employment patterns among low-to-middle-skilled men who have health limitations, who are most likely to be on the margin between working and receiving SSDI benefits. While we do not explicitly estimate the elasticity of SSDI applications with respect to earnings and employment, the elasticity that would be required to explain the full decline in SSDI applications is comparable in magnitude to estimates from the limited quasi-experimental evidence from the literature (Autor and Duggan, 2003).

Since the application decline is concentrated among potential applicants with higher-severity conditions, the results suggest that higher-severity potential applicants are the marginal workers, while lower-severity potential applicants (who are mostly rejected) are much more disconnected from the labor market. Indeed, consistent with Deshpande and Li (2019) and Deshpande and Lockwood (2022), we find that higher-severity applicants are much more likely to have worked in the years leading up to their application than lower-severity applicants. Strong employment opportunities in recent years appear to have pulled higher-severity potential applicants into the labor market and diverted them from SSDI. An important question going forward is whether these same potential applicants will apply for (and likely be awarded) SSDI benefits if and when their employment opportunities become more limited. The result also suggests that training and employment opportunities may be critical for reducing SSDI enrollment among workers with health conditions.

Related literature. We make several contributions to the literature on disability benefits. We conduct the first comprehensive statistical and causal analysis of both the increase in SSDI enrollment in the 1990s and 2000s and the decline in SSDI enrollment in the 2010s. This is also the first paper of which we aware to use individual-level SSA administrative data in a decomposition of changes in SSDI benefits. Our paper builds on evaluations of the increase in SSDI enrollment in the 1990s and 2000s (Autor and Duggan, 2003, 2006; Reno, 2011; Congressional Budget Office, 2012; Liebman, 2015), particularly Liebman (2015), who conducts a sequential decomposition of the SSDI increase in the 1990s and 2000s using aggregated administrative data. Our statistical decomposition method combined with individual-level administrative data on all applications and awards allows for additional insights into both the increase in and subsequent decrease in SSDI benefits. We also build on analyses of the current SSDI decrease (Glenn and Goss, 2018; Social Security Administration, 2019; Liu and Quinby, 2023; Ruffing, 2023; Mohamed et al., 2024; Center on Budget and Policy Priorities, 2025), particularly Liu and Quinby (2023), who decompose the decline into

four components—population aging, the Great Recession, field office closings, and a residual term—using SSA administrative data aggregated by state and year.

Our finding that improved employment and earnings prospects among individuals with health conditions is consistent with evidence on higher employment rates among people with disabilities in recent years. Ne'eman and Maestas (2023) find that, after decreasing in the Great Recession, employment rates among people with disabilities began recovering in 2014. Bloom, Dahl and Rooth (2024) find that the work-from-home revolution created by the COVID-19 pandemic can potentially explain much of the rapid rise in post-pandemic employment among people disabilities documented by Ne'eman and Maestas (2023). Although our analysis ends before the pandemic, it is possible that remote work played a role in increasing employment opportunities among people with disabilities even before the pandemic.

1 Data and institutional background

1.1 Administrative and survey data

The data for the statistical decomposition and parts of the causal analysis come from the Social Security Administration's Continuous Work History Sample, which is a 10% sample of Social Security Numbers. Using the CWHS, we link individuals to the following data:

- Demographic characteristics from the Numident, including age, sex, race, and immigrant status;
- Annual earnings (1951–2022) from the Master Earnings File (MEF) Summary Earnings File (SER), which us allows to construct financial eligibility for SSDI in each year; average annual earnigns between the ages of 25 and 34, which we use as a measure of socioeconomic status; as well as average monthly indexed earnings (AIME), primary insurance amount (PIA), and SSDI replacement rate (PIA divided by a measure of potential earnings);
- Annual earnings by employer (1978–2022) from the Master Earnings File (MEF) Detailed Earnings Record (DER), which allows us to link individuals to firm information such as industry from the Department of Labor F5500 using Employer Identification Number (EIN);
- SSDI applications from the F831 file (1990–2022), which include application date, initial (DDS) decision date, initial (DDS) decision, body system code, primary and

secondary diagnosis, medical diary reason (how often the approved applicant is supposed to get a medical review in the future), years of education, state, and ZIP code (for some years);

- Additional application information from MEDIB (2005-2019), including ZIP code and legal representation;
- OASDI payments from the Payment History Update System (PHUS) at the monthly level (1984–2022), which serve as our primary measure of SSDI enrollment; and
- SSDI enrollment data from the Master Beneficiary Record (MBR) (1970–2022), which allow us to measure exit from SSDI via recovery (i.e., medical review).

Using this administrative data, we calculate financial eligibility for each individual in the sample, link SSDI applications to awards to calculate application rates and award rates by year of application, and track individuals from SSDI entry to SSDI exit, and document the type of exit (death, retirement, recovery, or other). In Appendix Section A.1, we show that our data match public data on enrollment, eligibility, application, award, and exit numbers well.

We also use a 1% version of the CWHS that includes ZIP codes from the Master Earnings File in order to calculate changes in primary insurance amount across geographic areas.

We link information from publicly available data sources to get additional characteristics of individuals and geographic areas:

- Department of Labor Form 5500: We link DOL F5500 to the DER using EIN to get industry (NAICS) codes for the industry in which an individual worked early in life and immediately before applying. We use this measure to study heterogeneity by early-career industry and recent industry.
- Publicly available military EINs: Military EINs are publicly available.[5] We use the military EINs to identify veterans. We use this measure to study heterogeneity by veteran status.
- Pollution: We use data provided by Isen, Rossin-Slater and Walker (2017) to identify individuals born in places that were either required or not required to abate pollution under the Clean Air Act of 1970. We use this measure to study heterogeneity by local pollution abatement.

[5]See, e.g., https://www.dfas.mil/Portals/98/Documents/Garnishments/06_Quick_Guide_201603.pdf?ver=2020-02-20-133132-973.

- Remote work: We use data on the prevalence of working from home by industry (NAICS codes) constructed by Dingel and Neiman (2020).[6] We use this measure to study heterogeneity by the availability of remote work.

- ZIP code and county level data, linked to applicants in the F831:

  - Opioid deaths by county (1999–2020) from the Centers for Disease Control and Prevention Wonder tool;
  - Social mobility measures by county from Chetty, Hendren, Kline, Saez and Turner (2014b);[7]
  - Unemployment rate by county from 2010–2017 from the Department of Labor Bureau of Labor Statistics; and
  - Minimum wage data by state and locality collected by Vaghul and Zipperer (2022)[8].

We complement the administrative data file with Survey of Income and Program Participation (SIPP) linked to SSA administrative data. Although the sample size is much smaller, the SIPP has many useful features for our analysis. Most importantly, it includes measures of health status for the full population that are lacking in administrative data. It also provides information on spouses and family members and measures of educational attainment.

1.2 Background on SSDI program

Social Security Disability Insurance (SSDI) is intended to provide assistance to Americans who cannot work because of a severe health condition. An individual is considered disabled if (i) "[they] cannot do work that [they] did before," (ii) "[SSA] decide[s] that [they] cannot adjust to other work because of [their] medical condition(s)," *and* (iii) "[their] disability has lasted or is expected to last for at least one year or to result in death" (see https://www.ssa.gov/benefits/disability/qualify.html). Non-health factors, such as age and education, factor in through the medical-vocational grids.

SSDI eligibility is limited to individuals with qualifying earnings histories. To qualify for SSDI, individuals between the ages of 30 and 42 years old must have at least 20 quarters of qualifying earnings. The required number of quarters increases by one for every year past age 42. Workers under 30 qualify with fewer credits.

[6] See https://github.com/jdingel/DingelNeiman-workathome.
[7] See https://opportunityinsights.org/paper/land-of-opportunity/
[8] See https://github.com/benzipperer/historicalminwage/releases/tag/v1.4.0.

SSDI benefits are increasing in past earnings, at a decreasing rate. The average annual SSDI cash benefit is around $15,000, and beneficiaries qualify for Medicare after a two-year waiting period.[9] Disabled workers are not permitted to earn more than the substantial gainful activity (SGA) level, which was $1,260 per month ($15,120 per year) in 2020.

2 Statistical decomposition method

Our goal is to decompose the difference between actual SSDI enrollment and counterfactual SSDI enrollment into the share attributable to various components: changes in composition across groups, and changes in behavior (including eligibility, application, award, and exit) within groups. To do the decomposition, we first define counterfactual SSDI enrollment by deciding which parameters to hold fixed at their baseline values, and which parameters to allow to evolve over time. We construct counterfactual SSDI enrollment by simulating what SSDI enrollment would have been in future years had certain parameters (e.g., SSDI entry and exit rates) been held fixed at their baseline values. We then decompose the difference between raw and counterfactual SSDI enrollment into various components.

2.1 Defining counterfactual SSDI enrollment

We start by defining counterfactual SSDI enrollment. We can write SSDI enrollment as an accounting equation, where enrollment among working-age adult SSDI beneficiaries at the end of year t is determined by enrollment among SSDI beneficiaries in year $t-1$, net of entry and exit that occurred in year t. Letting $S_{t,g}$ denote SSDI enrollment ("stock") among those in calendar year t with fixed observable characteristics g ("group"), this accounting identity can be expressed as:

$$S_{t,g} = S_{t-1,g} + N_{t,g}(P_{t-1,g} - S_{t-1,g}) - X_{t,g}S_{t-1,g} \tag{1}$$

where $P_{t,g}$ denotes the working-age population count with characteristics g in year t, and $N_{t,g}$ and $X_{t,g}$ denote their rate of entry onto and exit from SSDI, respectively. Exit includes death, aging into the retirement program, recovery (i.e., determined by medical review), and all other reasons. In our baseline exercises, we define g to represent individuals with a common birth cohort, sex, and socioeconomic status.[10]

[9] Annual Statistical Report on the Social Security Disability Insurance Program, 2018.

[10] We use average annual earnings between ages 25 and 34 years as a proxy for socioeconomic status. We divide individuals into 5 bins: $0, above $0 but less than $10,000, above $10,000 but less than $30,000, above $30,000 but less than $60,000, and above $60,000.

From a start year normalized as $t = 0$, we characterize the SSDI enrollment that would have arisen in future year t given some counterfactual path of entry and exit flows between years 0 and t by recursive substitution of equation (1):

$$S_{t,g}(\mathbf{N}_g, \mathbf{X}_g, S_{0,g}) = \sum_{i=0}^{t} N_{t-i,g} P_{t-i,g} K(g, i, t) + S_{0,g} K(g, t+1, t) \tag{2}$$

$$K(g, i, t) \equiv \begin{cases} \prod_{j=1}^{i} (1 - N_{t-j+1,g} - X_{t-j+1,g}) & \text{if } i \geq 1 \\ 1 & \text{if } i = 0 \end{cases} \tag{3}$$

where $\mathbf{N}_g$ and $\mathbf{X}_g$ denote vectors of entry and exit flows, each of length $t + 1$. The counterfactual SSDI enrollment can be translated into a counterfactual SSDI enrollment rate ($O_{t,g}$) given the population count in year t: $O_{t,g}(\mathbf{N}_g, \mathbf{X}_g, S_{0,g}, P_g) \equiv \frac{S_{t,g}(\mathbf{N}_g, \mathbf{X}_g, S_{0,g})}{P_g}$. The aggregate counterfactual SSDI enrollment rate can be expressed as a population-weighted average of the covariate-specific rates:

$$O_t(\mathbb{N}, \mathbb{X}, \mathbf{S}_0, \mathbf{P}) = \sum_g O_{t,g}(\mathbf{N}_g, \mathbf{X}_g, S_{0,g}, P_g) \times w_{t,g}, \quad w_g \equiv \frac{P_g}{\sum_g P_g} \tag{4}$$

As seen in equations (2) and (4), aggregate SSDI enrollment rates are a non-linear function of entry flows, exit flows, and the distribution of observables across all intervening years. Still, it is useful to decompose them into additively separable components that can be attributed to each component.

To do that, we compare the actual path of SSDI enrollment to a counterfactual benchmark in which entry rates and exit rates (conditional on sex, socioeconomic status, and *age*) are held fixed at their initial, year-0 values. This is the counterfactual SSDI enrollment we would have expected in year t had no aging, sex composition changes, or changes in the income distribution occurred, and if SSDI entry rates and exit rates conditional on observables had remained stable over time. To be precise, we define:

$$N^c_{t,g} = N^r_{t,a(g,t)}, \quad X^c_{t,g} = X^r_{t,a(g,t)}, \quad w^c_{t,g} = w^r_{t,a(g,t)} \quad \forall \quad 0 \leq s \leq t, \quad g \tag{5}$$

where c denotes the counterfactual value and r denotes the actual value. $a(g, t)$ denotes the group sharing the same socioeconomic status and sex as group g, but born t years earlier than group g; thus, group $a(g, t)$ is the same age in year 0 as group g is in year t. We plug these values into equation (2) to construct the counterfactual path of SSDI enrollment.[11]

[11]Population counts $P_{t,g}$ should follow their own accounting equation, depending on mortality and net migration of SSDI beneficiaries and non-beneficiaries. In deriving these expressions, we assume $P^c_{t,g} \approx P^r_{t,g}$ for simplicity and omit the superscript. In practice though, we account for how changing the mortality

2.2 Decomposing SSDI enrollment into components of interest

Having constructed the counterfactual path of SSDI enrollment, we decompose the difference in actual SSDI enrollment and counterfactual SSDI enrollment into various components of interest.

Changes in SSDI due to changes in observables: Oaxaca-Blinder. The conventional Oaxaca-Blinder decomposition allows us to attribute the difference between actual and counterfactual SSDI enrollment rates into changes in SSDI enrollment conditional on population characteristics, changes in the composition of population characteristics, and their interaction:

$$O_t^r - O_t^c = \underbrace{\sum_g O_{t,g}^r (w_{t,g}^r - w_{t,g}^c)}_{\text{change in characteristics}} + \underbrace{\sum_g (O_{t,g}^r - O_{t,g}^c) w_{t,g}^r}_{\text{change from conditional SSDI rates}} + \underbrace{\sum_g (O_{t,g}^r - O_{t,g}^c)(w_{t,g}^r - w_{t,g}^c)}_{\text{characteristics} \times \text{SSDI rate interaction}} \tag{6}$$

Note that the terms that we attribute to characteristics and to conditional SSDI rates are *symmetric*; each holds its counterpart components fixed at their true observed values (r as opposed to c). The interaction term reflects the ambiguity inherent in how SSDI rates can be attributed to these two factors when both are changing at the same time. We can load this interaction term into the first two terms in order to arrive at alternative attributions. For instance, if we load the interaction term fully into the second term (attributing it to changes in group SSDI rates), then we arrive at an *asymmetric*, two-term Oaxaca-Blinder decomposition where population weights are fixed at their counterfactual values (c) when judging the impact of changes in conditional SSDI rates.

Changes in SSDI due to changes in entry and exit flows. Equation (6) allows us to assess how aggregate SSDI rates have been driven by changes in SSDI rates fixing observable characteristics, but *not* how those rates have been driven by changes in entry flows versus exit flows. To accomplish that, consider the year-1 difference in counterfactual versus truly observed SSDI rates for each group g. Using equation (1), we can express that difference

and net migration of SSDI beneficiaries can affect population counts, and track it using an additional term in the decomposition: a "population friction" accounting for the fact that O_t^r and O_t^c have different denominators. This component is small because mortality rates for SSDI beneficiaries are generally low, and SSDI beneficiaries are a small fraction of the overall population.

in terms of additively separable components attributable to changes in entry rates versus changes in exit rates:

$$O^r_{1,g} - O^c_{1,g} = \frac{S^r_{1,g} - S^c_{1,g}}{P_{1,g}} = \underbrace{(N^r_{1,g} - N^c_{1,g})\frac{(P_{0,g} - S_{0,g})}{P_{1,g}}}_{\text{change from conditional entry rate}} - \underbrace{(X^r_{1,g} - X^c_{1,g})\frac{S_{0,g}}{P_{1,g}}}_{\text{change from conditional exit rate}} \tag{7}$$

where we use that $S^c_{0,g} = S^r_{0,g} = S_{0,g}$ by construction.

Recursion for $t > 0$. For years of the exercise beyond the first, decomposing the counterfactual difference in SSDI rates becomes complicated by the fact that pre-existing differences in SSDI stocks accumulated in prior years can contribute to determining the impact of *current* differences in entry and exit flows. Using the stock accounting equation (equation 1) and rearranging terms, we can write for any $t > 0$:

$$\begin{aligned}
O^r_{t+1,g} - O^c_{t+1,g} =& \frac{S^r_{t+1,g} - S^c_{t+1,g}}{P_{t+1,g}} \\
S^r_{t+1,g} - S^c_{t+1,g} =& \underbrace{(N^r_{t,g} - N^c_{t,g})(P_{t,g} - S^r_{t,g})}_{a_{t,g}\text{: change in conditional entry}} - \underbrace{(X^r_{t,g} - X^c_{t,g})S^r_{t,g}}_{b_{t,g}\text{: change in conditional exit}} \\
&+ \underbrace{(1 - N^r_{t,g} - X^r_{t,g})(S^r_{t,g} - S^c_{t,g})}_{c_{t,g}\text{: change in past conditional SSDI rate}} \\
&- \underbrace{(N^r_{t,g} - N^c_{t,g})(S^r_{t,g} - S^c_{t,g})}_{d_{t,g}\text{: entry} \times \text{past SSDI rate interaction}} - \underbrace{(X^r_{t,g} - X^c_{t,g})(S^r_{t,g} - S^c_{t,g})}_{e_{t,g}\text{: exit} \times \text{past SSDI rate interaction}}
\end{aligned} \tag{8}$$

This expression involves new interaction terms ($d_{t,g}$, $e_{t,g}$) which describe how the impact of counterfactual changes in entry and exit depends on initial SSDI stocks (or equivalently, how counterfactual changes in SSDI stocks carry over from year to year in a way that depends on entry and exit rates).

The natural next step is to recursively substitute for past differences in SSDI rates ($S^r_{t,g} - S^c_{t,g}$) to arrive at an expression that depends only on counterfactual differences in entry and exit rates. However, each recursive step introduces new interaction terms, reflecting that past differences SSDI stocks *at some point* arose due to a difference in entry rates or exit rates. It is therefore useful for tractability to take a stand on where to assign those interactions. If we attribute the past-rate interaction terms ($d_{a,t}$) and ($e_{a,t}$) to changes in past SSDI rates

$(c_{a,t})$, we arrive at a simpler expression:

$$S^r_{t+1,g+1} - S^c_{t+1,g+1} = \underbrace{\sum_{i=0}^{t}(N^r_{t-i,g} - N^c_{t-i,g})(P_{t-i,g} - S^r_{t-i,g})K^c_{g,i,t}}_{\text{cumulative change from conditional entry rate}} \\ \underbrace{-\sum_{i=0}^{t}(X^r_{t-i,g} - X^c_{t-i,g})S^r_{t-i,g}K^c_{g,i,t}}_{\text{cumulative change from conditional exit rate}} \tag{9}$$

Notice that we can formulate other versions of this recursive decomposition by loading the interaction terms instead into conditional entry rates and exit rates.[12] The choice of how to allocate the interaction terms forms the basis of our bounding exercise, outlined in detail in Appendix Section B. To construct our bounds, we restrict to decompositions in which these interaction terms are assigned in a way that is consistent over time and across groups. That is, if we assign term $d_{t,g}$ to changes in conditional entry for one particular t and g, then we do the same *for all* t and g. Our bounds therefore nest many ways to decompose SSDI stocks into additively separable terms, but are not guaranteed to nest all reasonable linear decompositions of SSDI rates without conditions on how flows have changed over time.[13] We specify the full range of estimates that we construct for this step and the remaining steps to follow in Appendix Section B.

Decomposition of changes in characteristics We consider how to attribute the change due to observable characteristics as a whole into the change due to a specific observable characteristic—e.g., sex, aging, or socioeconomic status. The answer to that question depends on how we view interactions between changes in observables and in what order we decompose the characteristics. For instance, if the decline in SSDI is driven by a rise in socioeconomic status exclusively among men, one order of characteristics (sex then earnings) will attribute this change to earnings (intuitively more correct) while another order (earnings then sex) will attribute some of the change to sex.

[12] As was the case for equation (6), we continue to assume here that $P^c_{t,g} \approx P^r_{t,g}$, meaning that changing SSDI exits due to mortality does not meaningfully affect the population. In practice, that difference creates an additional term in the decomposition that we label "population difference," which captures the idea that the impact of entry rates in year $t-i$ on SSDI stocks in year t depends on the size of the surviving population in year $t-i$.

[13] One notable decomposition approach which is not nested in our set of decompositions is a "sequential" decomposition as in Liebman (2015). However, each term of a sequential decomposition is guaranteed to lie in the range of values generated by our decomposition for that term, so long as changes in entry and exit flows are both driving an increases in SSDI rates or decreases in SSDI rates for all t. This is approximately true for the periods of time we examine.

To formalize the alternative ways we can define the contribution of different observables, notice that the population weight for group g amounts to the joint density evaluated at g, which in our main exercise represents the share of the population in a specific age (a), sex (s), and socioeconomic bin (e) in year t. We can express this weight as a product of conditional probabilities:

$$w_{t,g} \equiv w_{t,s\times a\times e} = \underbrace{\sum_{a,e} w_{t,s\times a\times e}}_{P(s|t)\equiv\Omega_s} \underbrace{\frac{\sum_{e} w_{t,s\times a\times e}}{\sum_{a,e} w_{t,s\times a\times e}}}_{P(a|s,t)\equiv b_{s,a}} \underbrace{\frac{w_{t,s\times a\times e}}{\sum_{e} w_{t,s\times a\times e}}}_{P(e|a,s,t)\equiv f_{s,a,e}} \tag{10}$$

We can then decompose counterfactual differences in these weights into additively separable terms reflecting the impact of changes in the marginal sex distribution, the conditional distribution of age given sex, the conditional distribution of socioeconomic status given sex and age, and interaction terms:

$$\begin{aligned} w^r_{t,g} - w^c_{t,g} &\equiv w^r_{t,s\times a\times e} - w^c_{t,s\times a\times e} \\ &= (\Omega^r b^r f^r) - (\Omega^c b^c f^c) \\ \text{(sex composition)} &= (\Omega^r - \Omega^c) b^r f^r \\ \text{(age composition fixing sex)} &+ \Omega^r (b^r - b^c) f^r \\ \text{(SES fixing age and sex)} &+ \Omega^r b^r (f^r - f^c) \\ &+ \text{ (interaction terms)} \end{aligned} \tag{11}$$

The interaction terms consist of four components: three representing the possible ways that any two covariates could jointly change, and one representing joint changes in all three covariates. However, note that the order of covariates in this sequence is important for the magnitude and interpretation of the terms, as conditional and unconditional changes in the composition can be very different. For instance, the unconditional impact of changes in sex composition (as in the ordering of equation (11)) is empirically close to zero because the sex distribution of the working-age population has not evolved much over time. If we instead swap the positions of sex and socioeconomic status in the decomposition, then we would find a modest contribution from changes in the composition of sex *conditional on age and socioeconomic status* as men are increasingly likely to have relatively high earnings early in their working careers.

Further decomposing changes in entry Distinguishing the source of changes in exit rates is straightforward as total exits are simply a sum of exits due to the three observed exit channels (retirement, mortality, and recovery) plus all other exits.

$$X_{t,g} = \text{Retirement Rate}_{t,g} + \text{Mortality Rate}_{t,g} + \text{Recovery Rate}_{t,g} + \text{Other Exit Rate}_{t,g} \quad (12)$$

Decomposing entry is more complicated. We can decompose entry into SSDI further into contributions from financial eligibility, applications conditional on eligibility, awards conditional on applying, and the interaction between three terms. Recall that the definition of $N_{t,g}$ is the entry rate of non-SSDI beneficiaries who existed in the year-initial of year t for group g. We can write:

$$\begin{aligned} N_{t,g} &= \frac{\text{entrants}_{t,g}}{\text{initial non-DI beneficiaries}_{t,g}} \\ &= \underbrace{\frac{\text{entrants}_{t,g}}{\text{applicants}_{t,g}}}_{B_{t,,g}=\text{award}_{t,g}} \underbrace{\frac{\text{applicants}_{t,g}}{\text{elig pop}_{t,g}}}_{A_{t,g}=\text{application}_{t,g}} \underbrace{\frac{\text{elig pop}_{t,g}}{P_{t-1,g} - S_{t-1,g}}}_{E_{t,g}=\text{eligibility}_{t,g}} \end{aligned}$$

We decompose the difference in entry rates $(N^r_{g,a,t} - N^c_{g,a,t})$ into differences in award rates $B_{g,a,t}$, application rates $A_{g,a,t}$ and eligibility rates $E_{g,t}$:

$$\begin{aligned} N^r_{g,a,t} - N^c_{g,a,t} =& B^r_{g,a,t}A^r_{g,a,t}E^r_{g,a,t} - B^c_{g,a,t}A^c_{g,a,t}E^c_{g,a,t} \\ =& \underbrace{(B^r_{g,a,t} - B^c_{g,a,t})A^r_{g,a,t}E^r_{g,a,t}}_{\text{partial award}} + \underbrace{B^r_{g,a,t}(A^r_{g,a,t} - A^c_{g,a,t})E^r_{g,a,t}}_{\text{partial apply}} + \underbrace{B^r_{g,a,t}A^r_{g,a,t}(E^r_{g,a,t} - E^c_{g,a,t})}_{\text{partial elig}} \\ &+ \underbrace{B^r_{g,a,t}(A^r_{g,a,t} - A^c_{g,a,t})(E^r_{g,a,t} - E^c_{g,a,t})}_{\text{apply} \times \text{elig}} \\ &+ \underbrace{(B^r_{g,a,t} - B^c_{g,a,t})A^r_{g,a,t}(E^r_{g,a,t} - E^c_{g,a,t})}_{\text{award} \times \text{elig}} \\ &+ \underbrace{(B^r_{g,a,t} - B^c_{g,a,t})(A^r_{g,a,t} - A^c_{g,a,t})E^r_{g,a,t}}_{\text{award} \times \text{apply}} \\ &+ \underbrace{(B^r_{g,a,t} - B^c_{g,a,t})(A^r_{g,a,t} - A^c_{g,a,t})(E^r_{g,a,t} - E^c_{g,a,t})}_{\text{award} \times \text{apply} \times \text{elig}} \end{aligned} \quad (13)$$

substituting this expression for $(N^r_{t-i,g} - N^c_{t-i,g})$ in equation (9), we arrive at a decompo-

sition of DI stocks that distinguishes between the impact of eligibility, applications among the eligible, and awards among applicants.

Incorporating characteristics observed only for applicants Because we have detailed application data, there are many characteristics that we observe for SSDI applicants (and therefore also for SSDI recipients) that we do not observe for the population as a whole (e.g., diagnosis, severity of health condition, geographic location). We want to use these characteristics to study heterogeneity in application and award changes—e.g., whether mental, musculoskeletal, or other conditions drive the decline in SSDI applications. Since we do not observe these characteristics for the full population, we cannot use the decomposition method outlined above.

Instead, we propose a "secondary decomposition" of SSDI entry nested within the decomposition outlined in the previous section. We partition the sample of applications into subgroups according to the applicant-specific characteristic (e.g., for diagnosis, this could be mental, musculoskeletal, other conditions). We then decompose the SSDI entry rate among eligible individuals ($B_{t,g}A_{t,g}$), using diagnosis category d as an example:

$$\begin{aligned} B^r_{t,g}A^r_{t,g} - B^c_{t,g}A^c_{t,g} = &\sum_d (b^r_{t,g,d} - b^c_{t,g,d})a^r_{t,g,d} + \sum_d (a^r_{t,g,d} - a^c_{t,g,d})b^r_{t,g,d} \\ &+ \sum_d (b^r_{t,g,d} - b^c_{t,g,d})(a^r_{t,g,d} - a^c_{t,g,d}) \end{aligned} \tag{14}$$

where $b_{t,g,d}$ is the diagnosis-specific award rate and $a_{t,g,d}$ is the rate at which individuals of group g submit applications for diagnostic category d in year t. Note this is distinct from the application rate for individuals who have condition d (which would required diagnosis information for the full population).

We then incorporate the entry rate among the eligible into a decomposition of entry rates:

$$
\begin{aligned}
N^r_{t,g} - N^c_{t,g} =& B^r_{t,g} A^r_{t,g} E^r_{t,g} - B^c_{t,g} A^c_{t,g} E^c_{t,g} && (15)\\
=& \underbrace{BA^c_{t,g}}_{\equiv B^c_{t,g} A^c_{t,g}} E^c_{t,g} - \underbrace{BA^r_{t,g}}_{\equiv B^r_{t,g} A^r_{t,g}} E^r_{t,g} && (16)\\
=& \underbrace{(BA^c_{t,g} - BA^r_{t,g}) E^r_{t,g}}_{\text{partial entry among eligible}} && (17)\\
&+ \underbrace{BA^r_{t,g}(E^r_{t,g} - E^c_{t,g})}_{\text{partial eligibility}} && (18)\\
&+ \underbrace{(BA^r_{t,g} - BA^c_{t,g})(E^r_{t,g} - E^c_{t,g})}_{\text{interaction with eligibility}} && (19)
\end{aligned}
$$

Taking equation (14) in combination with equation (15) to the cumulative change from conditional entry rates in equation 9, one arrives at a decomposition of DI stocks which distinguishes between the impact of changes in application rates and award rates coming from the alternative diagnostic groups.

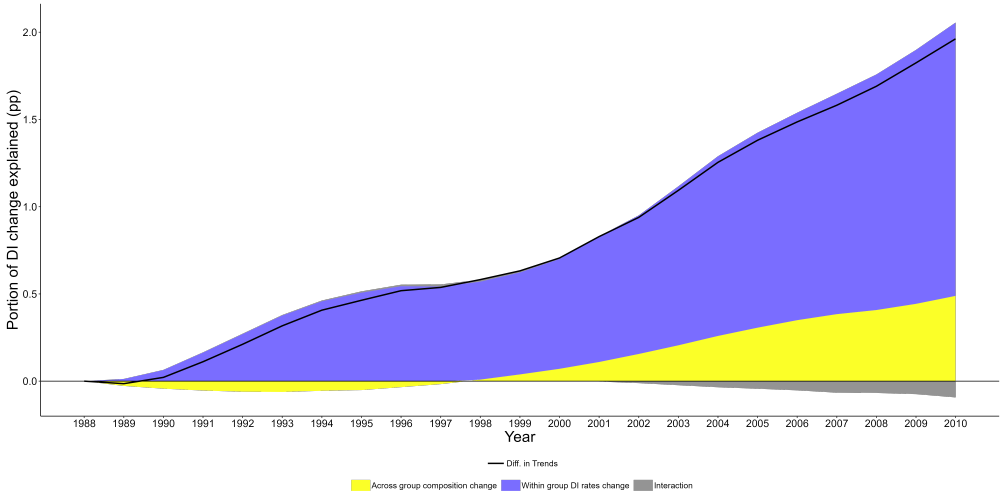
One important caveat to this applicant-specific analysis is that the contribution of a particular diagnostic group to a decline in applications could come from two different channels: applications from a diagnosis group could fall because individuals with the condition are less likely to apply for SSDI, or because the diagnosis itself has become rarer in the working-age population. Interpreting the results from our applicant-specific analysis as a change in the applicant composition requires the assumption that the characteristic has remained constant in the population.

3 Decomposition results

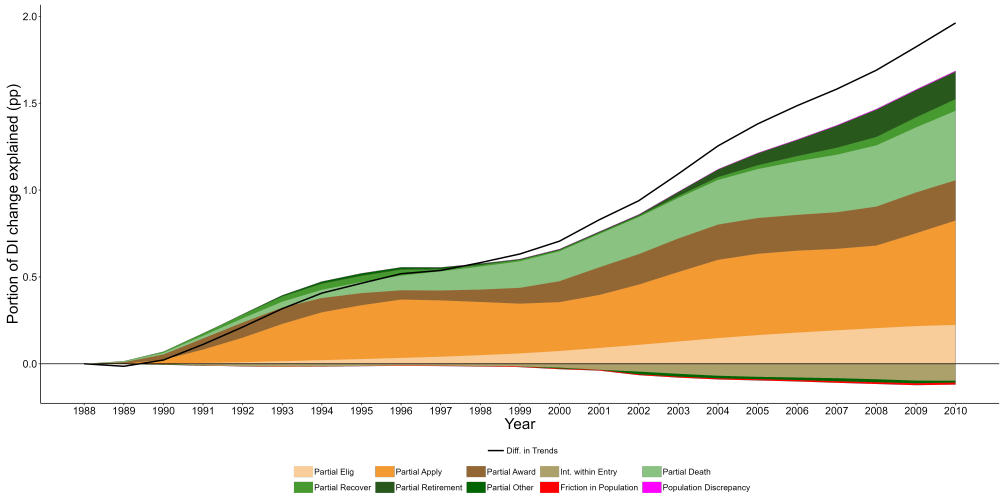
3.1 Applying decomposition method to SSDI increase (1988–2010)

We start by applying our decomposition method to the increase in SSDI enrollment from 1988–2010. Table 1 presents the main results, which are largely consistent with Liebman (2015). Higher within-group entry rates account for most of the increase in SSDI enrollment, but lower within-group exit rates are also an important part of the story. Changes in composition play a positive but relatively small role in the SSDI increase.

Figure 2: Decomposition of the increase in SSDI enrollment from 1988 to 2010



(a) Across-group versus within-group changes



(b) Within-group changes in behavior

Notes: Top figure plots the decomposition of the increase in SSDI enrollment rates from 1988 to 2010 into across-group composition change, within-group change in SSDI enrollment rate, and the interaction between the two, as given in equation (6). Bottom figure plots the decomposition of the within-group change in SSDI enrollment rate into specific components of SSDI entry, SSDI exit, friction in the population, and population discrepancy. The specific components of SSDI entry are partial eligibility (i.e., the part that can only be attributed to eligibility and no other component), partial application, partial award, and the sum of interactions between the three entry components (eligibility, application, and award), as given in equation (13). The specific components of SSDI exit are partial death, partial retirement (defined as aging into the retirement program), partial recovery (defined as being found no longer eligible due to continuing disability review), and partial other (any remaining exit after removing death, retirement, and recovery), as given in equation (12). "Friction in population" and "Population discrepancy" are described in footnotes 11 and 12. See Section 2.1 for details on the decomposition method. See Table 1 for exact estimates.

Table 1: Decomposition results and bounds for the increase in SSDI enrollment from 1988 to 2010

Variable		Portion of DI change (pp)		Contribution(%)	Min(%)	Max (%)
Across-group composition change		0.49		24.90	20.15	24.90
Sex		0.00		0.01	-4.67	1.32
Age		0.70		35.59	20.20	49.09
Earningbin		0.01		0.46	-13.16	7.92
Birthplace		-0.20		-10.12	-12.74	-4.71
Int. within Char.		-0.02		-1.04		
Within-group DI rates change		1.57		79.85	75.10	79.85
Entry		0.96		48.90	46.54	56.71
	Elig		0.22	11.39	5.27	12.90
	Apply		0.60	30.64	26.80	40.88
	Award		0.23	11.83	4.60	14.21
	Int. within Entry		-0.10	-4.95		
Exit		0.61		31.31	21.37	31.57
	Death		0.40	20.37	12.07	22.53
	Recover		0.07	3.40	2.18	3.82
	Retirement		0.16	8.09	5.09	8.88
	Other		-0.01	-0.55	-0.67	0.09
Friction in Population		-0.01		-0.62	-0.97	-0.56
Population Discrepancies		0.01		0.26	0.20	0.38
Interaction at group level		-0.09		-4.75		

Notes: Table presents decomposition of the increase in SSDI enrollment rates from 1988 to 2010 into various components. The counterfactual DI enrollment rate is 2.01 percent while the actual enrollment rate is 3.97 percent, creating 1.06 pp of DI increase to be decomposed. The first column presents across-group composition change, within-group change in SSDI enrollment rate, and the interaction between the two, as given in equation (6). The second column further decomposes across-group composition change into specific characteristics, as given in equation (11); and decomposes within-group chnage in SSDI enrollment rate into entry, exit, friction in population, and population discrepancies, aas given in equation (8) and footnotes 11 and 12. Third column further decomposes entry into partial eligibility (i.e., the part that can only be attributed to eligibility and no other component), partial application, partial award, and the sum of interactions between the three entry components (eligibility, application, and award), as given in equation (13). Third column also further decomposes exit into partial death, partial retirement (defined as aging into the retirement program), partial recovery (defined as being found no longer eligible due to continuing disability review), and partial other (any remaining exit after removing death, retirement, and recovery), as given in equation (12). See Section 2.1 for details on the decomposition method.

The administrative panel data allow us to expand on the findings in Liebman (2015). First, with respect to composition, we include characteristics beyond age and sex—specifically socioeconomic status, race, and birthplace—which allows for a larger potential role for composition. In practice, the role of composition is still small even with the additional characteristics. Second, with respect to entry, we can distinguish between applications and awards and estimate their contributions separately. We find that applications account for a much larger share of the increase than awards. Third, with respect to exit, we can model exits from retirement separately from exits from death or recovery. We find that while lower exits from death are the most important component of exits, lower exits from retirement (due to a higher full retirement age) are also an important component. Fourth, we can use our additional observable characteristics to study heterogeneity in the SSDI increase across groups (see Appendix Table C.1). We find that most of the increase in SSDI application rates came from low-skilled women (both younger and older), while men and higher-skilled individuals played a smaller role in the SSDI increase. Low-skilled women also disproportionately drove the increase in SSDI eligibility rates and SSDI award rates. Most of the increase in

applications and awards came from mental and musculoskeletal conditions (see Appendix Table D.5), consistent with the expansion in medical eligibility of these conditions (Autor and Duggan, 2003, 2006).

Figure 3: Breakdown of application increase and award increase by demographic group



(a) Application increase (b) Award increase (c) Group size in 2010

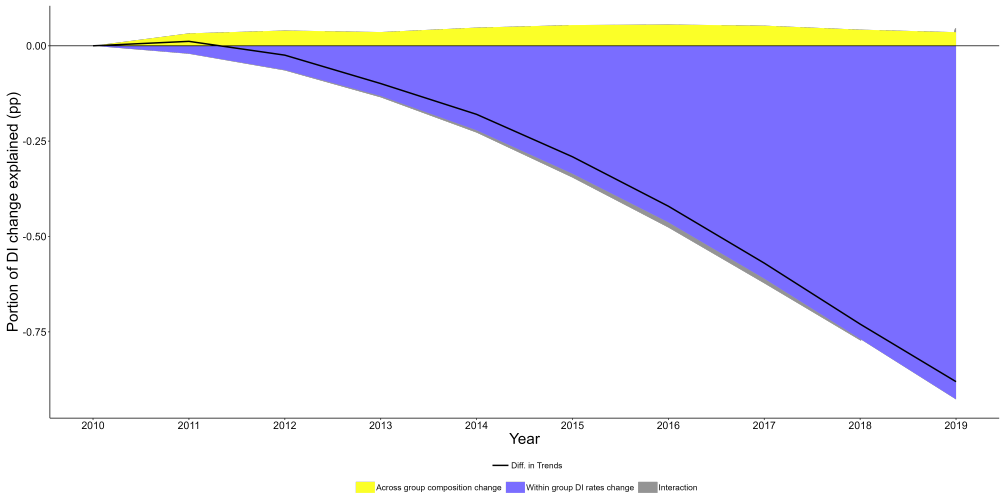
Notes: Left graph plots the fraction of the contribution of changes in application rate that can be attributed to specific demographic groups (i.e., of the 0.6pp increase in SSDI enrollment rates that is attributable to increases in application, how much of the 0.6pp can be attributed to each group). Middle graph plots the fraction of the contribution of changes in award rate that can be attributed to specific demographic groups (i.e., of the 0.23pp increase in SSDI enrollment rates that is attributable to increases in award, how much of the 0.23pp can be attributed to each group). Negative numbers in the left and middle graphs indicate that the group actually worked *against* the increase in applications or awards. Right graph plots the composition of the population in 2010 as a measure of group size. See Appendix Table C.1 for exact estimates.

3.2 Applying decomposition method to SSDI decline (2010–2019)

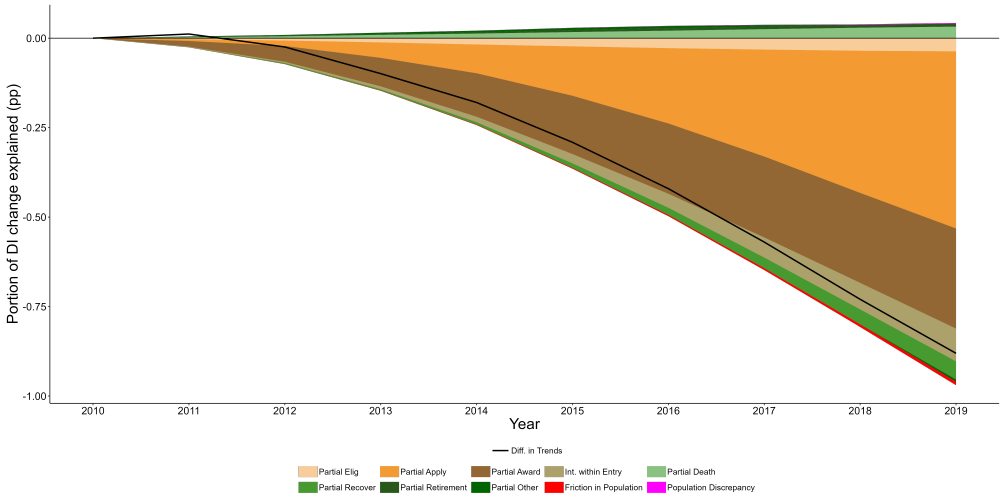
We now apply our decomposition method to the decrease in SSDI enrollment in the 2010s. We end our analysis at 2019 in order to focus on secular changes in SSDI rather than the exceptional circumstances of the COVID-19 pandemic. Figure 4b presents the main results, with estimates in Table 2. We find that virtually all of the decline in SSDI enrollment is attributable to decreases in within-group entry rates, rather than changes in composition or changes in exit. Within entry, most of the decrease comes from lower application rates, with

a smaller contribution from lower award rates. The role of award rates is perhaps expected given that the decline in award rates at the appeals level has been well-documented and attributed in part to retraining of administrative law judges (Hoynes, Maestas, and Strand 2024).To our knowledge, however, there is no policy change that obviously explains the decline in applications.

Figure 4: Decomposition of the decrease in SSDI enrollment from 2010 to 2019



(a) Across-group versus within-group changes



(b) Within-group changes in behavior

Notes: Top figure plots the decomposition of the decrease in SSDI enrollment rates from 2010 to 2019 into across-group composition change, within-group change in SSDI enrollment rate, and the interaction between the two, as given in equation (6). Bottom figure plots the decomposition of the within-group change in SSDI enrollment rate into specific components of SSDI entry, SSDI exit, friction in the population, and population discrepancy. The specific components of SSDI entry are partial eligibility (i.e., the part that can only be attributed to eligibility and no other component), partial application, partial award, and the sum of interactions between the three entry components (eligibility, application, and award), as given in equation (13). The specific components of SSDI exit are partial death, partial retirement (defined as aging into the retirement program), partial recovery (defined as being found no longer eligible due to continuing disability review), and partial other (any remaining exit after removing death, retirement, and recovery), as given in equation (12). "Friction in population" and "Population discrepancy" are described in footnotes 11 and 12. See Section 2.1 for details on the decomposition method. See Table 2 for exact estimates.

Table 2: Decomposition results and bounds for the increase in SSDI enrollment from 2010 to 2019

Variable		Portion of DI change (pp)		Contribution(%)	Min(%)	Max (%)
Across-group composition change		0.04		-4.05	-5.28	-4.05
Sex		0.00		-0.00	-0.91	1.96
Age		0.13		-14.70	-65.65	-5.61
Earningbin		-0.00		0.19	-8.68	50.34
Birthplace		-0.08		8.99	0.66	16.00
Int. within Char.		-0.01		1.47		
Within-group DI rates change		-0.93		105.28	104.05	105.28
Entry		-0.90		102.53	100.72	102.74
	Elig		-0.04	4.17	2.27	7.16
	Apply		-0.49	56.21	51.72	68.70
	Award		-0.28	31.80	31.67	44.37
	Int. within Entry		-0.09	10.36		
Exit		-0.02		1.85	1.83	2.38
	Death		0.03	-3.67	-3.81	-3.66
	Recover		-0.05	5.78	5.77	6.21
	Retirement		0.01	-0.95	-0.95	-0.72
	Other		-0.01	0.69	0.68	0.70
Friction in Population		-0.01		1.12	0.92	1.12
Population Discrepancies		0.00		-0.23	-0.23	-0.14
Interaction at group level		0.01		-1.22		

Notes: Table presents decomposition of the decrease in SSDI enrollment rates from 2010 to 2019 into various components. The counterfactual DI enrollment rate is 4.63 percent while the actual enrollment rate is 3.75 percent, creating 0.88 pp of DI decrease be decomposed. The first column presents across-group composition change, within-group change in SSDI enrollment rate, and the interaction between the two, as given in equation (6). The second column further decomposes across-group composition change into specific characteristics, as given in equation (11); and decomposes within-group chnage in SSDI enrollment rate into entry, exit, friction in population, and population discrepancies, as given in equation (8) and footnotes 11 and 12. Third column further decomposes entry into partial eligibility (i.e., the part that can only be attributed to eligibility and no other component), partial application, partial award, and the sum of interactions between the three entry components (eligibility, application, and award), as given in equation (13). Third column also further decomposes exit into partial death, partial retirement (defined as aging into the retirement program), partial recovery (defined as being found no longer eligible due to continuing disability review), and partial other (any remaining exit after removing death, retirement, and recovery), as given in equation (12). See Section 2.1 for details on the decomposition method.

Which demographic groups drive the increase in application rates? From Figure 5a, we see that older, middle-skilled men (and lower-skilled men, to a lesser extent) contribute disproportionately to the decline in SSDI applications. Notice that this is a different group than the low-skilled women who drove the increase in SSDI applications in 1990–2010. However, women account for a disproportionate share of the decline in *award* rates (Figure 5b). Looking across industries, the decline in SSDI applications comes from all industries, though manufacturing and agriculture/mining/utilities/construction are disproportionately large.

Figure 5: Breakdown of application decrease and award decrease by demographic group



(a) Application decrease (b) Award decrease (c) Group size in 2019

Notes: Left graph plots the fraction of the contribution of changes (in absolute term) in application rate that can be attributed to specific demographic groups (i.e., of the 0.56pp decrease in SSDI enrollment rates that is attributable to decreases in application, how much of the 0.56pp can be attributed to each group). Middle graph plots the fraction of the contribution of changes in award rate (in absolute term) that can be attributed to specific demographic groups (i.e., of the 0.32pp decrease in SSDI enrollment rates that is attributable to decreases in award, how much of the 0.32pp can be attributed to each group). Right graph plots the composition of the population in 2019 as a measure of group size. See Appendix Table C.2 for exact estimates.

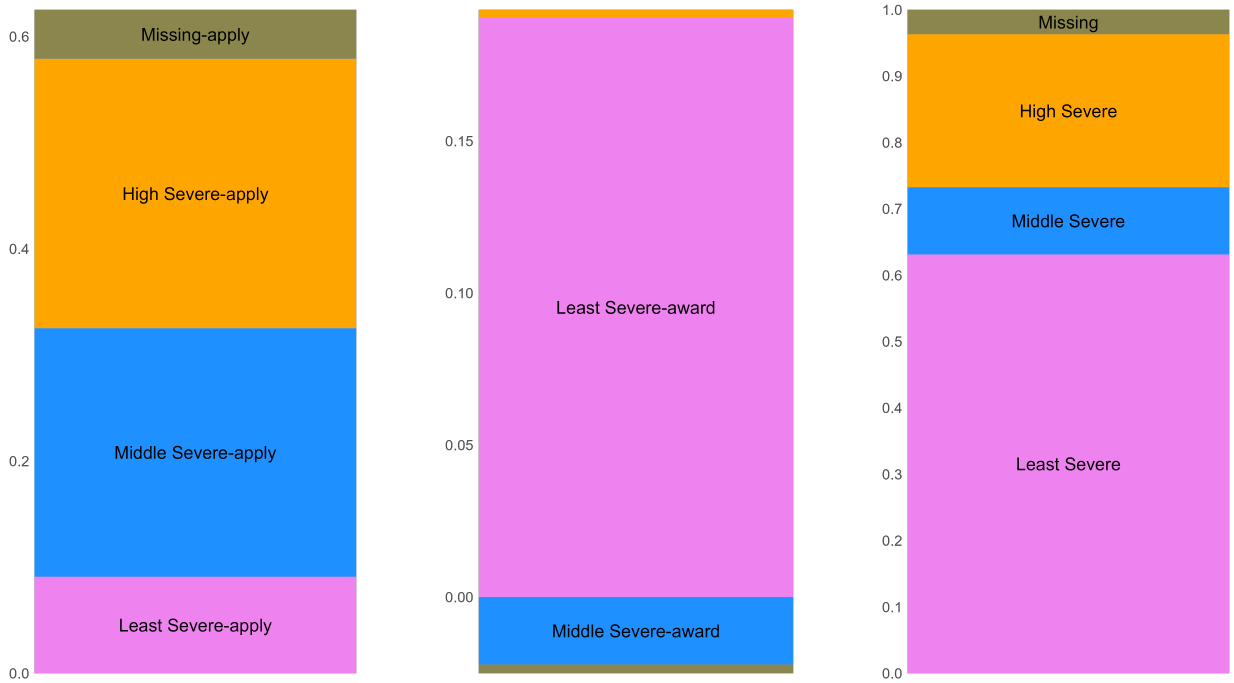
We look at heterogeneity in the decline in SSDI applications with respect to several different applicant characteristics in order to find clues about potential causes of the decline. We find no meaningful geographic heterogeneity with respect to state, urban/rural status, severity of the opioid crisis, economic mobility as measured by Chetty, Hendren, Kline and Saez (2014a), or the decline in SSDI allowance rates at the appeals level (see Appendix Tables D.9-D.24).

However, we find disproportionate effects with respect to two applicant characteristics. The first is the severity of the applicant's condition.[14] As shown in Figure 6, we find that middle- and high-severity potential applicants contribute the most to the decline in applica-

[14]We measure severity through a combination of whether the applicant was allowed or rejected at the initial level, and the frequency with which they were prescribed to receive medical reviews ("medical diary reason"). Our heterogeneity results with respect to severity rely on the assumption that decision-making at the initial (DDS) level did not change during this period. While we are not aware of any policy changes that would have affected DDS decision-making, it is still an assumption.

tions, while the least severe potential applicants contribute the least to the decline (though they are highly likely to be rejected).

Figure 6: Breakdown of application decrease and award decrease by applicant severity

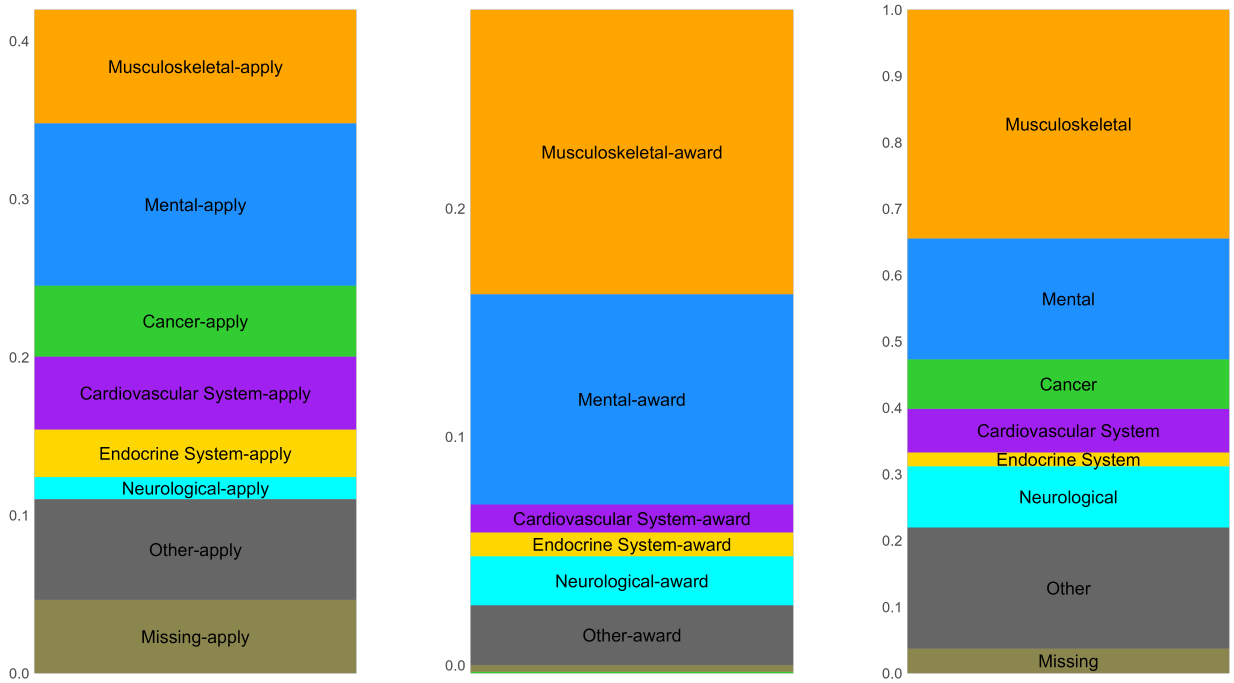


(a) Application decrease (b) Award decrease (c) Applicant share in 2019

Notes: Left graph plots the fraction of the contribution of changes (in absolute term) in application rate that can be attributed to specific applicant severity levels. Middle graph plots the fraction of the contribution of changes in award rate that can be attributed to specific applicant severity levels. Negative numbers in the left and middle graphs indicate that the group actually worked *against* the decrease in applications or awards. Right graph plots the composition of the SSDI applicant population in 2019 as a measure of group size. See Appendix Table D.3 and D.4 for exact estimates.

The second characteristic is diagnosis. Potential applicants with mental conditions, endocrine conditions (e.g., diabetes), cancers, and cardiovascular diseases contribute the most to the decline in applications (see Figure 7). Potential applicants with musculoskeletal conditions and neurological conditions contribute the least to the decline in applications. Appendix Tables D.7 and D.8 present relative contributions for a detailed list of diagnoses.

Figure 7: Breakdown of application decrease and award decrease by applicant diagnosis



(a) Application decrease (b) Award decrease (c) Applicant share in 2019

Notes: Left graph plots the fraction of the contribution of changes (in absolute term) in application rate that can be attributed to specific applicant diagnoses. Middle graph plots the fraction of the contribution of changes in award rate that can be attributed to specific applicant diagnoses. Negative numbers in the left and middle graphs indicate that the group actually worked *against* the decrease in applications or awards. Right graph plots the composition of the SSDI applicant population in 2019 as a measure of group size. See Appendix Tables D.7 and D.8 for exact estimates.

The heterogeneity in the application decline by severity and diagnosis may provide some initial clues about causal factors. Applicant severity is positively correlated with recent applicant earnings: more-severe applicants are *more* likely to have worked recently than less-severe applicants, who may be applying primarily for economic reasons than health reasons (and who are highly likely to be rejected).

4 Causal analysis of decline in SSDI applications

In the statistical decomposition, we find that nearly all of the decline in SSDI enrollment can be attributed to lower rates of SSDI entry within group, and that most of the decline in SSDI entry can be attributed to lower rates of SSDI application. A natural question then is why within-group application rates declined during this time period. In this section, we present a simple model of application behavior and use various empirical strategies to determine the importance of each parameter in the decline in SSDI applications.

We model the application decision as a tradeoff between applying and the outside option:

$$\text{Apply} \iff V_{i,t}^{apply} > V_{i,t}^{outside} \tag{20}$$

$$V_{i,t}^{apply} = P_{it}^{\text{award}} \beta_{i,t} - F_{it} \tag{21}$$

$$V_{i,t}^{outside} = P_{it}^{\text{emp}}(w_{it}\ell_{it} - C_{it}) + P_{it}^{\text{other}} b_{it} \tag{22}$$

where

- P_{it}^{award} is allowance probability conditional on applying;
- β_{it} is the annual DI benefit amount;
- F_{it} is the hassle cost of applying, including information and stigma;
- P_{it}^{emp} is the probability of employment if not applying for DI;
- $w_{it}\ell_{it}$ is potential earnings from work;
- C_{it} is the disutility of work, which could reflect both population health and workplace accommodations;
- P_{it}^{other} is the probability of receiving other social welfare benefits; and
- b_{it} is amount of those other benefits.

The number of applicants is then given by

$$N \times \mathbb{1}(V_{i,t}^{apply} > V_{i,t}^{outside}) \tag{23}$$

where N is the group size.

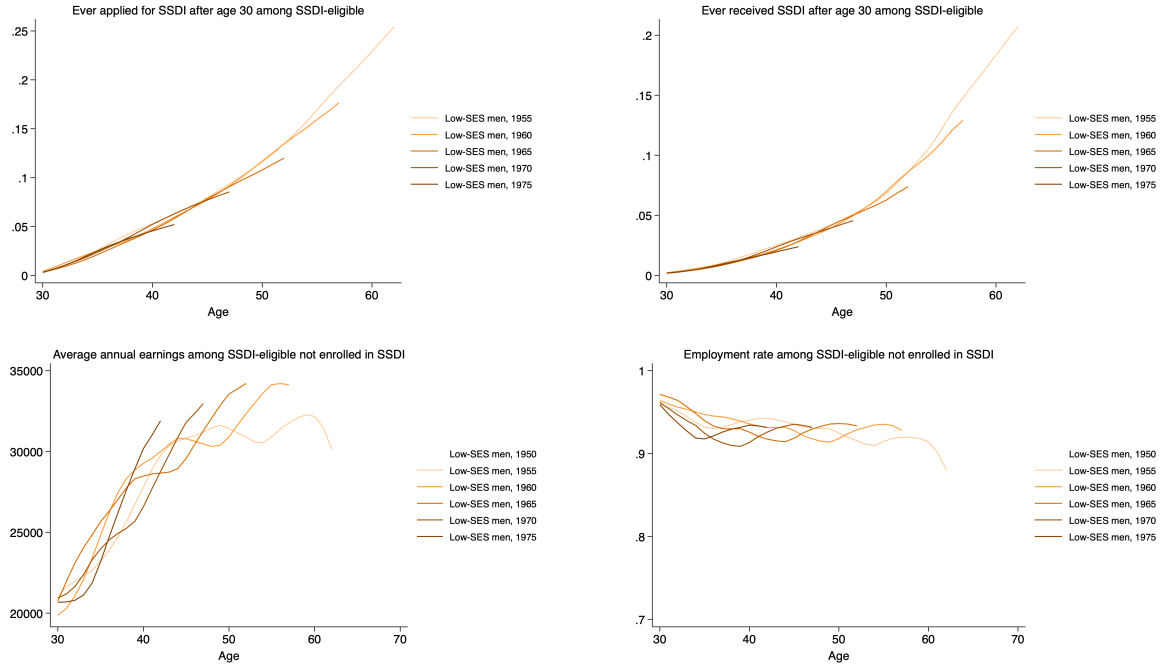
The contribution of each of these parameters to the change in application rates depends on two things: the change in the value of the parameter over the relevant time period, and the elasticity of SSDI applications with respect to the parameter. For each parameter, we first estimate its change over the 2010–2019 time period. For parameters that have changed in a direction that would contribute to lower application rates, we estimate the elasticity of application rates with respect to that parameter or determine how large the elasticity would have to be to explain a substantial amount of the decline in application rates. We also determine whether the change in the value of the parameter and the elasticity is largest for the groups that experience the largest declines in application rates.

4.1 Leading explanation: increases in employment and earnings among those on the margin between SSDI benefits and work

Two parameters of the model, the probability of employment if not applying for DI (P_{it}^{emp}) and potential earnings from work ($w_{it}\ell_{it}$), meet the necessary conditions for explaining the decline in SSDI applications: changing in the relevant direction and potentially having a large effect on SSDI applications. Figure 8 shows SSDI application, SSDI enrollment, inflation-adjusted earnings, and employment rates across birth cohorts by age using SSA administrative data, for middle-skilled (precisely, average annual earnings of \$10,000-\$30,000 between ages 25 to 34 years) male workers. Recall from Section 3 that this group experiences the largest reduction in SSDI applications relative to its size. In the past decade, younger cohorts of SSDI-eligible workers have experienced lower SSDI application and receipt rates, higher employment levels, and rapid earnings growth relative to older cohorts at the same age. It is particularly notable that neither lower-skilled nor higher-skilled workers, who have much smaller reductions in SSDI applications, experience historic earnings or employment levels.

Autor and Duggan (2003) argue that rising SSDI replacement rates—the SSDI benefit amount (PIA) a worker would receive if enrolled in SSDI (β_{it} in our model) relative to their potential earnings—contributed to the increase in SSDI applications and awards in the 1990s. To determine if the opposite story could be true for the decline, we calculate SSDI replacement rates for middle-skilled men across cohorts in Figure 9. We use the worker's average earnings in the past 3 years as a measure of their potential earnings. Average SSDI replacement rates at older ages are lower for younger cohorts, and the likelihood of having an SSDI replacement rate above 1 at older ages—meaning that SSDI benefits are higher than potential earnings—has fallen across cohorts. This is for two reasons: higher current earnings and employment raising potential earnings, and lower SSDI benefit amount (PIA) through lower employment rates in the recent past due to the Great Recession (see Appendix

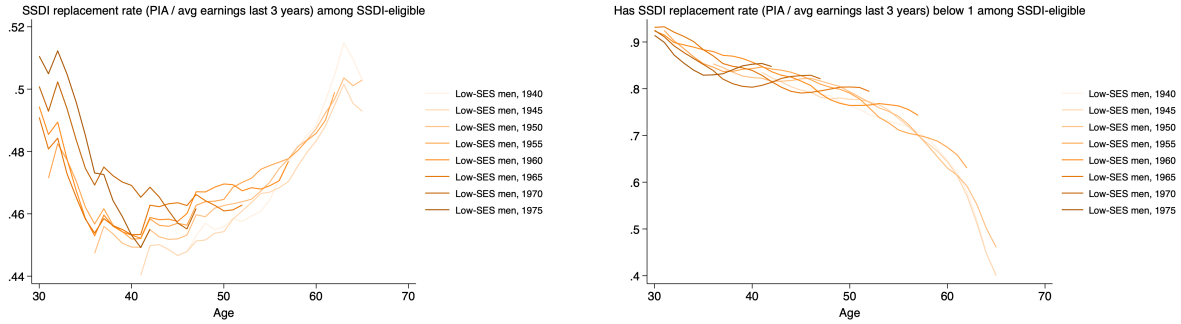
Figure 8: Younger birth cohorts have both lower SSDI application/receipt and higher earnings and employment



Notes: Figure plots the following outcomes by birth cohort and age for the SSDI-eligible population (blue) and SSDI-eligible low-skilled men (orange): ever applied for SSDI (top left), ever received SSDI (top right), average annual earnings (bottom left), and employment rates (bottom right). Employment is defined as earnings above $0. Younger cohorts have darker shading. The sample is derived from the Continuous Work History Sample linked to the Numident, F831 file, Payment History Update System, and Master Earnings File.

Figure F.1).

Figure 9: SSDI replacement rates for middle-skilled men across birth cohorts



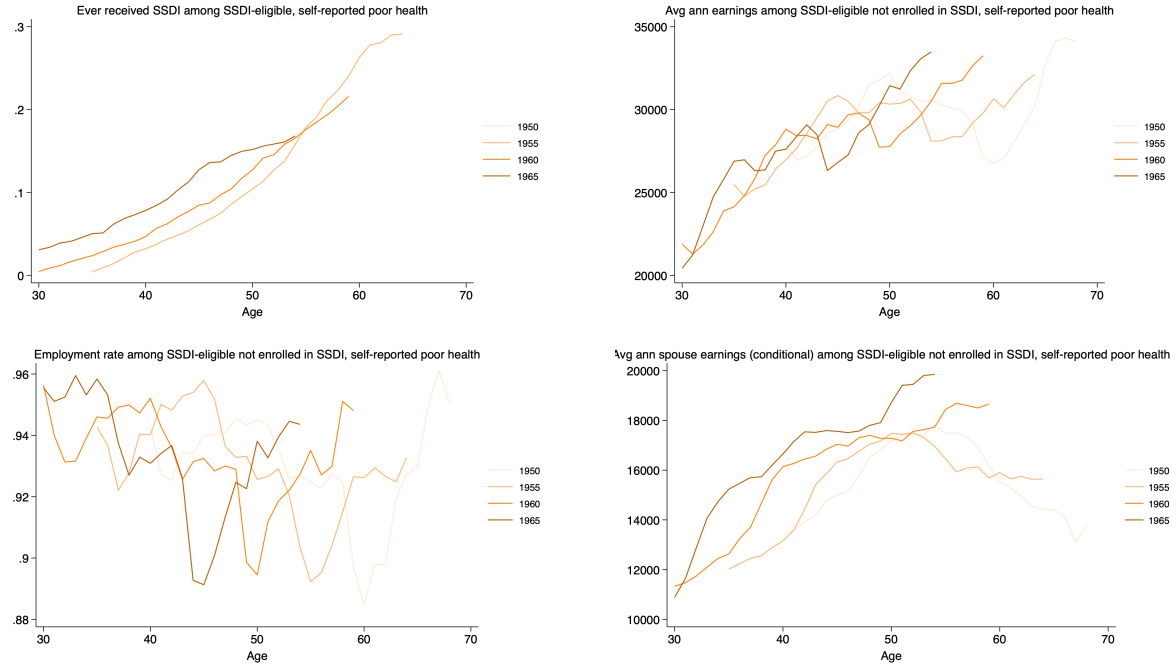
Notes: Figure plots the following outcomes by birth cohort and age for SSDI-eligible middle-skilled (i.e., average earnings between $10,000 and $30,000 between ages 25 to 34 years old) men (orange): SSDI replacement rate, defined as the primary insurance amount divided by average earnings over the past 3 years; and the likelihood of having a SSDI replacement rate below 1. Younger cohorts have darker shading. The sample is derived from the Continuous Work History Sample linked to the Numident and Master Earnings File.

These figures document that younger cohorts of middle-skilled men have experienced historically high levels of earnings and employment, paired with relatively low SSDI benefit amounts. Are the workers with higher earnings and employment the same workers who are less likely to apply for SSDI? We conduct two exercises to answer this question. First, we calculate the joint likelihood of employment and SSDI application across cohorts of middle-skiled men. The likelihood of applying for SSDI and not working ("don't work, apply") between ages 55 to 59 has declined from 7.9pp in older cohorts (YOB 1950-55) to 1.9pp in younger cohorts (YOB 1965-70). Across the same cohorts, the likelihood of not applying for SSDI and working ("work, don't apply") has increased from 68pp to 78pp, while the likelihood of not applying for SSDI and not working ("don't work, don't apply.") has remained steady (18pp to 20pp). This pattern suggests that the decline in SSDI applications is coming from people who are working, which is consistent with the work opportunity story. If, e.g., higher application costs were the main driver of the SSDI decline, we would expect to see increases in both "work, don't apply" and "don't work, don't apply."

Second, we test whether the increase in earnings and employment among low-skilled men applies to those with health conditions, who are most at risk for SSDI receipt. Since the administrative data do not have health measures for the full population, we use SIPP-SSA linked data to condition our analysis on health status reported in the SIPP. Figure 10 presents results from a similar birth cohort exercise as in Figure 8, but for low-education men with health conditions in the SIPP. In addition to lower rates of SSDI application and SSDI enrollment, SSDI-eligible individuals with health conditions have experienced historically high earnings and employment levels. The SIPP-SSA linked data also allow us to estimate spouse earnings, which are historically high for younger cohorts with health-limiting conditions. These results indicate that the increase in earnings and employment (and household resources) applies to low-skilled men who are at risk of applying for SSDI.

Having shown that recent cohorts of low-skilled men have experienced historic earnings and employment levels, we now ask whether this growth could have a large enough effect on SSDI applications to explain the decline. We would ideally estimate a causal effect of earnings and employment growth on SSDI applications. Lacking the appropriate variation for this causal estimate, we instead determine whether it is *possible* for the employment increases to explain application declines by comparing the trends in these two outcomes. In particular, we compare the total "missing" (i.e., counterfactual minus actual) applications over the years 2010 to 2019 to the total "excess" employment over the same period of time,

Figure 10: For low-skilled men with health conditions, lower SSDI receipt and higher own and spouse earnings



Notes: Figure plots the following outcomes by birth cohort and age for SSDI-eligible low-skilled men who report "fair" or "poor" health: ever received SSDI (top left), average annual earnings (top right), annual employment (bottom right), and average annual spouse earnings conditional on having a spouse (bottom right). The birth cohorts range from 1950–55 to 1965–70; younger cohorts have darker shading. The sample is derived from the 1996, 2001, 20024, 2008, and 2014 panels of the SIPP linked to the Numident, F831 file, Payment History Update System, and Master Earnings File.

aggregating across the population (or across low-to-mid-socioeconomic-status older men):

$$\Lambda \equiv \frac{\sum_g \sum_t (A^r_{g,t} - A^c_{g,t}) E^r_{g,t} w^r_{g,t}}{\sum_g \sum_t (\text{Emp}^r_{g,t} - \text{Emp}^c_{g,t}) w^r_{g,t}} \tag{24}$$

where $\text{Emp}_{g,t}$ is the employment rate observed for individuals of group g in year t. We calculate that, in aggregate, a 1 percentage point increase in the employment to population ratio would have to reduce SSDI application rates by 0.13 percentage points to explain the full decline in SSDI applications. Among the older low-to-middle skilled men who disproportionately drive the decline in applications, a 1 percentage point increase in employment would have to reduce SSDI application rates by 0.15 percentage points to explain the full decline. These values are comparable in magnitude to the sensitivity of DI applications to employment estimated by Autor and Duggan (2003) using a shift-share IV, but substantially larger than the estimates from Black, Daniel and Sanders (2002) and Charles, Li and Stephens (2017) using price shocks in energy-producing local areas.

An even stricter test of whether higher employment could explain the decline in SSDI applications would be to conduct the same exercise within fine demographic bins (by age, sex, socioeconomic status, and year). In particular, we want to make sure that the employment gains and SSDI application declines are coming from the *same* subgroup, not different subgroups. E.g., if the increase in employment were concentrated in young women in 2018 while the decrease in applications were concentrated in old men in 2012, then excess workers added to the economy could not be marginal DI applicants. We calculate $\Lambda_{g,t}$ for all g and t:

$$\Lambda_{g,t} \equiv \frac{(A^r_{g,t} - A^c_{g,t})E^r_{g,t}w^r_{g,t}}{(\text{Emp}^r_{g,t} - \text{Emp}^c_{g,t})w^r_{g,t}} \tag{25}$$

Appendix Figure F.5 shows the population-weighted density of $\Lambda_{g,t}$. Even within fine demographic bin (given g and t), the sensitivity of applications needed to explain the full decline in SSDI application is relatively small. The sensitivity needed to fully explain changes in applications (decreases or increases) lies between -0.25 and 0 for 78 percent of the population overall and 85 percent of older low-to-middle-skilled men. If we restrict to the g and t which experienced a decline in applications, then this range of sensitivities can fully explain the decline for nearly 93 percent of the decline-experiencing population overall, and 97 percent for older low-to-middle-skilled men.

4.2 Parameters that have either not changed in the relevant direction, or whose SSDI application elasticities are low

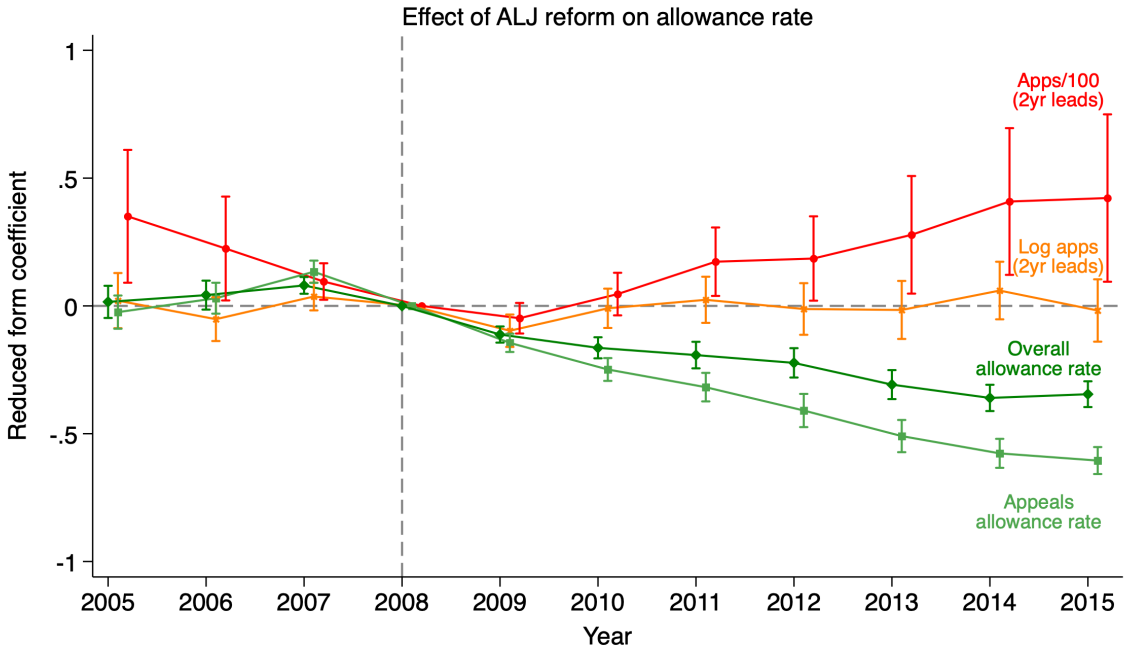
For each of the other parameters in the model, we find either that the parameter has not changed in a direction that would lead to a decline in SSDI applications, or that they do not have much of an effect on SSDI applications. Some of the evidence comes from our own empirical analysis, while other evidence comes from other papers.

Allowance probability conditional on applying (P^{award}_{it}). One of the leading hypotheses for the application decline is that the decline in award rates at the appeals level has discouraged potential applicants from applying for SSDI (Glenn and Goss, 2018; Social Security Administration, 2019; Ruffing, 2023; Center on Budget and Policy Priorities, 2025; Liu and Quinby, 2023; Mohamed et al., 2024). The decline in appeals award rates was at partly a result of a SSA policy change in the way administrative law judges (ALJs) were trained—in particular, an attempt to reduce variation across ALJs in decision-making (Hoynes Maestas Strand 2024).

We investigate whether the decline in award rates at the appeals level could have discouraged potential SSDI applicants from applying in sufficient numbers to explain the decline

in applications. Since ALJs have specific geographic jurisdictions, we compare counties that had high award rates at the appeals level in 2008 (prior to the policy reform) to counties that had low award rates at the appeals level in 2008. Using a difference-in-differences analysis, we find that areas with higher baseline appeals award rates do in fact experience a larger drop in both appeals award rates and overall award rates in the following years. However, as shown in Figure 11, they do not experience a larger reduction in SSDI applications in the following years. See Appendix Section E.3 for more details on this analysis.

Figure 11: Effect of ALJ reform on allowance rate and future applications



Notes: Figure plots estimates of the effect of a county having a higher baseline appeals award rate in 2008 on the following outcomes: SSDI appeals award rate in the county (light green), SSDI overall award rate in the county (dark green), number of SSDI applications two years later (divided by 100) in the county (red), and log SSDI applications two years later in the county (orange). The sample is constructed from the F831 file linked to the Payment History Update System. Appeals award rate is measured as the fraction of SSDI applications rejected at the initial level in the F831 that are eventually awarded SSDI benefits. Overall award rate is measured as the fraction of SSDI applications in the F831 that are eventually awarded SSDI benefits. See Appendix Section E.3 for more details on this analysis.

Probability of receiving, and amount of, other social welfare benefits (P_{it}^{other}, b_{it}). We consider how the enrollment and generosity of other social safety programs have changed since 2010. There is no increase in SNAP, TANF, or UI benefit amount or enrollment between 2010 and 2019 (see Appendix Figures F.2, F.3, and F.4). However, two other types of programs have experienced major expansions since 2010:

- Health insurance: The Affordable Care Act of 2010 expanded Medicaid to more low-income adults and made subsidized health insurance available to lower- and middle-income adults. If some potential SSDI applicants apply primarily to get health insurance coverage, these health insurance expansions could have contributed to the decline in SSDI applicants. However, several studies find that health insurance coverage does not have a large effect on SSDI or SSI enrollment—if anything, SSDI take-up increases in response to health insurance access (Anand, Hyde, Colby and O'Leary, 2019; Baicker, Finkelstein, Song and Taubman, 2014; Burns and Dague, 2017; Maestas, Mullen and Strand, 2014; Schmidt, Shore-Sheppard and Watson, 2020; Soni, Burns, Dague and Simon, 2017; Heim, Lurie, Mullen and Simon, 2021).

- Veterans Disability Compensation: Enrollment in Veterans Disability Compensation (VDC) has increased from 3.2 million in 2010 to 5.7 million in 2023, and the average benefit amount has increased from $11,365 to $23,500 (in nominal dollars) (U.S. Department of Veterans Affairs, 2010, 2023). While there is no restriction on receiving both VDC and SSDI benefits,[15] it is possible that higher VDC receipt could reduce SSDI application and enrollment through an income effect. To evaluate this hypothesis, we identify veterans in our data based on military EINs. We find that veterans do not disproportionately contribute to the decline in SSDI applications (see Appendix Figure C.1a). It is therefore unlikely that the growth of VDC can explain the decline in SSDI benefits.

Hassle cost of applying: field office closings and legal representation (F_{it}). A number of factors affecting the hassle cost of applying changed between 2010 and 2019:

- Field office closings: Deshpande and Li (2019) estimate that Social Security field office closings reduce SSDI applications and awards substantially in neighboring communities. However, given the limited number of closings during this time, we find that they could only explain 3–6% of the decline in SSDI application.

- Legal representation: Hoynes, Maestas and Strand (2022) document a decline in legal representation of SSDI applicants at the appeals level due to changes in compensation to third-party representatives, but find that this change actually increased representation at the initial application level.

- Processing times: Kearney, Price and Wilson (2021) show that, among areas where employment declined sharply during the recession, areas assigned to SSA offices with

[15] See, e.g., https://www.ssa.gov/pubs/EN-64-125.pdf

longer appeals processing times experienced less DI enrollment. However, the responses Kearney et al. (2021) document are small. Moreover, processing times have not risen systematically in recent years.[16]

- End of Social Security statement mailings: In 2011, SSA stopped mailing Social Security statements, which could have reduced worker awareness of SSDI benefits and their eligibility. While we cannot directly test this hypothesis, heterogeneity by severity and health condition in the decline in applications suggests that this explanation is unlikely. Individuals with more severe conditions contribute the most to the decline. If the primary driver was an information shock, we might have expected applications to decline proportionally by severity or even decline more for those with less severe conditions.

- Stigma: The stigma of disability receipt could have changed over this time period, given the spotlight on the safety net in the national political debate. While we do not have a direct measure of stigma, we find no substantial heterogeneity in the decline in applications by state or for urban versus rural areas (see Appendix Tables D.9- D.12).

Disutility of work: (C_{it}). The disutility of work includes both population health and workplace accommodation:

- Population health: Using data from the National Health Interview Survey (NHIS), we find that population health has not improved since 2010 and, if anything, has deteriorated. In particular, we find that limitations due to mental health and musculoskeletal conditions—two diagnostic groups contributing most to the decline in DI applications—*increased* in the population as a whole and in older low-to-middle-skilled men (see Appendix Table F.1). We also study the role of three specific health phenomena:

  - Pollution abatement: We follow the empirical strategy of Isen et al. (2017), who estimate the effect of the Clean Air Act by comparing health outcomes in geographic areas where pollution abatement was required to areas where it was not. We classify workers by the pollution abatement requirements of their place of birth, but find no heterogeneity in the decline in SSDI application based on this measure (see Appendix Section E.4 for more details and Appendix Figure C.2 for heterogeneity results).

[16]The SSA reports average processing times for all cases nationwide only starting from 2014 (https://www.ssa.gov/ssa-performance/disability-appeals-time).

- Decline in smoking: Smoking rates are known to have declined sharply over recent generations (Holford, Levy, McKay, Clarke, Racine, Meza, Land, Jeon and Feuer, 2014), which could have improved health and reduced the need for SSDI benefits. However, we find the decline in SSDI applications was smallest for cancers, which is inconsistent with smoking-related health changes.
- Improvements in mental health treatment: Since 2010, the use of antidepressants and antipsychotics has increased (see Appendix Figure E.1). Using estimates from Biasi, Dahl and Moser (2023) of the effect of mental health treatment in SSDI receipt, we find that the increase in mental health treatment could explain at most 13% of the decline in SSDI applications (see Appendix Section E.5 for more details).
- Opioid crisis. While drug addiction itself is no longer a qualifying condition for SSDI or SSI receipt, the opioid crisis could have led to comorbidities that do qualify individuals for SSDI receipt. We would expect such comorbidities to *increase* SSDI application and enrollment. On the other hand, if the opioid crisis resulted in the death or incapacitation of people who would have applied for SSDI, it could explain some of the decline in SSDI application. We conduct two exercises to estimate the role of the opioid crisis. First, we test for geographic heterogeneity in the decline SSDI application by the severity of the opioid crisis but find no meaningful heterogeneity (see Appendix Tables D.15 and D.16). Second, we estimate that even if every individual who died of an opioid overdose had applied for SSDI benefits (obviously an extreme elasticity), this could only account for 12% of the decline in SSDI application.

- Remote work: Bloom et al. (2024) estimate that the work-from-home revolution accounts for 80% of the post-pandemic increase in employment among people with disabilities. Although we study pre-pandemic patterns in SSDI applications, it is possible that remote work could explain some of the higher employment and lower SSDI application before 2019 as well. Using the Dingel and Neiman (2020) classification of industries by the extent to which remote work is feasible, we find no heterogeneity in the decline in SSDI enrollment by the worker's industry (Appendix Tables D.37 and D.38).

4.3 Summary of empirical results

We rule out several leading hypotheses for the decline in SSDI application with high confidence, including the decline in appeals award rates resulting from ALJ and other reforms;

generosity of other programs like health insurance and Veterans Disability Compensation; and increases in the administrative burden of applying. We rule out other hypotheses with lower confidence, including improvements in population health and increases in remote work.

The evidence is most consistent with improved employment and earnings prospects of individuals on the margin between working and applying for SSDI. Older middle-skilled men, who have the largest proportional drop in SSDI applications, have the largest earnings and employment gains relative to previous cohorts. These gains are not as large for other subgroups (lower-skilled men, higher-skilled men, and women). Recall from Section 3.2 that higher-severity individuals have larger decline in SSDI applications than lower-severity applicants. Consistent with Deshpande and Li (2019) and Deshpande and Lockwood (2022), this result suggests that middle- and high-severity applicants are the marginal workers, while low-severity applicants are much more disconnected from the labor market.

Prior economic recoveries in recent SSDI history occurred from 1993 to 2000, and from 2004 to 2006. A natural question is why these prior recoveries did not produce declines in SSDI applications. In the case of the 1993–2000 recovery, one obvious possibility is that there were countervailing forces pushing up applications: medical eligibility criteria for SSDI had been expanded in 1984, and the cohorts that aged immediately after that decision likely applied in greater numbers in response to that policy change. In addition, Autor and Duggan (2003) document stagnating real wages at the bottom of the earnings distribution during this time. The 2004–2006 economic recovery—just three years long, compared to 10 years for 2010–2019—may simply have been too short to produce meaningful declines in SSDI application before the start of the Great Recession.

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Online Appendix for:

Explaining the Historical Increase and Recent Decline in Social Security Disability Insurance Enrollment

Manasi Deshpande	Maxwell Kellogg	Magne Mogstad	Kuan-Ju Tseng
UChicago	University of Oslo	UChicago	UChicago

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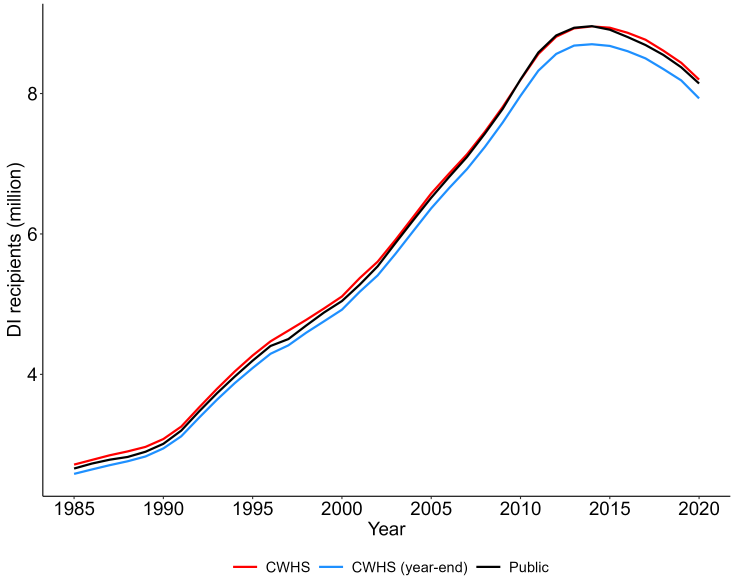
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A Data Appendix

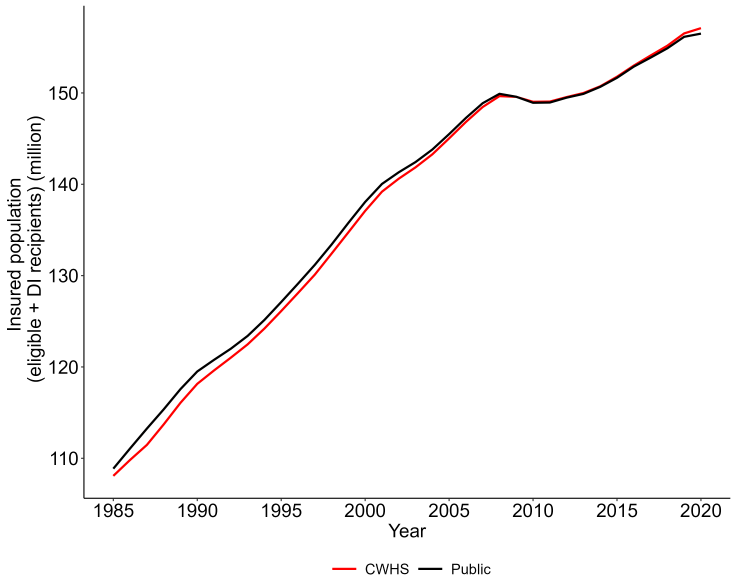
A.1 Matching public data on SSDI

Appendix Figure A.1: Comparing CWHS DI recipients to the Public data



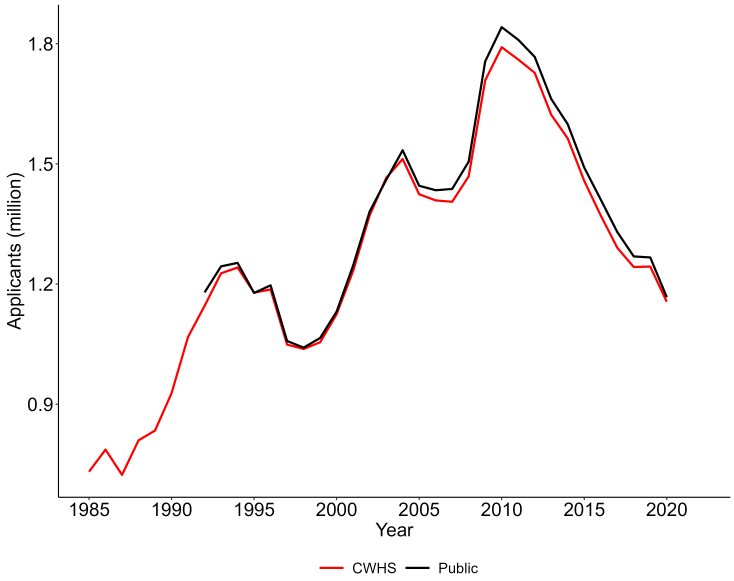
Notes: We identify DI recipients in CWHS through people receiving transfers in the PHUS data and before retirement. The blue line plots year-end DI recipients, which excludes DI recipients that died or terminated their status at each calender year-end. The red line includes all recipients that were on DI in the calendar year. The black line plots the DI recipients reported in the first column of Table 49 in Social Security Administration (2024) from the Public data.

Appendix Figure A.2: Comparing CWHS insured population to the Public data



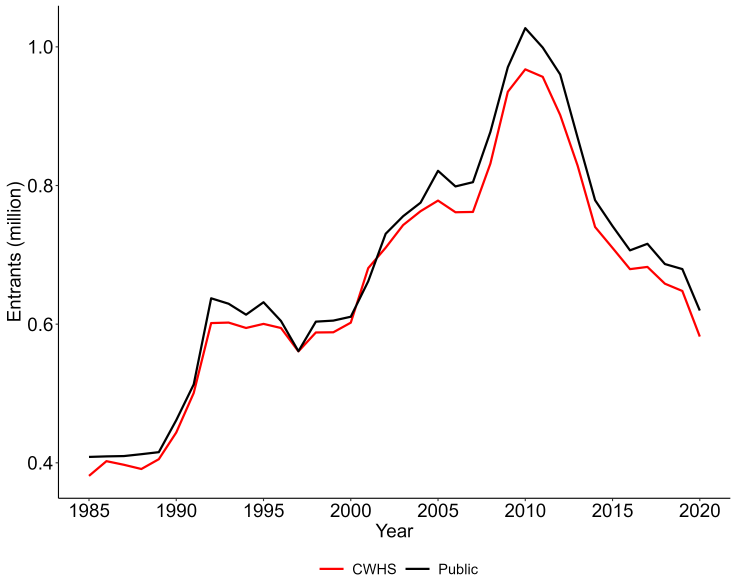
Notes: The red line plots insured population in CWHS by aggregating DI recipients and eligible population. Eligibility is identified through earning records in W2. The black line plots the DI recipients reported by Social Security Administration, estimates from the 2024 Trustees Report based in part on the Continuous Work History Sample, 1 percent sample. (https://www.ssa.gov/oact/STATS/table4c2DI.html)

Appendix Figure A.3: Comparing CWHS applicants to the Public data



Notes: The red line plots applicants in CWHS. We identified applicants by looking at the F831 data. The black line plots number of applicants in Table 60 from the 2023 Annual Statistical Report (Social Security Administration, 2024). We aggregated the number of pending and all four columns in medical decisions and exclude technical denials.

Appendix Figure A.4: Comparing CWHS entrants to the Public data



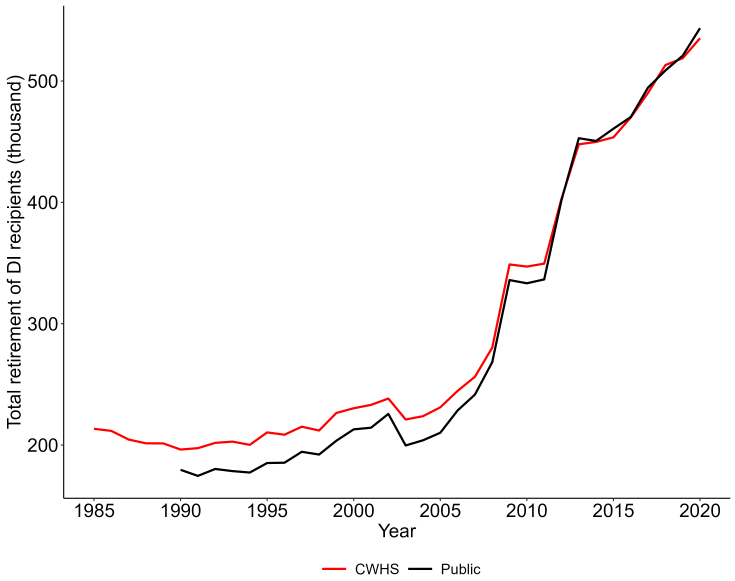
Notes: The red line plots entrants in CWHS. We identified entrants by looking at the PHUS data and the MBR data. The black line plots number of entrants in Table 39 from the 2023 Annual Statistical Report (Social Security Administration, 2024).

Appendix Figure A.5: Comparing CWHS exits to the Public data



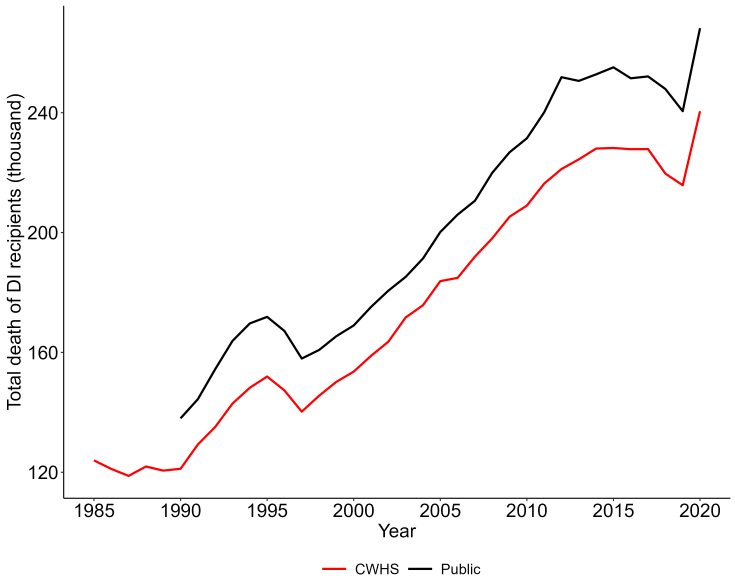
Notes: The red line plots number of exits in CWHS. We identified exits by looking at the PHUS data, the MBR data and the Numident data. The black line plots number of exits from the Annual Statistical Report in each year.

Appendix Figure A.6: Comparing CWHS exits due to retirement to the Public data



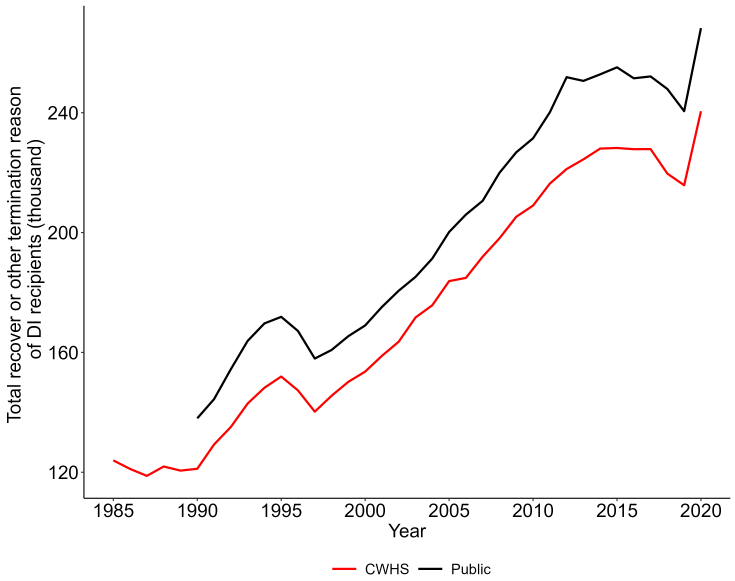
Notes: The red line plots number of exits due to retirement in CWHS. We identified exits due to retirement by looking at the PHUS data and the MBR data. The black line plots number of exits due to retirement from the Annual Statistical Report in each year.

Appendix Figure A.7: Comparing CWHS exits due to death to the Public data



Notes: The red line plots number of exits due to death in CWHS. We identified exits due to death by looking at the PHUS data and the MBR data and the death year in Numident. The black line plots number of exits due to death from the Annual Statistical Report in each year.

Appendix Figure A.8: Comparing CWHS exits due to recovery and other reasons to the Public data



Notes: The red line plots number of exits due to medical recovery or other reasons in CWHS. We identified them by looking at the PHUS data and the MBR data. The black line plots number of exits due to all non-retirement and death reason from the Annual Statistical Report in each year.

B Bounds for the decomposition estimates

Choice in $O^c_{t,g} - O^r_{t,g}$

As we break down $O^c_{t,g} - O^r_{t,g}$, we make a series of choices when defining each partial term. These choices involve where and how we load the interaction terms between two partial effects in a full decomposition. In addition to each partial term looking different depending on the choices we make, the discounting term (K) could also change based on how we allocate interaction terms. To account for this variation, we create bounds that encompaass all possible formats of partial effects and discounting. The bounds are reported in Tables X and Y.

B.0.1 Choice in Step 2: Entry / Exit Level

In Step 2, we decompose SSDI enrollment into the partial effects of entry and exit. In the point estimates, we choose to define partial effects based on raw population and raw DI stocks. However, for each of the partial effects, we can replace them with their counterfactual counterparts:

$$
\begin{aligned}
S^c_{t+1,g} - S^r_{t+1,g} = & \underbrace{(N^c_{t,g} - N^r_{t,g})(P_{t,g} - S^r_{t,g})}_{\text{Partial Entry}} \underbrace{-(Y^c_{t,g} - Y^r_{t,g})S^r_{t,g}}_{\text{Partial Exit (non Death)}} \underbrace{-(\delta^c_{t,g} - \delta^r_{t,g})S^r_{t,g}}_{\text{Partial Exit Death}} \\
& + \underbrace{(1 - N^c_{t,g} - X^c_{t,g})}_{K^c}(S^c_{t,g} - S^r_{t,g}) \\
& = \underbrace{\sum_{i=1}^{t}(N^c_{t-i,g} - N^r_{t-i,g})(P^r_{t-i,g} - S^r_{t-i,g})K^c_{g,i,t}}_{\text{cumulative partial change from conditional entry rate}} \\
& \underbrace{- \sum_{i=1}^{t}(Y^c_{a-i,t-i} - Y^r_{a-i,t-i})S^r_{a-i,t-i}K^c_{a,i,t}}_{\text{cumulative partial change from conditional exit rate}} \\
& \underbrace{- \sum_{i=1}^{t}(\delta^c_{a-i,t-i} - \delta^r_{a-i,t-i})S^r_{a-i,t-i}K^c_{a,i,t}}_{\text{cumulative partial change from conditional exit rate}} \\
& + \underbrace{\sum_{i=1}^{t}(\alpha^c_{a-i,t-i} - \alpha^r_{a-i,t-i})K^c_{a,i,t}}_{\text{cumulative partial change immigrant entrants}} \\
& + \underbrace{\sum_{i=1}^{t-1}\left[N^c_{a-i,t-i}(P^c_{a-i,t-i} - P^r_{a-i,t-i})\right]K^c_{a,i,t}}_{\text{cumulative change from pop. discrepancies}} \\
& + \underbrace{N^c_{a-t,0}(P^c_{a-t,0} - P^r_{a-t,0})K^c_{a,t,t} + K^c_{a,t+1,t}(S^c_{a-t,0} - S^r_{a-t,0})}_{\text{initial difference}}
\end{aligned}
$$

where

$$
K^c_{a,i,t} = \begin{cases} 1 & \text{if } i = 0 \\ \prod_{j=1}^{i}(1 - N^c_{a-j+1,t-j+1} - X^c_{a-j+1,t-j+1}) & \text{if } i \geq 1 \end{cases}
$$

We could instead define cumulative partial entry as:

$$\underbrace{\sum_{i=1}^{t}(N^c_{a-i,t-i} - N^r_{a-i,t-i})(P^c_{a-i,t-i} - S^c_{a-i,t-i})K'_{a,i,t}}_{\text{cumulative partial change from conditional entry rate}}$$

In order to make the equation hold, we have to adjust for the discounting factor K and how we defined population discrepancy:

$$\begin{aligned}
S^c_{a+1,t+1} - S^r_{a+1,t+1} &= \underbrace{(N^c_{a,t} - N^r_{a,t})(P^c_{a,t} - S^c_{a,t})}_{\text{Partial Entry}} \underbrace{-(Y^c_{a,t} - Y^r_{a,t})S^r_{a,t}}_{\text{Partial Exit (non Death)}} \underbrace{-(\delta^c_{a,t} - \delta^r_{a,t})S^r_{a,t}}_{\text{Partial Exit Death}} \\
&+ \underbrace{(\alpha^c_{a,t} - \alpha^r_{a,t})}_{\text{Immigrant entry effect}} + \underbrace{N^r_{a,t}(P^c_{a,t} - P^r_{a,t})}_{\text{Population Discrepancy}} + \underbrace{(1 - N^r_{a,t} - X^c_{a,t})}_{K'}(S^c_{a,t} - S^r_{a,t}) \\
&= \underbrace{\sum_{i=1}^{t}(N^c_{a-i,t-i} - N^r_{a-i,t-i})(P^c_{a-i,t-i} - S^c_{a-i,t-i})K'_{a,i,t}}_{\text{cumulative partial change from conditional entry rate}} \\
&\underbrace{-\sum_{i=1}^{t}(Y^c_{a-i,t-i} - Y^r_{a-i,t-i})S^r_{a-i,t-i}K'_{a,i,t}}_{\text{cumulative partial change from conditional exit rate}} \\
&\underbrace{-\sum_{i=1}^{t}(\delta^c_{a-i,t-i} - \delta^r_{a-i,t-i})S^r_{a-i,t-i}K'_{a,i,t}}_{\text{cumulative partial change from conditional exit rate}} \\
&+ \underbrace{\sum_{i=1}^{t}(\alpha^c_{a-i,t-i} - \alpha^r_{a-i,t-i})K'_{a,i,t}}_{\text{cumulative partial change immigrant entrants}} \\
&\underbrace{+\sum_{i=1}^{t-1}\left[N^r_{a-i,t-i}(P^c_{a-i,t-i} - P^r_{a-i,t-i})\right]K'_{a,i,t}}_{\text{cumulative change from pop. discrepancies}} \\
&\underbrace{+ N^r_{a-t,0}(P^c_{a-t,0} - P^r_{a-t,0})K'_{a,t,t} + K'_{a,t+1,t}(S^c_{a-t,0} - S^r_{a-t,0})}_{\text{initial difference}}
\end{aligned}$$

With a different definition on partial entry, the discounting factor K and the definition of

population discrepancy changes accordingly. There are two choice in each of partial entry, exit and exit death, creating total of eight different models. Along with the choices we made in Step 2, there are in total 16 (8*2) different ways to decompose difference in DI rate into partial entry, exit and exit death and friction.

B.0.2 Choice in Step 4: Further Decompose Entry / Exit

There are two stands changes from entry rates into award, application and eligibility rates:

(a) Partition Effects Within Partial Entry If we view the model as given partial entry effect, how would we allocate between effect from award, application and eligibility and interactions. Under this setting, in the P-S part, all four terms would take the same value. The difference lies in how we allocate interactions between award, apply and elig, which would affect the first part (i.e the non P-S part) in the definition.

For instance, we could define the first part of partial award as either $(B^c - B^r)A^r E^c$ or $(B^c - B^r)A^c E^c$ or other similar forms. The same applies for partial apply and partial elig. Once these terms are fixed, the interaction terms would be the residual of partial entry effect and the sum of partial award, apply and elig. Therefore, there are $2^2 * 2^2 * 2^2 = 64$ additional variation when we partition entry into award, application and eligibility effects. It is worth noting that since here we are partitioning within partial entry, the bound for all elements would not be affected by this step.

$$
\begin{aligned}
S^c_{a+1,t+1} - S^r_{a+1,t+1} &= \underbrace{(N^c_{a,t} - N^r_{a,t})(P^r_{a,t} - S^r_{a,t})}_{\text{Partial Entry}} \quad \underbrace{-(Y^c_{a,t} - Y^r_{a,t})S^r_{a,t}}_{\text{Partial Exit (non Death)}} \quad \underbrace{-(\delta^c_{a,t} - \delta^r_{a,t})S^r_{a,t}}_{\text{Partial Exit Death}} \\
&+ \quad \underbrace{(\alpha^c_{a,t} - \alpha^r_{a,t})}_{\text{Immigrant entry effect}} \quad + \quad \underbrace{N^c_{a,t}(P^c_{a,t} - P^r_{a,t})}_{\text{Population Discrepancy}} \quad + \underbrace{(1 - N^c_{a,t} - X^c_{a,t})}_{K^c}(S^c_{a,t} - S^r_{a,t}) \\
&= \underbrace{(B^c_{a,t} - B^r_{a,t})A^r_{a,t}E^r_{a,t}(P^r_{a,t} - S^r_{a,t})}_{\text{Partial Award}} \\
&+ \underbrace{B^r_{a,t}(A^c_{a,t} - A^r_{a,t})E^r_{a,t}(P^r_{a,t} - S^r_{a,t})}_{\text{Partial Apply}} \\
&+ \underbrace{B^r_{a,t}A^r_{a,t}(E^c_{a,t} - E^r_{a,t})(P^r_{a,t} - S^r_{a,t})}_{\text{Partial Elig}} \\
&+ \underbrace{((N^c_{a,t} - N^r_{a,t}) - (B^c_{a,t} - B^r_{a,t})A^r_{a,t}E^r_{a,t} - B^r_{a,t}(A^c_{a,t} - A^r_{a,t})E^r_{a,t} - B^r_{a,t}A^r_{a,t}(E^c_{a,t} - E^r_{a,t}))(P^r_{a,t} - S^r_{a,t})}_{\text{Interaction}} \\
&- (Y^c_{a,t} - Y^r_{a,t})S^r_{a,t} - (\delta^c_{a,t} - \delta^r_{a,t})S^r_{a,t} \\
&+ (\alpha^c_{a,t} - \alpha^r_{a,t}) + N^c_{a,t}(P^c_{a,t} - P^r_{a,t}) + \underbrace{(1 - N^c_{a,t} - X^c_{a,t})}_{K^c}(S^c_{a,t} - S^r_{a,t}) \\
&= \underbrace{(N^c_{a,t} - N^r_{a,t})(P^c_{a,t} - S^c_{a,t})}_{\text{Partial Entry}} \quad \underbrace{-(Y^c_{a,t} - Y^r_{a,t})S^r_{a,t}}_{\text{Partial Exit (non Death)}} \quad \underbrace{-(\delta^c_{a,t} - \delta^r_{a,t})S^r_{a,t}}_{\text{Partial Exit Death}} \\
&+ \quad \underbrace{(\alpha^c_{a,t} - \alpha^r_{a,t})}_{\text{Immigrant entry effect}} \quad + \quad \underbrace{N^r_{a,t}(P^c_{a,t} - P^r_{a,t})}_{\text{Population Discrepancy}} \quad + \underbrace{(1 - N^r_{a,t} - X^c_{a,t})}_{K'}(S^c_{a,t} - S^r_{a,t}) \\
&= \underbrace{(B^c_{a,t} - B^r_{a,t})A^r_{a,t}E^r_{a,t}(P^c_{a,t} - S^c_{a,t})}_{\text{Partial Award}} \\
&+ \underbrace{B^r_{a,t}(A^c_{a,t} - A^r_{a,t})E^r_{a,t}(P^c_{a,t} - S^c_{a,t})}_{\text{Partial Apply}} \\
&+ \underbrace{B^r_{a,t}A^r_{a,t}(E^c_{a,t} - E^r_{a,t})(P^c_{a,t} - S^c_{a,t})}_{\text{Partial Elig}} \\
&+ \underbrace{((N^c_{a,t} - N^r_{a,t}) - (B^c_{a,t} - B^r_{a,t})A^r_{a,t}E^r_{a,t} - B^r_{a,t}(A^c_{a,t} - A^r_{a,t})E^r_{a,t} - B^r_{a,t}A^r_{a,t}(E^c_{a,t} - E^r_{a,t}))(P^c_{a,t} - S^c_{a,t})}_{\text{Interaction}} \\
&- (Y^c_{a,t} - Y^r_{a,t})S^r_{a,t} - (\delta^c_{a,t} - \delta^r_{a,t})S^r_{a,t} \\
&+ (\alpha^c_{a,t} - \alpha^r_{a,t}) + N^r_{a,t}(P^c_{a,t} - P^r_{a,t}) + \underbrace{(1 - N^r_{a,t} - X^c_{a,t})}_{K'}(S^c_{a,t} - S^r_{a,t}) \\
&= \underbrace{(B^c_{a,t} - B^r_{a,t})A^c_{a,t}E^c_{a,t}(P^c_{a,t} - S^c_{a,t})}_{\text{Partial Award}} \\
&+ \underbrace{B^c_{a,t}(A^c_{a,t} - A^r_{a,t})E^c_{a,t}(P^c_{a,t} - S^c_{a,t})}_{\text{Partial Apply}} \\
&+ \underbrace{B^c_{a,t}A^c_{a,t}(E^c_{a,t} - E^r_{a,t})(P^c_{a,t} - S^c_{a,t})}_{\text{Partial Elig}} \\
&+ \underbrace{((N^c_{a,t} - N^r_{a,t}) - (B^c_{a,t} - B^r_{a,t})A^c_{a,t}E^c_{a,t} - B^c_{a,t}(A^c_{a,t} - A^r_{a,t})E^c_{a,t} - B^c_{a,t}A^c_{a,t}(E^c_{a,t} - E^r_{a,t}))(P^c_{a,t} - S^c_{a,t})}_{\text{Interaction}} \\
&- (Y^c_{a,t} - Y^r_{a,t})S^r_{a,t} - (\delta^c_{a,t} - \delta^r_{a,t})S^r_{a,t} \\
&+ (\alpha^c_{a,t} - \alpha^r_{a,t}) + N^r_{a,t}(P^c_{a,t} - P^r_{a,t}) + \underbrace{(1 - N^r_{a,t} - X^c_{a,t})}_{K'}(S^c_{a,t} - S^r_{a,t})
\end{aligned}
$$

The similar argument can be applied to decomposition of exit (non-death). The only

difference is that recovery, retirement and other are additive separable, therefore are no additional variations.

(b) Allowing Variations in P/S across Partial Award/Apply/Elig If we replace entry rate by award, apply, and elig rate in the original model and perform everything else accordingly. In this case, not only can we choose how we allocate interaction terms into the three elements, we will also allow partial award, apply, elig and even interaction terms to take different values in the non-DI stock P-S, which could affect the discounting K and create a new model not included in the previous steps.

We define partial entry as the sum of partial award, apply and elig and their interactions. By allowing these components to take different values in P-S, the discounting part and the definition of population discrepancy would be affected, thus creating a bigger bound for all elements due to increasing model complexity.

$$
\begin{aligned}
&S^c_{a+1,t+1} - S^r_{a+1,t+1} \\
&= \underbrace{(N^c_{a,t} - N^r_{a,t})(P^r_{a,t} - S^r_{a,t})}_{\text{Partial Entry}} \quad \underbrace{-(Y^c_{a,t} - Y^r_{a,t})S^r_{a,t}}_{\text{Partial Exit (non Death)}} \quad \underbrace{-(\delta^c_{a,t} - \delta^r_{a,t})S^r_{a,t}}_{\text{Partial Exit Death}} \\
&+ \quad \underbrace{(\alpha^c_{a,t} - \alpha^r_{a,t})}_{\text{Immigrant entry effect}} \quad + \quad \underbrace{N^c_{a,t}(P^c_{a,t} - P^r_{a,t})}_{\text{Population Discrepancy}} \quad + \underbrace{(1 - N^c_{a,t} - X^c_{a,t})}_{K^c}(S^c_{a,t} - S^r_{a,t}) \\
&= \underbrace{(B^c_{a,t} - B^r_{a,t})A^c_{a,t}E^c_{a,t}(P^r_{a,t} - S^r_{a,t})}_{\text{Partial Award}} \\
&+ \underbrace{B^c_{a,t}(A^c_{a,t} - A^r_{a,t})E^c_{a,t}(P^r_{a,t} - S^r_{a,t})}_{\text{Partial Apply}} \\
&+ \underbrace{B^c_{a,t}A^c_{a,t}(E^c_{a,t} - E^r_{a,t})(P^r_{a,t} - S^r_{a,t})}_{\text{Partial Elig}} \\
&+ \underbrace{((N^c_{a,t} - N^r_{a,t}) - (B^c_{a,t} - B^r_{a,t})A^c_{a,t}E^c_{a,t} - B^c_{a,t}(A^c_{a,t} - A^r_{a,t})E^c_{a,t} - B^c_{a,t}A^c_{a,t}(E^c_{a,t} - E^r_{a,t}))(P^r_{a,t} - S^r_{a,t})}_{\text{Interaction}} \\
&- (Y^c_{a,t} - Y^r_{a,t})S^r_{a,t} - (\delta^c_{a,t} - \delta^r_{a,t})S^r_{a,t} \\
&+ (\alpha^c_{a,t} - \alpha^r_{a,t}) + N^c_{a,t}(P^c_{a,t} - P^r_{a,t}) + \underbrace{(1 - N^c_{a,t} - X^c_{a,t})}_{K^c}(S^c_{a,t} - S^r_{a,t}) \\
&= \underbrace{(B^c_{a,t} - B^r_{a,t})A^c_{a,t}E^c_{a,t}(P^r_{a,t} - S^r_{a,t})}_{\text{Partial Award}} \\
&+ \underbrace{B^c_{a,t}(A^c_{a,t} - A^r_{a,t})E^c_{a,t}(P^r_{a,t} - S^r_{a,t})}_{\text{Partial Apply}} \\
&+ \underbrace{B^c_{a,t}A^c_{a,t}(E^c_{a,t} - E^r_{a,t})(P^c_{a,t} - S^c_{a,t})}_{\text{Partial Elig}} \\
&+ \underbrace{((N^c_{a,t} - N^r_{a,t}) - (B^c_{a,t} - B^r_{a,t})A^c_{a,t}E^c_{a,t} - B^c_{a,t}(A^c_{a,t} - A^r_{a,t})E^c_{a,t} - B^c_{a,t}A^c_{a,t}(E^c_{a,t} - E^r_{a,t}))(P^c_{a,t} - S^c_{a,t})}_{\text{Interaction}} \\
&- (Y^c_{a,t} - Y^r_{a,t})S^r_{a,t} - (\delta^c_{a,t} - \delta^r_{a,t})S^r_{a,t} \\
&+ (\alpha^c_{a,t} - \alpha^r_{a,t}) + N^c_{a,t}(P^c_{a,t} - P^r_{a,t}) + \underbrace{(1 - N^c_{a,t} - X^c_{a,t})}_{K^c}(S^c_{a,t} - S^r_{a,t}) \\
&- B^c_{a,t}A^c_{a,t}(E^c_{a,t} - E^r_{a,t})\left[(P^c_{a,t} - S^c_{a,t}) - (P^r_{a,t} - S^r_{a,t})\right] \\
&- ((N^c_{a,t} - N^r_{a,t}) - (B^c_{a,t} - B^r_{a,t})A^c_{a,t}E^c_{a,t} - B^c_{a,t}(A^c_{a,t} - A^r_{a,t})E^c_{a,t} - B^c_{a,t}A^c_{a,t}(E^c_{a,t} - E^r_{a,t}))\left[(P^c_{a,t} - S^c_{a,t}) - (P^r_{a,t} - S^r_{a,t})\right] \\
&= \underbrace{(B^c_{a,t} - B^r_{a,t})A^c_{a,t}E^c_{a,t}(P^r_{a,t} - S^r_{a,t})}_{\text{Partial Award}} \\
&+ \underbrace{B^c_{a,t}(A^c_{a,t} - A^r_{a,t})E^c_{a,t}(P^r_{a,t} - S^r_{a,t})}_{\text{Partial Apply}} \\
&+ \underbrace{B^c_{a,t}A^c_{a,t}(E^c_{a,t} - E^r_{a,t})(P^c_{a,t} - S^c_{a,t})}_{\text{Partial Elig}} \\
&+ \underbrace{((N^c_{a,t} - N^r_{a,t}) - (B^c_{a,t} - B^r_{a,t})A^c_{a,t}E^c_{a,t} - B^c_{a,t}(A^c_{a,t} - A^r_{a,t})E^c_{a,t} - B^c_{a,t}A^c_{a,t}(E^c_{a,t} - E^r_{a,t}))(P^c_{a,t} - S^c_{a,t})}_{\text{Interaction}} \\
&- (Y^c_{a,t} - Y^r_{a,t})S^r_{a,t} - (\delta^c_{a,t} - \delta^r_{a,t})S^r_{a,t} \\
&+ (\alpha^c_{a,t} - \alpha^r_{a,t}) \\
&+ \left[N^c_{a,t} - B^c_{a,t}A^c_{a,t}(E^c_{a,t} - E^r_{a,t}) - ((N^c_{a,t} - N^r_{a,t}) - (B^c_{a,t} - B^r_{a,t})A^c_{a,t}E^c_{a,t} - B^c_{a,t}(A^c_{a,t} - A^r_{a,t})E^c_{a,t} - B^c_{a,t}A^c_{a,t}(E^c_{a,t} - E^r_{a,t}))\right](P^c_{a,t} - P^r_{a,t}) \\
&+ \underbrace{\left[(1 - N^c_{a,t} - X^c_{a,t}) + B^c_{a,t}A^c_{a,t}(E^c_{a,t} - E^r_{a,t}) + ((N^c_{a,t} - N^r_{a,t}) - (B^c_{a,t} - B^r_{a,t})A^c_{a,t}E^c_{a,t} - B^c_{a,t}(A^c_{a,t} - A^r_{a,t})E^c_{a,t} - B^c_{a,t}A^c_{a,t}(E^c_{a,t} - E^r_{a,t}))\right]}_{K''}(S^c_{a,t} -
\end{aligned}
$$

Including the choice of r or c in the P-S part, there are in total 2^3 combinations for each of award, apply and elig. In terms of interaction, we could choose between r and c in the P-S part. However, the first part is still defined to be the residual of $N^c - N^r$ and the sum of the first part in partial award, apply and elig. Therefore, there is only 2 forms of interaction, which is whether it would take r or c in the P-S part.

The similar argument can be applied to decomposition of exit (non-death) into recovery retirement and other reasons. In stand (a) we were implicitly force these three to take the same value in the S part. Here we allow different choices in S in these three components. This would also affect the discounting terms.

Accounting for all these partial effects to take different values, there would be $2*2^3$ (award)$*2^3$ (apply)$*2^3$ (elig)*2 (interaction)$*2^3$ (exit partition)* 2 (exit death) = 2^{15} kinds of variation.

Ordering of the components of $w^c_{t,g} - w^r_{t,g}$

With four covariates (sex, age, earningbin and birthplace), there are $4! = 24$ kinds of ordering that we have to go through to calculate the bounds.

However, if we account for that we can choose to use only sex, only use sex-age etc rather than using all covariates, there will be $4 + 2!\binom{4}{2} + 3!\binom{4}{3} + 4! = 64$ ordering.

C Heterogeneous decomposition results (Population-level decomposition results)

C.1 Demographic characteristics

Appendix Table C.1: Breakdown of SSDI increase by sex, age, and earnings between ages 25–34

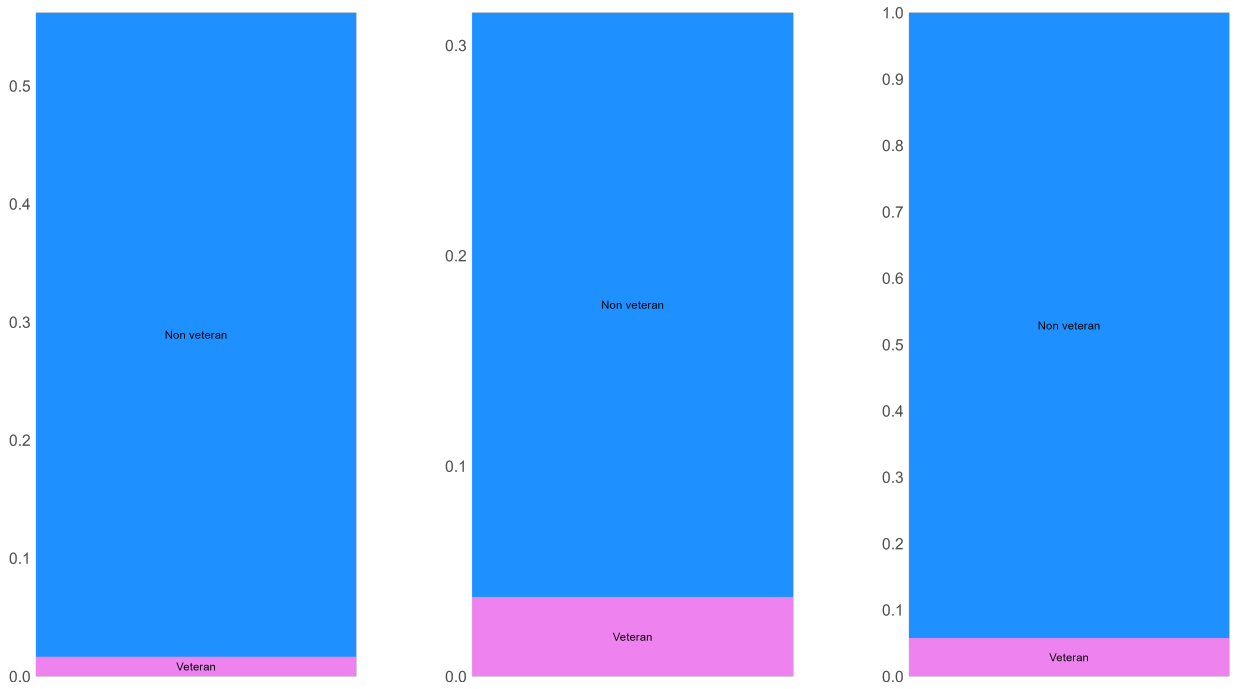
Earningbin	Women, younger	Women, older	Man, younger	Man, older
0K	0.57	0.94	0.42	-0.04
0 - 10K	2.59	4.29	1.26	2.62
10 - 30K	0.52	1.59	0.10	1.20
30 - 60K	-0.02	0.14	-0.09	-1.35
60K+	-0.05	1.26	-0.02	-0.72
Missing	0.03	-0.28	-0.01	-0.58

Appendix Table C.2: Breakdown of SSDI decrease by sex, age, and earnings between ages 25–34

Earningbin	Women, younger	Women, older	Man, younger	Man, older
0K	0.63	0.03	1.29	0.17
0 - 10K	0.97	0.35	2.10	2.21
10 - 30K	0.31	0.87	0.64	2.88
30 - 60K	0.15	0.80	0.16	2.04
60K+	0.02	-0.02	0.04	0.92
Missing	0.57	0.99	0.64	1.25

C.2 Veteran status

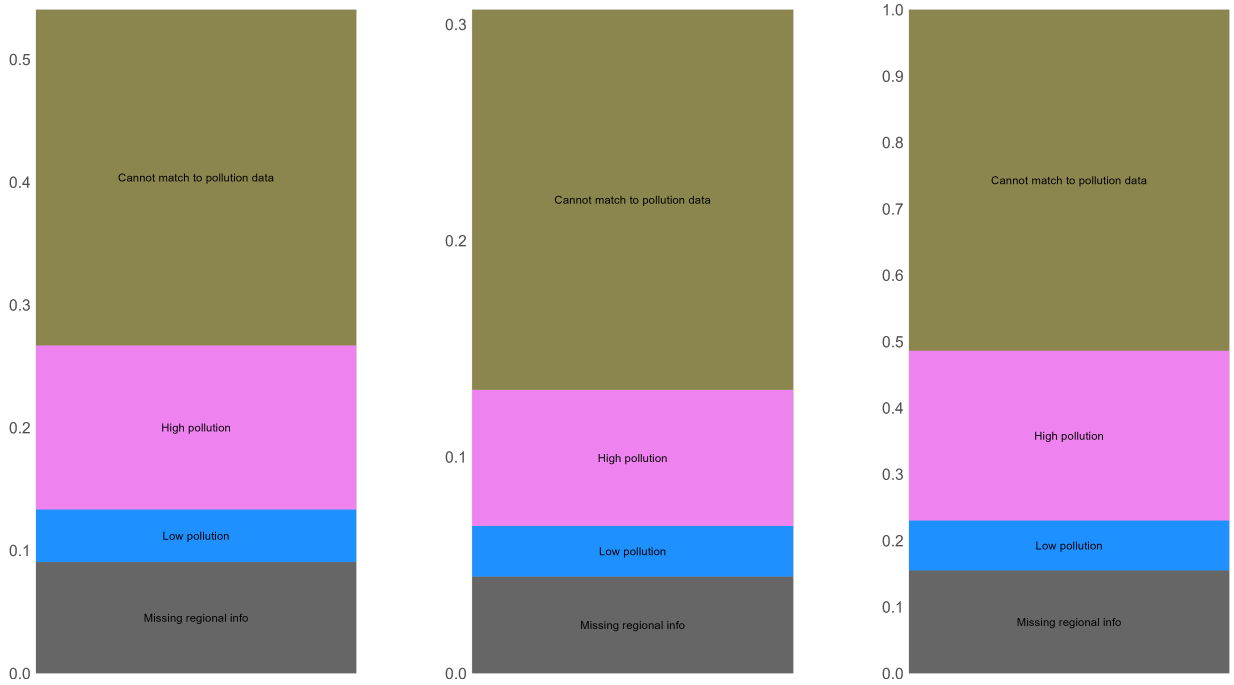
Appendix Figure C.1: Breakdown of application decrease and award decrease by veteran status



(a) Application decrease (b) Award decrease (c) Group size in 2019

Notes: Left graph plots the fraction of the contribution of changes (in absolute term) in application rate that can be attributed to specific demographic groups. Middle graph plots the fraction of the contribution of changes in award rate (in absolute term) that can be attributed to specific demographic groups. Negative numbers in the left and middle graphs indicate that the group actually worked *against* the decrease in applications or awards. Right graph plots the composition of the population in 2019 as a measure of group size.

Appendix Figure C.2: Breakdown of application decrease and award decrease by regional pollution



(a) Application decrease (b) Award decrease (c) Group size in 2019

Notes: Left graph plots the fraction of the contribution of changes (in absolute term) in application rate that can be attributed to specific demographic groups. Middle graph plots the fraction of the contribution of changes in award rate (in absolute term) that can be attributed to specific demographic groups. Negative numbers in the left and middle graphs indicate that the group actually worked *against* the decrease in applications or awards. Right graph plots the composition of the population in 2019 as a measure of group size.

D Heterogenous decomposition results (Applicant-specific decomposition results)

D.1 Severity

Appendix Table D.1: Heterogeneity in SSDI application increase (1988–2010) by severity

Severity	Portion of DI change (pp)	Cont. (%)	Share app. 2010 (%)	Ratio	Share app. 1988 (%)	Ratio
Least Severe	-0.24	36.22	62.77	0.58	61.86	0.59
Middle Severe	0.07	-10.72	11.58	-0.93	23.31	-0.46
High Severe	-0.44	67.63	22.06	3.07	9.74	6.94
Missing	-0.04	6.87	3.59	1.91	5.09	1.35

Notes: Table partitions contribution of partial apply among eligible to the increase in SSDI enrollment rates from 1988 to 2010 by different severity levels. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial apply in absolute term. The fourth and sixth columns are the share of applicants in 1988 and 2010. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

Appendix Table D.2: Heterogeneity in SSDI award increase (1988–2010) by severity

Severity	Portion of DI change (pp)	Cont. (%)	Share app. 2010 (%)	Ratio	Share app. 1988 (%)	Ratio
Least Severe	-0.19	54.51	62.77	0.87	61.86	0.88
Middle Severe	-0.06	18.82	11.58	1.62	23.31	0.81
High Severe	-0.07	21.17	22.06	0.96	9.74	2.17
Missing	-0.02	5.50	3.59	1.53	5.09	1.08

Notes: Table partitions contribution of partial award to the increase in SSDI enrollment rates from 1988 to 2010 by different severity levels. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial award in absolute term. The fourth and sixth columns are the share of applicants in 1988 and 2010. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

Appendix Table D.3: Heterogeneity in SSDI application decrease (2010–19) by diagnosis

Severity	Portion of DI change (pp)	Cont. (%)	Share app. 2019 (%)	Ratio	Share app. 2010 (%)	Ratio
Least Severe	0.09	14.55	63.12	0.23	62.77	0.23
Middle Severe	0.23	37.46	10.13	3.70	11.58	3.23
High Severe	0.25	40.58	23.04	1.76	22.06	1.84
Missing	0.05	7.41	3.71	2.00	3.59	2.06

Notes: Table partitions contribution of partial apply to the decrease in SSDI enrollment rates from 2010 to 2019 by different severity levels. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial apply in absolute term. The fourth and sixth columns are the share of applicants in 2010 and 2019. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

Appendix Table D.4: Heterogeneity in SSDI award decrease (2010–19) by diagnosis

Severity	Portion of DI change (pp)	Cont. (%)	Share app. 2019 (%)	Ratio	Share app. 2010 (%)	Ratio
Least Severe	0.19	113.35	63.12	1.80	62.77	1.81
Middle Severe	-0.02	-13.19	10.13	-1.30	11.58	-1.14
High Severe	0.00	1.57	23.04	0.07	22.06	0.07
Missing	-0.00	-1.73	3.71	-0.47	3.59	-0.48

Notes: Table partitions contribution of partial award to the decrease in SSDI enrollment rates from 2010 to 2019 by different severity levels. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial award in absolute term. The fourth and sixth columns are the share of applicants in 2010 and 2019. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

D.2 Diagnosis

Appendix Table D.5: Heterogeneity in SSDI application increase (1988–2010) by diagnosis

Diagnosis	Portion of DI change (pp)	Cont. (%)	Share app. 2010 (%)	Ratio	Share app. 1988 (%)	Ratio
Musculoskeletal	-0.23	33.22	33.04	1.01	30.93	1.07
Neurological	-0.04	5.57	7.19	0.78	7.98	0.70
Mental	-0.28	41.72	19.73	2.11	14.86	2.81
Cancer	0.00	-0.11	6.01	-0.02	6.94	-0.02
Other	-0.12	17.05	19.39	0.88	20.13	0.85
Cardiovascular System	0.07	-9.82	7.23	-1.36	11.53	-0.85
Endocrine System	-0.04	5.76	3.81	1.51	2.56	2.25
Missing	-0.04	6.61	3.59	1.84	5.09	1.30

Notes: Table partitions contribution of partial apply to the increase in SSDI enrollment rates from 1988 to 2010 by different diagnosis. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial apply in absolute term. The fourth and sixth columns are the share of applicants in 1988 and 2010. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

Appendix Table D.6: Heterogeneity in SSDI award increase (1988–2010) by diagnosis

Diagnosis	Portion of DI change (pp)	Cont. (%)	Share app. 2010 (%)	Ratio	Share app. 1988 (%)	Ratio
Musculoskeletal	-0.20	49.31	33.04	1.49	30.93	1.59
Neurological	-0.02	3.78	7.19	0.53	7.98	0.47
Mental	0.05	-13.58	19.73	-0.69	14.86	-0.91
Cancer	-0.03	7.56	6.01	1.26	6.94	1.09
Other	-0.14	35.18	19.39	1.81	20.13	1.75
Cardiovascular System	-0.03	7.69	7.23	1.06	11.53	0.67
Endocrine System	-0.02	5.31	3.81	1.39	2.56	2.08
Missing	-0.02	4.76	3.59	1.32	5.09	0.93

Notes: Table partitions contribution of partial award to the decrease in SSDI enrollment rates from 1988 to 2010 by different diagnosis. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial award in absolute term. The fourth and sixth columns are the share of applicants in 1988 and 2010. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

Appendix Table D.7: Heterogeneity in SSDI application decrease (2010–19) by diagnosis

Diagnosis	Portion of DI change (pp)	Cont. (%)	Share app. 2019 (%)	Ratio	Share app. 2010 (%)	Ratio
Musculoskeletal	0.07	17.13	34.49	0.50	33.04	0.52
Neurological	0.01	3.33	9.22	0.36	7.19	0.46
Mental	0.10	24.46	18.21	1.34	19.73	1.24
Cancer	0.04	10.69	7.46	1.43	6.01	1.78
Other	0.06	15.19	18.26	0.83	19.39	0.78
Cardiovascular System	0.05	11.00	6.57	1.67	7.23	1.52
Endocrine System	0.03	7.14	2.08	3.43	3.81	1.87
Missing	0.05	11.05	3.71	2.98	3.59	3.08

Notes: Table partitions contribution of partial apply to the decrease in SSDI enrollment rates from 2010 to 2019 by different diagnosis. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial apply in absolute term. The fourth and sixth columns are the share of applicants in 2010 and 2019. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

Appendix Table D.8: Heterogeneity in SSDI award decrease (2010–19) by diagnosis

Diagnosis	Portion of DI change (pp)	Cont. (%)	Share app. 2019 (%)	Ratio	Share app. 2010 (%)	Ratio
Musculoskeletal	0.12	43.96	34.49	1.27	33.04	1.33
Neurological	0.02	7.56	9.22	0.82	7.19	1.05
Mental	0.09	32.47	18.21	1.78	19.73	1.65
Cancer	-0.00	-0.23	7.46	-0.03	6.01	-0.04
Other	0.03	9.26	18.26	0.51	19.39	0.48
Cardiovascular System	0.01	4.33	6.57	0.66	7.23	0.60
Endocrine System	0.01	3.67	2.08	1.76	3.81	0.96
Missing	-0.00	-1.02	3.71	-0.28	3.59	-0.29

Notes: Table partitions contribution of partial award to the decrease in SSDI enrollment rates from 2010 to 2019 by different diagnosis. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial award in absolute term. The fourth and sixth columns are the share of applicants in 2010 and 2019. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

D.3 Regional characteristics

Appendix Table D.9: Heterogeneity in SSDI application decrease (2010–19) by state

State	Portion of DI change (pp)	Cont. (%)	Share app. 2019 (%)	Ratio	Share app. 2010 (%)	Ratio
Unknown	-0.00	-0.31	0.11	-278.76	0.10	-326.67
North Dakota	-0.00	-0.30	0.19	-154.80	0.14	-216.63
Wyoming	-0.00	-0.22	0.16	-140.01	0.15	-147.47
Alaska	-0.00	-0.17	0.16	-108.85	0.16	-109.03
District of Columbia	-0.00	-0.19	0.18	-107.39	0.18	-105.13
Hawaii	-0.00	-0.26	0.34	-75.27	0.28	-92.48
South Dakota	-0.00	-0.12	0.23	-53.94	0.20	-63.57
Nebraska	-0.00	-0.18	0.47	-37.50	0.43	-41.05
Idaho	-0.00	-0.10	0.49	-21.01	0.43	-23.76
Delaware	-0.00	-0.03	0.28	-10.18	0.30	-9.39
Vermont	-0.00	-0.01	0.20	-4.52	0.21	-4.41
Connecticut	0.00	0.17	0.97	17.36	0.87	19.40
Oklahoma	0.00	0.35	1.86	18.84	1.46	23.92
Utah	0.00	0.11	0.54	21.00	0.53	21.44
West Virginia	0.00	0.19	0.84	22.48	0.86	22.17
Iowa	0.00	0.22	0.95	22.77	0.83	26.26
New Mexico	0.00	0.20	0.70	29.15	0.66	31.00
Virgin Islands	0.00	0.96	2.33	41.12	2.12	45.12
Nevada	0.00	0.33	0.76	43.84	0.73	45.68
Maryland	0.00	0.80	1.80	44.23	1.64	48.49
Washington	0.00	0.98	1.90	51.46	1.89	51.72
New Jersey	0.00	1.15	2.07	55.42	1.96	58.63
Arizona	0.00	1.00	1.77	56.53	1.67	59.97
Rhode Island	0.00	0.19	0.33	57.68	0.36	52.37
Minnesota	0.00	0.81	1.34	60.04	1.30	61.76
Pennsylvania	0.01	3.00	4.24	70.81	4.25	70.70
Montana	0.00	0.21	0.30	70.95	0.33	64.89
Mississippi	0.00	1.14	1.53	74.61	1.53	74.71
Kansas	0.00	0.61	0.81	75.19	0.84	72.78
Maine	0.00	0.35	0.45	77.38	0.52	67.93
Texas	0.02	6.04	7.76	77.78	6.97	86.58
New York	0.02	4.29	5.22	82.13	4.88	87.92
Massachusetts	0.01	1.51	1.82	82.88	1.84	82.19
South Carolina	0.01	1.60	1.88	85.13	1.84	87.13
Arkansas	0.00	1.27	1.45	87.78	1.43	88.81
Kentucky	0.01	1.69	1.91	88.83	2.10	80.52
Oregon	0.00	1.05	1.18	88.84	1.21	86.33
Alabama	0.01	2.01	2.24	89.65	2.29	87.56
Georgia	0.01	3.16	3.45	91.57	3.26	96.94
Indiana	0.01	2.20	2.32	94.83	2.33	94.70
Louisiana	0.01	1.63	1.65	99.05	1.78	91.90
North Carolina	0.01	3.49	3.35	104.16	3.51	99.19
Missouri	0.01	2.49	2.37	104.77	2.46	101.00
Florida	0.03	6.90	6.35	108.70	6.24	110.51
Ohio	0.02	4.18	3.79	110.36	4.01	104.25
Colorado	0.00	1.25	1.06	118.34	1.19	104.85
New Hampshire	0.00	0.49	0.41	119.81	0.45	109.07
California	0.05	11.60	8.31	139.52	8.58	135.21
Michigan	0.02	4.63	3.29	140.90	3.66	126.76
Tennessee	0.01	3.71	2.57	144.37	2.83	130.94
Wisconsin	0.01	2.46	1.62	152.61	1.78	138.87
Illinois	0.02	5.31	3.20	166.06	3.48	152.48
Missing	0.05	11.86	3.71	319.96	3.59	330.12
Puerto Rico	0.02	4.30	0.78	549.93	1.37	314.64

Notes: Table partitions contribution of partial apply to the decrease in SSDI enrollment rates from 2010 to 2019 by different state. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial apply in absolute term. The fourth and sixth columns are the share of applicants in 2010 and 2019. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

Appendix Table D.10: Heterogeneity in SSDI award decrease (2010–19) by state

State	Portion of DI change (pp)	Cont. (%)	Share app. 2019 (%)	Ratio	Share app. 2010 (%)	Ratio
Unknown	-0.00	-0.57	0.11	-510.72	0.10	-598.51
Vermont	-0.00	-0.38	0.20	-188.35	0.21	-183.69
Rhode Island	-0.00	-0.62	0.33	-187.02	0.36	-169.79
Alaska	-0.00	-0.28	0.16	-174.67	0.16	-174.96
Wyoming	-0.00	-0.27	0.16	-172.68	0.15	-181.87
South Dakota	-0.00	-0.34	0.23	-145.02	0.20	-170.90
North Dakota	-0.00	-0.25	0.19	-129.17	0.14	-180.76
Delaware	-0.00	-0.22	0.28	-78.96	0.30	-72.77
Iowa	-0.00	-0.65	0.95	-67.72	0.83	-78.07
District of Columbia	-0.00	-0.11	0.18	-60.42	0.18	-59.15
Nebraska	-0.00	-0.28	0.47	-60.12	0.43	-65.81
New Hampshire	-0.00	-0.21	0.41	-51.15	0.45	-46.56
Missing	-0.00	-1.52	3.71	-40.89	3.59	-42.19
Hawaii	-0.00	-0.07	0.34	-21.26	0.28	-26.12
Wisconsin	-0.00	-0.15	1.62	-9.40	1.78	-8.55
Idaho	0.00	0.02	0.49	3.64	0.43	4.12
Connecticut	0.00	0.19	0.97	19.09	0.87	21.32
New Mexico	0.00	0.25	0.70	35.25	0.66	37.48
Minnesota	0.00	0.52	1.34	38.92	1.30	40.03
Kansas	0.00	0.36	0.81	44.54	0.84	43.11
Louisiana	0.00	0.94	1.65	57.32	1.78	53.18
Montana	0.00	0.20	0.30	66.81	0.33	61.11
Maine	0.00	0.34	0.45	74.15	0.52	65.09
Ohio	0.01	2.88	3.79	76.11	4.01	71.90
Oregon	0.00	0.90	1.18	76.64	1.21	74.48
Oklahoma	0.00	1.44	1.86	77.71	1.46	98.67
Massachusetts	0.00	1.42	1.82	77.99	1.84	77.34
Georgia	0.01	3.04	3.45	88.21	3.26	93.38
Maryland	0.00	1.63	1.80	90.76	1.64	99.50
North Carolina	0.01	3.06	3.35	91.47	3.51	87.10
Missouri	0.00	2.18	2.37	91.85	2.46	88.54
Illinois	0.01	2.98	3.20	93.33	3.48	85.70
Virgin Islands	0.00	2.20	2.33	94.48	2.12	103.69
Mississippi	0.00	1.46	1.53	95.34	1.53	95.46
Florida	0.01	6.07	6.35	95.53	6.24	97.13
Nevada	0.00	0.75	0.76	98.51	0.73	102.66
Michigan	0.01	3.32	3.29	100.85	3.66	90.73
Utah	0.00	0.55	0.54	101.09	0.53	103.20
Pennsylvania	0.01	4.50	4.24	106.17	4.25	106.00
Indiana	0.01	2.56	2.32	110.31	2.33	110.16
Tennessee	0.01	2.87	2.57	111.58	2.83	101.20
South Carolina	0.00	2.22	1.88	117.89	1.84	120.66
Arkansas	0.00	1.78	1.45	123.23	1.43	124.68
Washington	0.00	2.35	1.90	123.97	1.89	124.61
California	0.02	11.26	8.31	135.50	8.58	131.31
Arizona	0.00	2.40	1.77	135.89	1.67	144.14
Colorado	0.00	1.45	1.06	137.44	1.19	121.78
West Virginia	0.00	1.28	0.84	152.13	0.86	150.04
Texas	0.02	12.05	7.76	155.32	6.97	172.88
Kentucky	0.01	3.25	1.91	170.61	2.10	154.65
Alabama	0.01	3.95	2.24	176.37	2.29	172.25
New York	0.02	9.95	5.22	190.45	4.88	203.87
New Jersey	0.01	4.50	2.07	217.23	1.96	229.80
Puerto Rico	0.01	2.81	0.78	359.37	1.37	205.62

Notes: Table partitions contribution of partial award to the decrease in SSDI enrollment rates from 2010 to 2019 by different state. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial award in absolute term. The fourth and sixth columns are the share of applicants in 2010 and 2019. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

Appendix Table D.11: Heterogeneity in SSDI application decrease (2010–19) by population density

Urbanization	Portion of DI change (pp)	Cont. (%)	Share app. 2019 (%)	Ratio	Share app. 2010 (%)	Ratio
Big City	0.32	66.42	66.26	1.00	66.11	1.00
Big City CZ	0.03	6.76	9.82	0.69	9.60	0.70
Small City	0.05	9.86	10.86	0.91	11.19	0.88
Rural Area	0.04	7.98	8.68	0.92	9.05	0.88
Other	-0.00	-0.68	0.67	-1.02	0.45	-1.51
Missing	0.05	9.66	3.71	2.61	3.59	2.69

Notes: Table partitions contribution of partial apply to the decrease in SSDI enrollment rates from 2010 to 2019 by different urbanization. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial apply in absolute term. The fourth and sixth columns are the share of applicants in 2010 and 2019. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

Appendix Table D.12: Heterogeneity in SSDI award decrease (2010–19) by population density

Urbanization	Portion of DI change (pp)	Cont. (%)	Share app. 2019 (%)	Ratio	Share app. 2010 (%)	Ratio
Big City	0.19	70.65	66.26	1.07	66.11	1.07
Big City CZ	0.03	10.19	9.82	1.04	9.60	1.06
Small City	0.03	11.14	10.86	1.03	11.19	1.00
Rural Area	0.03	9.65	8.68	1.11	9.05	1.07
Other	-0.00	-0.56	0.67	-0.84	0.45	-1.24
Missing	-0.00	-1.08	3.71	-0.29	3.59	-0.30

Notes: Table partitions contribution of partial award to the decrease in SSDI enrollment rates from 2010 to 2019 by different urbanization. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial award in absolute term. The fourth and sixth columns are the share of applicants in 2010 and 2019. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

Appendix Table D.13: Heterogeneity in SSDI application decrease (2010–19) by 2008 ALJ award rate

AFJ reform	Portion of DI change (pp)	Cont. (%)	Share app. 2019 (%)	Ratio	Share app. 2010 (%)	Ratio
Less affected	0.35	71.68	80.90	0.89	79.93	0.90
More affected	0.06	13.27	12.36	1.07	12.71	1.04
Other	0.03	5.52	3.04	1.82	3.77	1.46
Missing	0.05	9.52	3.71	2.57	3.59	2.65

Notes: Table partitions contribution of partial apply to the decrease in SSDI enrollment rates from 2010 to 2019 by different ALJ award rate. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial apply in absolute term. The fourth and sixth columns are the share of applicants in 2010 and 2019. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

Appendix Table D.14: Heterogeneity in SSDI award decrease (2010–19) by 2008 ALJ award rate

AFJ reform	Portion of DI change (pp)	Cont. (%)	Share app. 2019 (%)	Ratio	Share app. 2010 (%)	Ratio
Less affected	0.22	79.69	80.90	0.99	79.93	1.00
More affected	0.04	16.30	12.36	1.32	12.71	1.28
Other	0.01	5.08	3.04	1.67	3.77	1.35
Missing	-0.00	-1.07	3.71	-0.29	3.59	-0.30

Notes: Table partitions contribution of partial award to the decrease in SSDI enrollment rates from 2010 to 2019 by different ALJ award rate. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial award in absolute term. The fourth and sixth columns are the share of applicants in 2010 and 2019. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

Appendix Table D.15: Heterogeneity in SSDI application decrease (2010–19) by 2010–16 opioid death rate

Opioid crisis	Portion of DI change (pp)	Cont. (%)	Share app. 2019 (%)	Ratio	Share app. 2010 (%)	Ratio
Less affected	0.31	64.66	69.35	0.93	68.50	0.94
More affected	0.04	8.04	8.15	0.99	8.58	0.94
Other	0.09	17.76	18.79	0.95	19.32	0.92
Missing	0.05	9.54	3.71	2.57	3.59	2.66

Notes: Table partitions contribution of partial apply to the decrease in SSDI enrollment rates from 2010 to 2019 by opioid death rate. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial apply in absolute term. The fourth and sixth columns are the share of applicants in 2010 and 2019. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

Appendix Table D.16: Heterogeneity in SSDI award decrease (2010–19) by 2010–16 opioid death rate

Opioid crisis	Portion of DI change (pp)	Cont. (%)	Share app. 2019 (%)	Ratio	Share app. 2010 (%)	Ratio
Less affected	0.19	69.75	69.35	1.01	68.50	1.02
More affected	0.02	8.67	8.15	1.06	8.58	1.01
Other	0.06	22.64	18.79	1.20	19.32	1.17
Missing	-0.00	-1.06	3.71	-0.29	3.59	-0.30

Notes: Table partitions contribution of partial award to the decrease in SSDI enrollment rates from 2010 to 2019 by opioid death rate. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial award in absolute term. The fourth and sixth columns are the share of applicants in 2010 and 2019. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

Appendix Table D.17: Heterogeneity in SSDI application decrease (2010–19) by 2017 unemployment rate

Unemployment rate in 2017	Portion of DI change (pp)	Cont. (%)	Share app. 2019 (%)	Ratio	Share app. 2010 (%)	Ratio
Low	0.13	27.75	28.30	0.98	28.05	0.99
Mid	0.24	50.33	55.33	0.91	54.99	0.92
High	0.03	7.14	10.09	0.71	10.09	0.71
Unknown	0.03	5.20	2.58	2.02	3.27	1.59
Missing	0.05	9.57	3.71	2.58	3.59	2.66

Notes: Table partitions contribution of partial apply to the decrease in SSDI enrollment rates from 2010 to 2019 by 2017 unemployment rate levels. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial apply in absolute term. The fourth and sixth columns are the share of applicants in 2010 and 2019. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

Appendix Table D.18: Heterogeneity in SSDI award decrease (2010–19) by 2017 unemployment rate

Unemployment rate in 2017	Portion of DI change (pp)	Cont. (%)	Share app. 2019 (%)	Ratio	Share app. 2010 (%)	Ratio
Low	0.07	27.31	28.30	0.97	28.05	0.97
Mid	0.16	58.40	55.33	1.06	54.99	1.06
High	0.03	10.97	10.09	1.09	10.09	1.09
Unknown	0.01	4.40	2.58	1.71	3.27	1.34
Missing	-0.00	-1.08	3.71	-0.29	3.59	-0.30

Notes: Table partitions contribution of partial award to the decrease in SSDI enrollment rates from 2010 to 2019 by 2017 unemployment rate levels. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial award in absolute term. The fourth and sixth columns are the share of applicants in 2010 and 2019. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

Appendix Table D.19: Heterogeneity in SSDI application decrease (2010–19) by 2010–16 change in unemployment rate

Unemployment change since GR	Portion of DI change (pp)	Cont. (%)	Share app. 2019 (%)	Ratio	Share app. 2010 (%)	Ratio
Large drop in UE rate after GR	0.13	26.09	23.63	1.10	24.62	1.06
Moderate drop in UE rate after GR	0.18	37.23	36.20	1.03	37.03	1.01
Some drop in UE rate after GR	0.09	19.14	28.57	0.67	26.62	0.72
Small drop in UE rate after GR	0.01	2.68	5.31	0.51	4.87	0.55
Other	0.03	5.23	2.58	2.03	3.27	1.60
Missing	0.05	9.63	3.71	2.60	3.59	2.68

Notes: Table partitions contribution of partial apply to the decrease in SSDI enrollment rates from 2010 to 2019 by change in unemployment rate levels. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial apply in absolute term. The fourth and sixth columns are the share of applicants in 2010 and 2019. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

Appendix Table D.20: Heterogeneity in SSDI award decrease (2010–19) by 2010–16 change in unemploymen rate

Unemployment change since GR	Portion of DI change (pp)	Cont. (%)	Share app. 2019 (%)	Ratio	Share app. 2010 (%)	Ratio
Large drop in UE rate after GR	0.06	23.71	23.63	1.00	24.62	0.96
Moderate drop in UE rate after GR	0.10	37.92	36.20	1.05	37.03	1.02
Some drop in UE rate after GR	0.08	30.56	28.57	1.07	26.62	1.15
Small drop in UE rate after GR	0.01	4.50	5.31	0.85	4.87	0.93
Other	0.01	4.37	2.58	1.70	3.27	1.34
Missing	-0.00	-1.08	3.71	-0.29	3.59	-0.30

Notes: Table partitions contribution of partial award to the decrease in SSDI enrollment rates from 2010 to 2019 by change in unemployment rate levels. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial award in absolute term. The fourth and sixth columns are the share of applicants in 2010 and 2019. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

Appendix Table D.21: Heterogeneity in SSDI application decrease (2010–19) by 2017 minimum wage

Minimum wage in 2017	Portion of DI change (pp)	Cont. (%)	Share app. 2019 (%)	Ratio	Share app. 2010 (%)	Ratio
Federal	0.14	29.43	34.59	0.85	34.19	0.86
Low	0.06	12.50	12.49	1.00	12.77	0.98
Some	0.07	15.28	17.85	0.86	17.58	0.87
High	0.07	14.15	12.46	1.14	12.83	1.10
Unknown	0.09	18.97	18.90	1.00	19.03	1.00
Missing	0.05	9.67	3.71	2.61	3.59	2.69

Notes: Table partitions contribution of partial apply to the decrease in SSDI enrollment rates from 2010 to 2019 by 2017 minimum wage levels. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial apply in absolute term. The fourth and sixth columns are the share of applicants in 2010 and 2019. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

Appendix Table D.22: Heterogeneity in SSDI award decrease (2010–19) by 2017 minimum wage

Minimum wage in 2017	Portion of DI change (pp)	Cont. (%)	Share app. 2019 (%)	Ratio	Share app. 2010 (%)	Ratio
Federal	0.09	34.56	34.59	1.00	34.19	1.01
Low	0.03	10.92	12.49	0.87	12.77	0.85
Some	0.06	21.72	17.85	1.22	17.58	1.24
High	0.03	12.04	12.46	0.97	12.83	0.94
Unknown	0.06	21.83	18.90	1.15	19.03	1.15
Missing	-0.00	-1.07	3.71	-0.29	3.59	-0.30

Notes: Table partitions contribution of partial award to the decrease in SSDI enrollment rates from 2010 to 2019 by 2017 minimum wage levels. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial award in absolute term. The fourth and sixth columns are the share of applicants in 2010 and 2019. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

Appendix Table D.23: Heterogeneity in SSDI application decrease (2010–19) by 2010–16 change in minimum wage

Minimum wage change since GR	Portion of DI change (pp)	Cont. (%)	Share app. 2019 (%)	Ratio	Share app. 2010 (%)	Ratio
No increase	0.14	30.14	35.22	0.86	34.81	0.87
Low increase	0.08	16.44	16.50	1.00	16.83	0.98
Some increase	0.09	19.72	21.94	0.90	21.74	0.91
Large increase	0.02	5.04	3.73	1.35	4.00	1.26
Unknown	0.09	18.98	18.90	1.00	19.03	1.00
Missing	0.05	9.68	3.71	2.61	3.59	2.69

Notes: Table partitions contribution of partial apply to the decrease in SSDI enrollment rates from 2010 to 2019 by change in minimum wage levels. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial apply in absolute term. The fourth and sixth columns are the share of applicants in 2010 and 2019. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

Appendix Table D.24: Heterogeneity in SSDI award decrease (2010–19) by 2010–16 change in minimum wage

Minimum wage change since GR	Portion of DI change (pp)	Cont. (%)	Share app. 2019 (%)	Ratio	Share app. 2010 (%)	Ratio
No increase	0.10	35.42	35.22	1.01	34.81	1.02
Low increase	0.04	15.96	16.50	0.97	16.83	0.95
Some increase	0.07	25.63	21.94	1.17	21.74	1.18
Large increase	0.01	2.32	3.73	0.62	4.00	0.58
Unknown	0.06	21.74	18.90	1.15	19.03	1.14
Missing	-0.00	-1.07	3.71	-0.29	3.59	-0.30

Notes: Table partitions contribution of partial award to the decrease in SSDI enrollment rates from 2010 to 2019 by change in minimum wage levels. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial award in absolute term. The fourth and sixth columns are the share of applicants in 2010 and 2019. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

D.4 Employment and earning history

Appendix Table D.25: Heterogeneity in SSDI application decrease (2010–19) by pre-application employment

Earning history	Portion of DI change (pp)	Cont. (%)	Share app. 2019 (%)	Ratio	Share app. 2010 (%)	Ratio
No earning	-0.00	-0.47	5.87	-0.08	4.14	-0.11
Some earning	0.04	8.52	16.71	0.51	17.59	0.48
Steady earning	0.43	83.05	73.71	1.13	74.69	1.11
Missing	0.05	8.89	3.71	2.40	3.59	2.47

Notes: Table partitions contribution of partial apply to the decrease in SSDI enrollment rates from 2010 to 2019 by pre-application employment levels. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial apply in absolute term. The fourth and sixth columns are the share of applicants in 2010 and 2019. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

Appendix Table D.26: Heterogeneity in SSDI award decrease (2010–19) by pre-application employment

Earning history	Portion of DI change (pp)	Cont. (%)	Share app. 2019 (%)	Ratio	Share app. 2010 (%)	Ratio
No earning	0.01	4.96	5.87	0.84	4.14	1.20
Some earning	0.05	22.09	16.71	1.32	17.59	1.26
Steady earning	0.18	74.14	73.71	1.01	74.69	0.99
Missing	-0.00	-1.18	3.71	-0.32	3.59	-0.33

Notes: Table partitions contribution of partial award to the decrease in SSDI enrollment rates from 2010 to 2019 by pre-application full-time-full-year earnings levels. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial award in absolute term. The fourth and sixth columns are the share of applicants in 2010 and 2019. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

Appendix Table D.27: Heterogeneity in SSDI application decrease (2010–19) by pre-application full-time-full-year earnings

Employment history	Portion of DI change (pp)	Cont. (%)	Share app. 2019 (%)	Ratio	Share app. 2010 (%)	Ratio
Low stability	0.08	15.90	17.42	0.91	20.63	0.77
Middle stability	0.14	30.10	29.68	1.01	32.79	0.92
High stability	0.21	44.34	49.19	0.90	42.98	1.03
Missing	0.05	9.66	3.71	2.61	3.59	2.69

Notes: Table partitions contribution of partial apply to the decrease in SSDI enrollment rates from 2010 to 2019 by pre-application full-time-full-year earnings levels. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial apply in absolute term. The fourth and sixth columns are the share of applicants in 2010 and 2019. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

Appendix Table D.28: Heterogeneity in SSDI award decrease (2010–19) by pre-application full-time-full-year earnings

Employment history	Portion of DI change (pp)	Cont. (%)	Share app. 2019 (%)	Ratio	Share app. 2010 (%)	Ratio
Low stability	0.06	22.75	17.42	1.31	20.63	1.10
Middle stability	0.10	36.63	29.68	1.23	32.79	1.12
High stability	0.12	41.66	49.19	0.85	42.98	0.97
Missing	-0.00	-1.04	3.71	-0.28	3.59	-0.29

Notes: Table partitions contribution of partial award to the decrease in SSDI enrollment rates from 2010 to 2019 by pre-application full-time-full-year earnings. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial award in absolute term. The fourth and sixth columns are the share of applicants in 2010 and 2019. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

Appendix Table D.29: Heterogeneity in SSDI application decrease (2010–19) by pre-application earnings stability

Firm stability	Portion of DI change (pp)	Cont. (%)	Share app. 2019 (%)	Ratio	Share app. 2010 (%)	Ratio
Non stability	0.09	18.43	18.88	0.98	21.24	0.87
Mid stability	0.17	33.47	26.60	1.26	28.19	1.19
High stability	0.20	39.53	41.02	0.96	38.92	1.02
Unemployed	-0.00	-0.42	5.31	-0.08	3.71	-0.11
Employed, no etin	-0.00	-0.22	4.48	-0.05	4.34	-0.05
Missing	0.05	9.20	3.71	2.48	3.59	2.56

Notes: Table partitions contribution of partial apply to the decrease in SSDI enrollment rates from 2010 to 2019 by pre-application earnings stability. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial apply in absolute term. The fourth and sixth columns are the share of applicants in 2010 and 2019. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

Appendix Table D.30: Heterogeneity in SSDI award decrease (2010–19) by pre-application earnings stability

Firm stability	Portion of DI change (pp)	Cont. (%)	Share app. 2019 (%)	Ratio	Share app. 2010 (%)	Ratio
Non stability	0.06	25.04	18.88	1.33	21.24	1.18
Mid stability	0.08	30.57	26.60	1.15	28.19	1.08
High stability	0.09	36.57	41.02	0.89	38.92	0.94
Unemployed	0.01	4.32	5.31	0.81	3.71	1.16
Employed, no etin	0.01	4.67	4.48	1.04	4.34	1.08
Missing	-0.00	-1.17	3.71	-0.32	3.59	-0.33

Notes: Table partitions contribution of partial award to the decrease in SSDI enrollment rates from 2010 to 2019 by pre-application earnings stability. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial award in absolute term. The fourth and sixth columns are the share of applicants in 2010 and 2019. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

Appendix Table D.31: Heterogeneity in SSDI application decrease (2010–19) by pre-application industry stability

Industrial history	Portion of DI change (pp)	Cont. (%)	Share app. 2019 (%)	Ratio	Share app. 2010 (%)	Ratio
Low stability	0.08	16.63	18.20	0.91	18.84	0.88
Mid stability	0.08	16.80	14.07	1.19	14.62	1.15
High stability	0.12	23.13	23.32	0.99	21.97	1.05
Unemployed	-0.00	-0.45	5.65	-0.08	4.00	-0.11
Employed, indus NA	0.17	34.62	35.05	0.99	36.97	0.94
Missing	0.05	9.26	3.71	2.50	3.59	2.58

Notes: Table partitions contribution of partial apply to the decrease in SSDI enrollment rates from 2010 to 2019 by pre-application industry stability. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial apply in absolute term. The fourth and sixth columns are the share of applicants in 2010 and 2019. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

Appendix Table D.32: Heterogeneity in SSDI award decrease (2010–19) by pre-application industry stability

Industrial history	Portion of DI change (pp)	Cont. (%)	Share app. 2019 (%)	Ratio	Share app. 2010 (%)	Ratio
Low stability	0.06	22.55	18.20	1.24	18.84	1.20
Mid stability	0.04	15.38	14.07	1.09	14.62	1.05
High stability	0.05	19.05	23.32	0.82	21.97	0.87
Unemployed	0.01	4.60	5.65	0.81	4.00	1.15
Employed, indus NA	0.10	39.55	35.05	1.13	36.97	1.07
Missing	-0.00	-1.14	3.71	-0.31	3.59	-0.32

Notes: Table partitions contribution of partial award to the decrease in SSDI enrollment rates from 2010 to 2019 by pre-application industry stability. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial award in absolute term. The fourth and sixth columns are the share of applicants in 2010 and 2019. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

D.5 Industry characteristics

Appendix Table D.33: Heterogeneity in SSDI application decrease (2010–19) by pre-application industry

Recent Industry	Portion of DI change (pp)	Cont. (%)	Share app. 2019 (%)	Ratio	Share app. 2010 (%)	Ratio
Military	-0.00	-0.23	0.69	-0.33	0.81	-0.28
Agriculture	0.05	10.42	6.24	1.67	7.35	1.42
Manufacture	0.06	12.79	6.93	1.85	7.80	1.64
Retail	0.05	9.57	11.23	0.85	10.19	0.94
Management	0.04	8.71	11.84	0.74	11.09	0.79
Other service	0.07	14.91	18.67	0.80	18.19	0.82
Unemployed	-0.00	-0.45	5.65	-0.08	4.00	-0.11
Employed, indus NA	0.17	34.92	35.05	1.00	36.97	0.94
Missing	0.05	9.34	3.71	2.52	3.59	2.60

Notes: Table partitions contribution of partial apply to the decrease in SSDI enrollment rates from 2010 to 2019 by pre-application industry. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial apply in absolute term. The fourth and sixth columns are the share of applicants in 2010 and 2019. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

Appendix Table D.34: Heterogeneity in SSDI award decrease (2010–19) by pre-application industry

Recent Industry	Portion of DI change (pp)	Cont. (%)	Share app. 2019 (%)	Ratio	Share app. 2010 (%)	Ratio
Military	0.00	1.64	0.69	2.37	0.81	2.02
Agriculture	0.01	5.43	6.24	0.87	7.35	0.74
Manufacture	0.01	5.93	6.93	0.86	7.80	0.76
Retail	0.03	10.41	11.23	0.93	10.19	1.02
Management	0.03	13.38	11.84	1.13	11.09	1.21
Other service	0.05	18.67	18.67	1.00	18.19	1.03
Unemployed	0.01	4.76	5.65	0.84	4.00	1.19
Employed, indus NA	0.10	40.96	35.05	1.17	36.97	1.11
Missing	-0.00	-1.18	3.71	-0.32	3.59	-0.33

Notes: Table partitions contribution of partial award to the decrease in SSDI enrollment rates from 2010 to 2019 by pre-application industry. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial award in absolute term. The fourth and sixth columns are the share of applicants in 2010 and 2019. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

Appendix Table D.35: Heterogeneity in SSDI application decrease (2010–19) by pre-application China shock exposure

Industrial China-shock	Portion of DI change (pp)	Cont. (%)	Share app. 2019 (%)	Ratio	Share app. 2010 (%)	Ratio
No	0.00	0.40	0.40	0.99	0.55	0.73
Yes	-0.00	-0.08	0.12	-0.66	0.16	-0.50
Other industry	0.28	58.70	55.07	1.07	54.72	1.07
Unemployed or Industry Unknown	0.15	31.40	40.70	0.77	40.97	0.77
Missing	0.05	9.58	3.71	2.58	3.59	2.67

Notes: Table partitions contribution of partial apply to the decrease in SSDI enrollment rates from 2010 to 2019 by pre-application China shock exposure. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial apply in absolute term. The fourth and sixth columns are the share of applicants in 2010 and 2019. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

Appendix Table D.36: Heterogeneity in SSDI award decrease (2010–19) by pre-application China shock exposure

Industrial China-shock	Portion of DI change (pp)	Cont. (%)	Share app. 2019 (%)	Ratio	Share app. 2010 (%)	Ratio
No	-0.00	-0.01	0.40	-0.03	0.55	-0.02
Yes	-0.00	-0.39	0.12	-3.17	0.16	-2.39
Other industry	0.14	53.38	55.07	0.97	54.72	0.98
Unemployed or Industry Unknown	0.13	48.09	40.70	1.18	40.97	1.17
Missing	-0.00	-1.07	3.71	-0.29	3.59	-0.30

Notes: Table partitions contribution of partial award to the decrease in SSDI enrollment rates from 2010 to 2019 by pre-application China shock exposure. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial award in absolute term. The fourth and sixth columns are the share of applicants in 2010 and 2019. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

Appendix Table D.37: Heterogeneity in SSDI application decrease (2010–19) by pre-application remote work exposure

Industial WFH ability	Portion of DI change (pp)	Cont. (%)	Share app. 2019 (%)	Ratio	Share app. 2010 (%)	Ratio
Low WFH	0.01	2.97	3.88	0.77	3.70	0.80
Some WFH	0.11	21.42	14.37	1.49	15.51	1.38
Mid WFH	0.06	11.98	13.37	0.90	13.31	0.90
High WFH	0.10	19.51	22.87	0.85	21.69	0.90
Employed, unknown WFH	0.18	35.33	36.14	0.98	38.20	0.93
Unemployed	-0.00	-0.45	5.66	-0.08	4.00	-0.11
Missing	0.05	9.23	3.71	2.49	3.59	2.57

Notes: Table partitions contribution of partial apply to the decrease in SSDI enrollment rates from 2010 to 2019 by pre-application remote work exposure. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial apply in absolute term. The fourth and sixth columns are the share of applicants in 2010 and 2019. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

Appendix Table D.38: Heterogeneity in SSDI award decrease (2010–19) by pre-application remote work exposure

Industial WFH ability	Portion of DI change (pp)	Cont. (%)	Share app. 2019 (%)	Ratio	Share app. 2010 (%)	Ratio
Low WFH	0.01	2.93	3.88	0.76	3.70	0.79
Some WFH	0.03	12.22	14.37	0.85	15.51	0.79
Mid WFH	0.04	14.41	13.37	1.08	13.31	1.08
High WFH	0.06	24.07	22.87	1.05	21.69	1.11
Employed, unknown WFH	0.11	42.86	36.14	1.19	38.20	1.12
Unemployed	0.01	4.67	5.66	0.83	4.00	1.17
Missing	-0.00	-1.16	3.71	-0.31	3.59	-0.32

Notes: Table partitions contribution of partial award to the decrease in SSDI enrollment rates from 2010 to 2019 by pre-application remote work exposure. The second column presents the actual change the group contributes to the increase. The third column calculates the share the group contributes among all partial award in absolute term. The fourth and sixth columns are the share of applicants in 2010 and 2019. The fifth and seventh columns present the ratio of the third column to the fourth and sixth columns to allow comparison across groups of different sizes.

E Details of empirical analysis for application model

E.1 PIA, potential earnings, and replacement rates

We calculate average indexed monthly earnings (AIME) and the primary insurance amount (PIA) among SSDI-eligible workers by birth cohort over time, shown in Appendix Figure F.1. The PIA converts the AIME into an SSDI benefit amount using a progressive replacement rate. While the AIME has decreased to some extent among more recent cohorts due to the Great Recession, the PIA is about the same due to the progressive replacement rate.

E.2 Social Security field office closings

We obtain data from Deshpande and Li (2019). For each office closure, we estimate a decline of 157.408 in annual applications and 298.188 in annual awards. We use Figure 1 in Deshpande and Li (2019) to determine the number of office closures. Assuming these effects persist—meaning an office closure in a given year results in a sustained decline in all subsequent years. This allows us to calculate the counterfactual applications and awards without any office closing. Comparing the actual applications (or awards), the counterfactual applications (or awards) and the applications (or awards) in 2010, we can calculate the contribution of field office closures to the decline in applications and awards between 2010 and 2019. We find that 3-6% of decline in applications and 8-17% of decline in awards can be explained by field office closing[17].

E.3 Decline in appeals award rates

We seek to estimate the effect of award rates on applications and determine how much of the decline in SSDI applications from 2010–2019 can be explained by reductions in award rates.

We take advantage of a 2010 reform that reduced award rates at the appeals level through new training and guidelines for administrative law judges. We use geographic variation in baseline appeals allowance rates (i.e., likelihood of allowance conditional on being rejected at the initial level) to estimate the effect of a change in award rates on applications. We show that areas that had higher baseline appeals allowance rates experienced a larger decrease in both the appeals allowance rate and the overall allowance rate. We then use this strategy to estimate the effect of the reform on SSDI applications in future years.

[17]The difference in estimates depends on the assumptions on persistence.

The baseline reduced form specification is a difference-in-differences specification:

$$Y_{it} = \alpha_i + \gamma_t + \beta(\text{BaseAppealAllow}_i \times \text{PostReform}_t) + \delta X_{it} + \epsilon_{it} \tag{26}$$

where Y_{it} is an outcome like appeals award rate (first stage) or future applications (reduced form) for county i in year t; BaseAppealAllow_i is the baseline appeals allowance rate (share of applications rejected at the initial level that are allowed on appeal in the three years prior to the reform); PostReform_t is an indicator for a year after the reform (2008); α_i are county fixed effects; γ_t are year fixed effects; and X_{it} are time-varying characteristics of counties (e.g., unemployment rate). We weight counties by the number of applications in the three years prior to reform.

We measure the number of SSDI applications in a county-year using the F831 file, which includes ZIP code. We link ZIP codes to counties. To construct baseline appeals allowance rates (and overall allowance rates), we link the F831 file to payment data from the PHUS. We find that the ALJ reform reduced appeals allowance rates by 40–50 pp more for (hypothetical) places with a 100% baseline allowance rate relative to places with a 0% baseline allowance rate over the next 7 years, and overall allowance rates by 20–30 pp more. However, applications do not decline substantially over this time.

Using these estimates, we first determine the *actual* decline in overall allowance rates during this time from Hoynes Maestas Strand (2024). We multiply this decline by our estimate of the elasticity of application rates to allowance rates to get the decline in DI application resulting from the decline in allowance rates over this period.

E.4 Pollution abatement

We estimate the effect of local pollution on DI claims using variation from the Clean Air Act. To do this, we must first construct a crosswalk between the Social Security Administration's place of birth dat and counties, as pollution data is measured at the county level. This is a challenge because place of birth information in the registry data (a "city of birth" and a "state of birth") is hand-coded and recorded at varying levels of geographic granularity. Our strategy for constructing the crosswalk is based on Isen et al. (2017).

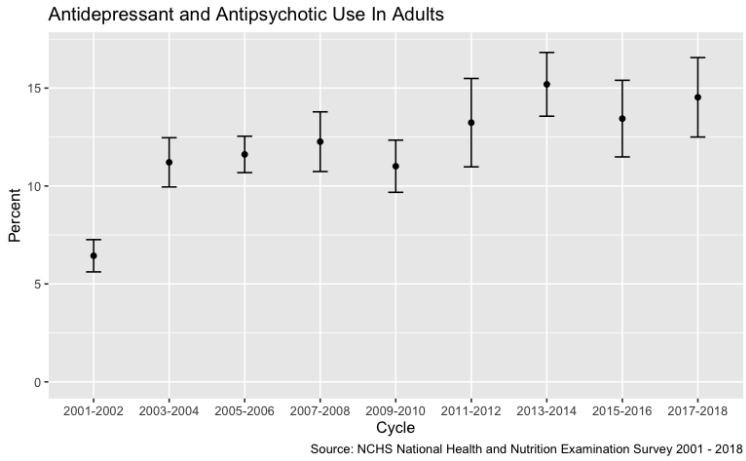
We construct a list of known geographic units that are linked to counties by stacking four databases: the Census Bureau's database of Census 1) places, 2) counties, and 3) minor civil divisions, as well as 4) the United States Geological Survey's Geographic Names Information System file. Each of these files provides a list of strings identifying local geographic units and the counties to which they belong. We then merge county information into the registry data using the following two procedure:

First, we exactly match individual city and state of birth in the registry file as-is to the constructed county information file. Second, we extract the first word from an individual's place of birth and match this to the first word of location names in the county file, keeping any successful matches which identify a unique county within the state.

This procedure is based on the matching procedure used by Isen et al. (2017), though Isen et al. (2017) undergo several additional steps to identify county of birth for as many individuals as possible. While the procedure we use is simple, Isen et al. (2017) find that it is ultimately responsible for 89 percent of their successful matches.

For the individuals with successful matches on place of birth, we then assign Clean Air Act non-attainment status at the county-level using classifications from Isen et al. (2017). We check if the decline in applications is disproportionately concentrated among individuals born in non-attainment counties, in which Clean Air Act regulations imposed improvements in air quality over time. We report our results in Appendix Figure C.2, finding these counties are not unique drivers of DI application declines.

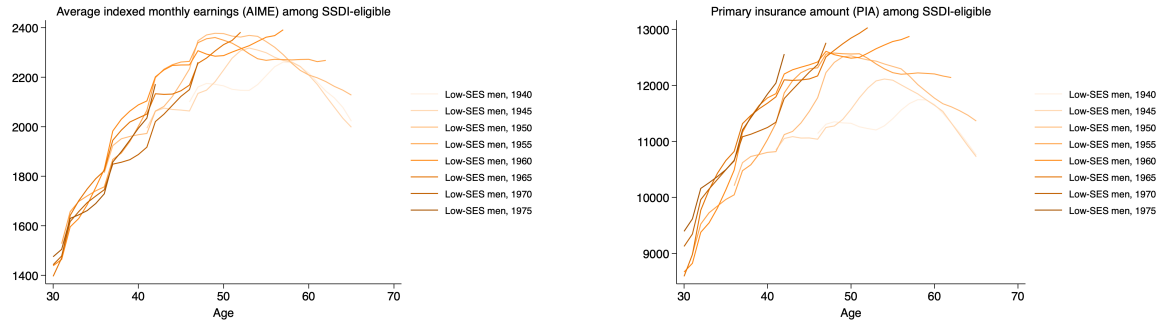
E.5 Mental health treatment



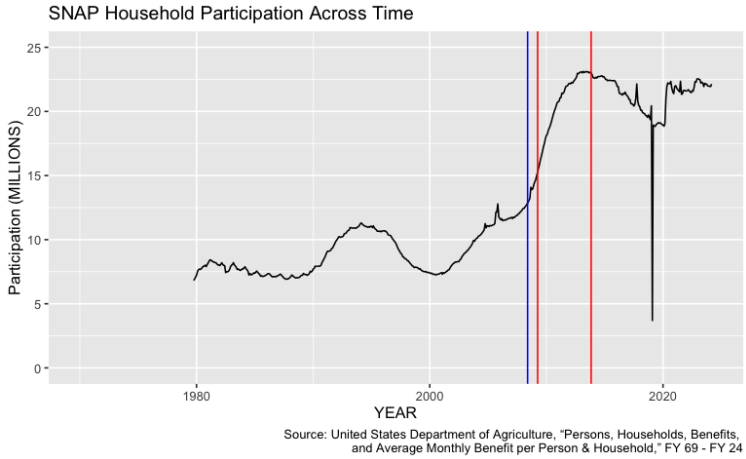
Appendix Figure E.1: Changes in use of antidepressants and antipsychotics

F Appendix Figures and Tables

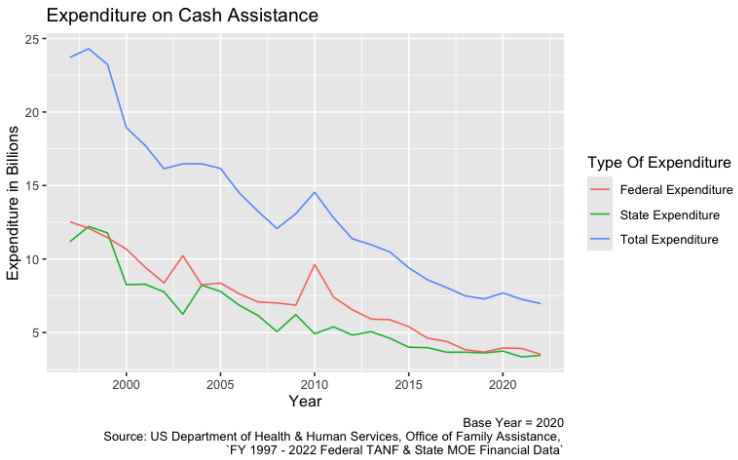
Appendix Figure F.1: Average indexed monthly earnings (AIME) and primary insurance amount (PIA) for low-skilled men across birth cohorts



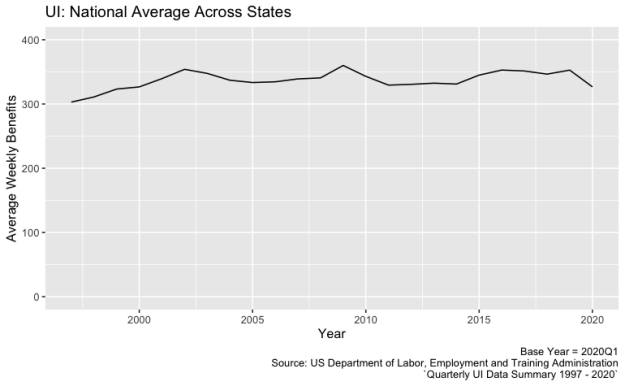
Notes: Figure plots CPI-adjusted average indexed monthly earnings and CPI-adjusted primary insurance amount by birth cohort and age for SSDI-eligible low-skilled men. Younger cohorts have darker shading. The sample is derived from the Continuous Work History Sample linked to the Numident and Master Earnings File.



Appendix Figure F.2: SNAP program participation by household, in millions



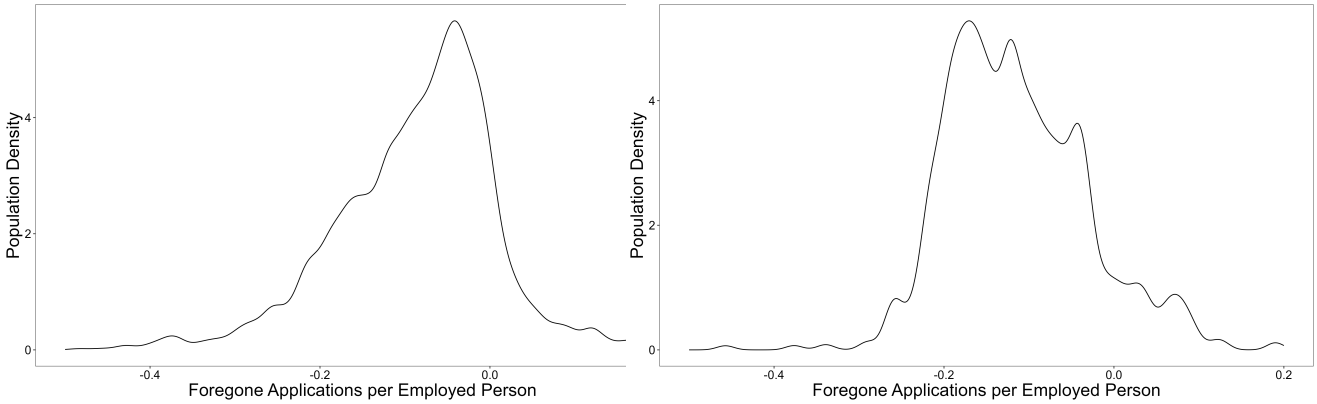
Appendix Figure F.3: TANF Expenditures by Federal and State Government, adjusted for inflation



Appendix Figure F.4: UI Expenditure Averaged Across States, adjusted for inflation

	All Adults			Older, Low SES Men		
		Health Limitation			Health Limitation	
Year	Smokes	Musculoskeletal	Mental	Smokes	Musculoskeletal	Mental
2002	0.119	0.009	0.017	0.146	0.012	0.025
2003	0.113	0.008	0.016	0.137	0.009	0.022
2004	0.108	0.009	0.014	0.139	0.016	0.020
2005	0.103	0.009	0.015	0.138	0.016	0.024
2006	0.104	0.009	0.016	0.146	0.012	0.026
2007	0.096	0.010	0.017	0.128	0.019	0.026
2008	0.094	0.011	0.018	0.133	0.019	0.027
2009	0.101	0.012	0.019	0.138	0.022	0.025
2010	0.091	0.012	0.018	0.128	0.019	0.025
2011	0.096	0.013	0.021	0.148	0.022	0.033
2012	0.088	0.012	0.020	0.122	0.017	0.031
2013	0.087	0.013	0.021	0.134	0.023	0.031
2014	0.080	0.013	0.020	0.116	0.025	0.028
2015	0.073	0.013	0.021	0.108	0.025	0.027
2016	0.074	0.014	0.023	0.115	0.025	0.031
2017	0.068	0.014	0.025	0.109	0.028	0.037
2018	0.068	0.014	0.023	0.121	0.030	0.032

Appendix Table F.1: Population Health Trends from the National Health Interview Survey



(a) Overall Population (b) Older low-to-mid-SES men

Appendix Figure F.5: Density of Implied Annual Sensitivities of Application Rates to Employment Rates, Year and by Demographic Group

Notes: This graph plots the population-weighted density of the sensitivity of applications to employment (the density of $\Lambda_{g,t}$ as defined in equation (25)). The sensitivity describes the decline in applications per worker by which employment rate increases relative to 2010 would entirely explain application rate decreases relative to 2010. Cells that did not experience a decline in applications (15 percent by population weight) have been omitted.