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EXPLAINING THE HISTORICAL RISE AND RECENT DECLINE IN SOCIAL SECURITY DISABILITY INSURANCE ENROLLMENT

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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 use detailed administrative data to quantify the contributions of various factors to trends in SSDI enrollment, focusing especially on the decline in the 2010s. A statistical decomposition suggests that the vast majority of the decline in SSDI enrollment since 2013 is attributable to declines in application rates—and, to a lesser extent, award rates—within demographic groups. There is very little contribution from changes over time in demographic characteristics, eligibility, or exit from SSDI. The decline in SSDI enrollment rates is disproportionately driven by low-to-middle-skilled men who, over time, have become less likely to apply for SSDI and more likely to work. Consistent with this descriptive evidence, we present results from a causal analysis suggesting that improved labor market opportunity for less-skilled men is a key explanation for the decline in SSDI enrollment. We also investigate several other popular hypotheses for the decline in SSDI applications, including lower award rates at the appeals level, and find evidence at odds with them.

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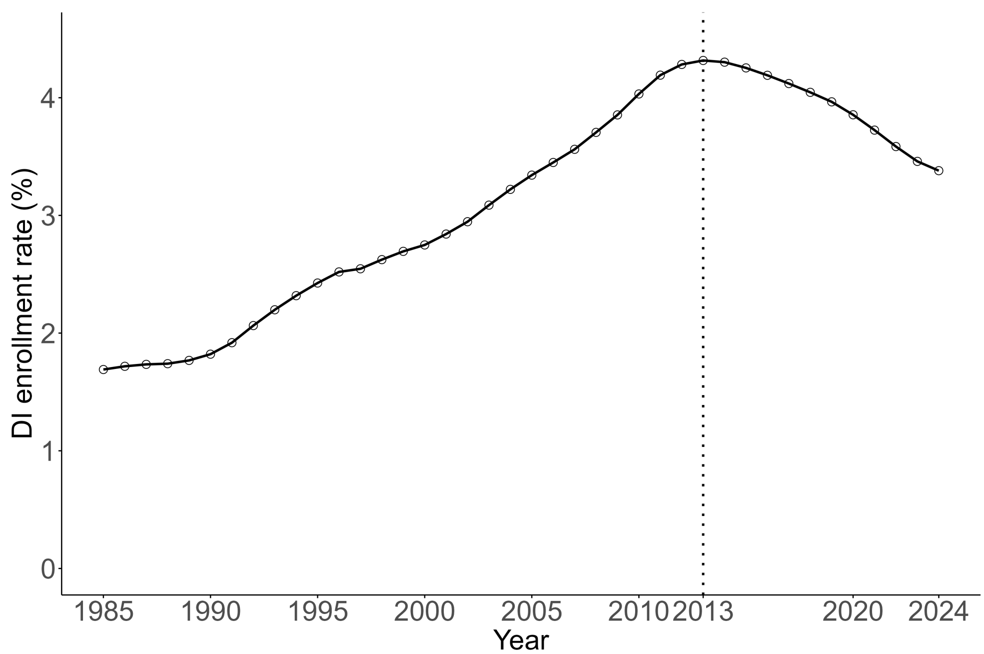
The growth of the U.S. Social Security Disability Insurance (SSDI) program in the 1990s and 2000s gained widespread attention from policymakers, researchers, and the public, fueling concerns about an impending fiscal crisis and about misaligned incentives for Americans who are potentially capable of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

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) and Social Security Administration (2023). See `https://www.ssa.gov/oact/HistEst/Population/2023/Population2023.html`.

Less attention has been paid to the fact that enrollment in the SSDI program has been declining since 2013, 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 are likely related to policy reforms that were intended to reduce 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.

Several explanations for the decline have been suggested. Perhaps the leading hypothesis is that the retraining of administrative law judges reduced award rates (Hoynes, Maestas and

Strand, 2024) may have additionally discouraged potential applicants from applying (Ruffing, 2020).[1] Another policy-related explanation is a higher burden of applying, potentially from field office closings or other administrative changes.[2] Other explanations relate to economic and demographic changes in the 2010s: population aging, which could have increased exits from SSDI through retirement and death; lower labor force participation among men, which could have reduced financial eligibility for SSDI; a shift to less physically demanding jobs, which could have improved population health; economic recovery following the Great Recession, which could have increased work opportunities for people with disabilities; and more access to other benefit programs, which could have served as substitutes for SSDI. 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 have mechanically kept SSDI recipients on SSDI longer; increases in earnings inequality, which could have increased demand for support programs; and population aging and the opioid crisis, which could have increased disability incidence.[3]

In this paper, we use 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. In Section 2, we develop a statistical decomposition method to quantify the role of various factors to the trend in SSDI enrollment. In contrast to existing methods, such as Oaxaca (1973) and Blinder (1973), our method allows us to take into account interactions across the many components of SSDI enrollment—population composition, financial eligibility, application, award, and various exit channels. We use our method to calculate upper and lower bounds on the contribution of each component.

In Section 3, we apply the decomposition method to individual-level administrative data from the Social Security Administration (SSA). The administrative data allow us to do a number of things that would not be possible in publicly available aggregated data: account for composition changes across a rich set of population and applicant characteristics, determine

[1]See also Glenn and Goss (2018), Social Security Administration (2019), Ruffing (2023), Center on Budget and Policy Priorities (2025), Liu and Quinby (2023), Mohamed, Burns and Cubanski (2024).

[2]See Glenn and Goss (2018), Ruffing (2023), Center on Budget and Policy Priorities (2025), vs Liu and Quinby (2023).

[3]Population aging: Ruffing (2023), Center on Budget and Policy Priorities (2025), Liu and Quinby (2023), Mohamed et al. (2024). Lower male LFP: Mohamed et al. (2024) vs Liu and Quinby (2023). Industry shift: Social Security Administration (2019) vs Liu and Quinby (2023). Economic recovery: Glenn and Goss (2018), Ruffing (2023), Center on Budget and Policy Priorities (2025), 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). 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).

financial eligibility for SSDI at the individual level, link SSDI applications to awards, track exit through multiple channels, and study joint outcomes (e.g., eligibility, application, and award) in addition to marginal ones.

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 a large majority of the increase is attributable to a combination of higher entry onto SSDI and lower exit from SSDI within demographic groups, rather than changes in demographic characteristics of the population. Our data and method allow us to expand on previous studies of the increase in SSDI enrollment in a number of ways. Contrary to conventional wisdom, we find that low-skilled women, rather than men, drove the increase in entry in the 1990s and 2000s.[4] Mental and musculoskeletal conditions account for most of the increase in entry, consistent with the expansion of medical eligibility for these conditions (Autor and Duggan, 2003, 2006).

Next, we 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 demographic groups, rather than increases in exit or changes in demographic characteristics of the population. Most of this decline in SSDI entry is attributable to lower application rates, with some contribution from lower award rates; changes in financial eligibility contribute little to the decline in entry. The decline in award rates is consistent with previously documented policy changes that reduced award rates at the appeals levels (Hoynes et al., 2024), while the decline in application rates is not connected to an obvious policy change. We find that—in contrast to the increase in SSDI in the 1990s and 2000s—most of the decline in SSDI enrollment in the 2010s comes from men rather than women.

Since applications play the largest role in the decline in SSDI enrollment, we turn to a closer analysis of the decline in applications. In Section 4, we characterize the marginal non-applications during the decline period. The decline in applications comes disproportionately from applicants with higher-severity conditions and applicants who were working just prior to application. Consistent with Deshpande and Li (2019) and Deshpande and Lockwood (2022), we find that higher-severity applicants are more likely to be connected to the labor market. These more-severe, more-labor-force-attached applicants become less likely to apply after the Great Recession. Marginal non-applications are spread across all disability types, with musculoskeletal conditions underrepresented and mental and endocrine conditions overrepresented.

[4] See, e.g., Scott Winship, "Labor-Force Participation Among Men Is Declining As Disability Claims Rise," Jan 13, 2015; Joint Economic Committee, "The Reward of Work, Incentives, and Upward Mobility," December 1, 2016.

Turning to application and work outcomes, we find that low-to-middle-skilled men—who drive the decline in SSDI applications—had record-high earnings and employment following the Great Recession. Indeed, we find that during the 2010s these men became less likely to apply for SSDI and more likely to work, and that these changes are concentrated in men with health conditions. From a normative perspective, these facts suggest that the decline in SSDI applications are not necessarily associated with a large drop in income or consumption. From a causal perspective, any explanation for the decline in application rates must be consistent with higher labor force participation in the same population.

In Sections 5 and 6, we move beyond the accounting analysis of the decomposition to estimate the causal effects of several potential causes of the decline in SSDI applications. We start with a model of application behavior that we use to guide and interpret our analysis. We then use both existing and novel evidence to determine the causal effect of various factors on SSDI application rates. We combine the causal estimates with the model to quantify the empirical importance of the various factors for the observed decline in SSDI applications since 2010.

We find that the improved employment opportunities for less-skilled men are the most likely cause of the decline in SSDI enrollment, consistent with the descriptive evidence in Section 4. Our analysis of this hypothesis builds on Autor and Duggan (2003), who find that SSDI application rates are sensitive to changes in demand for less-skilled workers, especially after the 1984 expansion of medical eligibility. Guided by their finding and research design, we examine whether improvements in the labor market conditions of less-skilled men from 2010 to 2019 could have reduced SSDI application rates. Our results suggest that improved employment opportunities for less-skilled men explain nearly all of the decline in SSDI application rates (relative to the counterfactual) for men, and 57 percent of the overall decline.

We also evaluate several other hypotheses for the decline in SSDI applications and find evidence that is at odds with these explanations. First, we consider whether SSDI applications have declined because of lower award rates at the appeals level. We use variation across counties in the decline in award rates at the appeals level and find that the elasticity of applications with respect to award rates is close to zero. Second, we consider whether the administrative burden of applying has increased enough to explain the decline. We find that Social Security field office closings can explain only a small fraction of the decline. Other measures of hassle costs—like wait times and processing times—actually fell during this time period. Third, we consider whether population health improved enough to reduce SSDI applications. We find evidence at odds with pollution and smoking rates as major contributors, though improvements in mental health treatment may explain some of the decline. We also find no heterogeneity in the decline in SSDI applications with respect to the severity of the opioid crisis. Fourth, we consider greater generosity of other programs as an explanation. There were no significant expansions of SNAP, TANF, or unemployment insurance during this time period. Estimates from other studies rule out health insurance as a major contributor, and we find no relationship across states between health insurance increases and SSDI application declines. We also consider the large expansion of Veterans Disability Compensation during this time period. We can identify veterans directly in our data and find that, if anything, they contribute less than proportionally to the decline in SSDI applications. Fifth, we consider population aging as a potential explanation. We find that population aging during this time period actually worked against the SSDI decline, since the working-age population shifted to the highest-SSDI-receipt ages (just below the full retirement age). Only in future years will the population have aged enough to contribute to a decline in SSDI enrollment.

The combination of evidence consistent with improved labor market opportunities and inconsistent with other explanations points to labor demand as the most likely explanation for the decline in SSDI applications and enrollment. Improved employment opportunities in recent years appear to have pulled potential SSDI applicants into the labor market and diverted them from SSDI. If true, this explanation would mean that the decline in SSDI enrollment is the result of more opportunity and likely higher well-being among people with disabilities. Regarding the future trajectory of SSDI, this explanation suggests that some of these deterred applicants might apply in the future, if and when their employment opportunities become more limited.

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 data aggregated by state and year.

Our finding of improved labor market opportunities among individuals with health conditions is consistent with evidence on higher employment rates among people with disabilities in recent years. Ne'eman and Maestas (2023b) find that, after decreasing in the Great Recession, employment rates among people with disabilities began recovering in 2014. Bloom, Dahl and Rooth (2026) 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 (2023b).

Our paper also builds on and contributes to a literature on decomposition methods in economics. These decomposition methods are best understood as an accounting approach, in which observed outcomes for one group are used to construct counterfactual scenarios for another group (Katz and Autor, 1999; Fortin, Lemieux and Firpo, 2011a). In constructing these scenarios, we follow the literature on decomposition methods in abstracting from potentially important partial equilibrium considerations (e.g., selection on unobservables) and general equilibrium considerations (e.g., simultaneous determination of labor supply and the return to work).[5] Our decomposition method is tailored to sequential decision problems where actions taken at one stage (e.g., application stage) influence the options and outcomes at future stages (e.g., award stage). To the extent that application and award outcomes co-move, a statistical decomposition will not know to which stage to attribute the change. The bounds produced by our decomposition method take such interaction effects across stages into account.

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;

[5]See Fortin, Lemieux and Firpo (2011b) for a review of decomposition methods in economics and a discussion of these considerations.

- Annual earnings (1951–2022) from the Master Earnings File (MEF) Summary Earnings Record (SER), which us allows to construct financial eligibility for SSDI in each year; average annual earnings 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 do several things that would not be possible in publicly available aggregated SSDI data: 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, track individuals from SSDI entry to SSDI exit, and document the type of exit (death, retirement, recovery, or other). Most importantly, the SSA administrative data allow us to study joint outcomes (e.g., eligibility, application, and award for the same individual), rather than just marginal outcomes.

In Appendix Section D.1, we show that our data match public data on enrollment, eligibility, application, award, and exit numbers well. Appendix Figures D.9 and D.10 demonstrate the difference between calculating award rates using applications and award made in the same year, versus linking applications in a given year to whether they are ever allowed in the future.

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 Form 5500 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.[6] 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.

- Remote work: We use data on the prevalence of working from home by industry (NAICS codes) constructed by Dingel and Neiman (2020).[7] We link individuals to this measure of remote work prevalence in the industry they worked in just before applying for SSDI using NAICS codes from the F5500 (see above). 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);[8]
  - 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).[9]

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

[7] See https://github.com/jdingel/DingelNeiman-workathome.

[8] See https://opportunityinsights.org/paper/land-of-opportunity/

[9] See https://github.com/benzipperer/historicalminwage/releases/tag/v1.4.0.

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. Appendix Section B.1 provides more details on the SIPP analysis.

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."[10] 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.

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.[11] 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

[10] See `https://www.ssa.gov/benefits/disability/qualify.html`.

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

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, socioeconomic status, and immigrant status.[12]

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):

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

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

where $\mathbf{N}_g$ and $\mathbf{X}_g$ denote vectors of entry and exit flows, each of length $t+1$, and $K(g,i,t)$ captures how existing SSDI stocks transmit from year i to year t. 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 group-specific rates:

$$O_t(\mathbb{N}, \mathbb{X}, \mathbf{S}_0, \mathbf{P}) = \sum_g O_{t,g}(\mathbf{N}_g, \mathbf{X}_g, S_{0,g}, P_g) \times w_{t,g}, \quad w_g \equiv \frac{P_g}{\sum_g P_g} \tag{3}$$

[12]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.

As seen in equations (2) and (3), 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:

$$N_{t,g}^{c} = N_{t,a(g,t)}^{r}, \quad X_{t,g}^{c} = X_{t,a(g,t)}^{r}, \quad w_{t,g}^{c} = w_{t,a(g,t)}^{r} \quad \forall \quad 0 \leq s \leq t, \quad g \tag{4}$$

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.[13]

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:

[13]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 $P_{t,g}^{c} \approx P_{t,g}^{r}$ for simplicity and omit the superscript. In practice though, we account for how changing the mortality 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.

$$
\begin{aligned}
O_t^r - O_t^c = & \underbrace{\sum_g O_{t,g}^c (w_{t,g}^r - w_{t,g}^c)}_{\text{change in characteristics}} + \underbrace{\sum_g (O_{t,g}^r - O_{t,g}^c) w_{t,g}^c}_{\text{change from conditional SSDI rates}} \\
& + \underbrace{\sum_g (O_{t,g}^r - O_{t,g}^c)(w_{t,g}^r - w_{t,g}^c)}_{\text{characteristics } \times \text{SSDI rate interaction}}
\end{aligned} \tag{5}
$$

Note that the terms that we attribute to characteristics and to conditional SSDI rates are *symmetric*; each holds its counterpart components fixed at their counterfactual values (c as opposed to r). 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 true observed values (r) when judging the impact of changes in conditional SSDI rates.

Changes in SSDI due to changes in entry and exit flows. Equation (5) 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 real SSDI rates for each group g. Using equation (1), we can express that difference in terms of additively separable components attributable to changes in entry rates versus changes in exit rates:

$$
O_{1,g}^r - O_{1,g}^c = \frac{S_{1,g}^r - S_{1,g}^c}{P_{1,g}} = \underbrace{(N_{1,g}^r - N_{1,g}^c)\frac{(P_{0,g} - S_{0,g})}{P_{1,g}}}_{\text{change from conditional entry rate}} - \underbrace{(X_{1,g}^r - X_{1,g}^c)\frac{S_{0,g}}{P_{1,g}}}_{\text{change from conditional exit rate}}
$$

where we use that $S_{0,g}^c = S_{0,g}^r = S_{0,g}$ 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 $t > 0$:

$$O^r_{t+1,g} - O^c_{t+1,g} = \frac{S^r_{t+1,g} - S^c_{t+1,g}}{P^c_{t+1,g}} + S^r_{t+1,g}\left(\frac{1}{P^r_{t+1,g}} - \frac{1}{P^c_{t+1,g}}\right) \approx \frac{S^r_{t+1,g} - S^c_{t+1,g}}{P_{t+1,g}} \tag{6}$$

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

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 stated approximations come from observing that $P^c_{t,g} \approx P^r_{t,g}$ in practice.[14] In this section, we use this approximation to focus our decomposition only on its key components. See Appendix Section E for the exact version of the decomposition which we implement in practice.

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 ($d_{t,g}$) and ($e_{t,g}$) to changes in past SSDI rates ($c_{t,g}$), we arrive at a simpler expression:

$$\begin{aligned}
S^r_{t+1,g} - S^c_{t+1,g} \approx\ & \underbrace{\sum_{i=0}^{t}(N^r_{t-i,g} - N^c_{t-i,g})(P_{t-i,g} - S^c_{t-i,g})K^r_{g,i,t}}_{\text{cumulative change from conditional entry rate}} \\
& \underbrace{-\sum_{i=0}^{t}(X^r_{t-i,g} - X^c_{t-i,g})S^c_{t-i,g}K^r_{g,i,t}}_{\text{cumulative change from conditional exit rate}}
\end{aligned} \tag{7}$$

[14] As stated in Appendix E, the only difference between $P^c_{t,g}$ and $P^r_{t,g}$ comes from differences in the mortality rates of SSDI beneficiaries. This has a very limited effect on population counts because mortality rates are always fairly low and SSDI beneficiaries are a small fraction of the overall population.

where $K_{g,i,t}$ is defined as in equation (2), rearranging its arguments as subscripts.

Notice that we can formulate other versions of this recursive decomposition by loading the interaction terms instead into conditional entry rates and exit rates.[15] The choice of how to allocate the interaction terms forms the basis of our bounding exercise, outlined in detail in Appendix Section F. 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.[16] We specify the full range of estimates that we construct for this step and the remaining steps to follow in Appendix Section F.

Further decomposing changes in exit and 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.

$$X_{t,g} = \text{Retirement Rate}_{t,g} + \text{Mortality Rate}_{t,g} + \text{Recovery Rate}_{t,g} + \text{Other Exit Rate}_{t,g} \quad (8)$$

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:

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

[15]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 $t-i$.

[16]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.

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

$$
\begin{aligned}
N^r_{t,g} - N^c_{t,g} =& B^r_{t,g}A^r_{t,g}E^r_{t,g} - B^c_{t,g}A^c_{t,g}E^c_{t,g} \\
=& \underbrace{(B^r_{t,g} - B^c_{t,g})A^c_{t,g}E^c_{t,g}}_{\text{partial award}} + \underbrace{B^c_{t,g}(A^r_{t,g} - A^c_{t,g})E^c_{t,g}}_{\text{partial apply}} + \underbrace{B^c_{t,g}A^c_{t,g}(E^r_{t,g} - E^c_{t,g})}_{\text{partial elig}} \\
&+ \underbrace{B^c_{t,g}(A^r_{t,g} - A^c_{t,g})(E^r_{t,g} - E^c_{t,g})}_{\text{apply} \times \text{elig}} \\
&+ \underbrace{(B^r_{t,g} - B^c_{t,g})A^c_{t,g}(E^r_{t,g} - E^c_{t,g})}_{\text{award} \times \text{elig}} \\
&+ \underbrace{(B^r_{t,g} - B^c_{t,g})(A^r_{t,g} - A^c_{t,g})E^c_{t,g}}_{\text{award} \times \text{apply}} \\
&+ \underbrace{(B^r_{t,g} - B^c_{t,g})(A^r_{t,g} - A^c_{t,g})(E^r_{t,g} - E^c_{t,g})}_{\text{award} \times \text{apply} \times \text{elig}}
\end{aligned} \tag{9}
$$

Substituting this expression for $(N^r_{t-i,g} - N^c_{t-i,g})$ in equation (7), we arrive at a decomposition of SSDI stocks that distinguishes between the impact of eligibility, applications among the eligible, and awards among applicants. Substituting the contribution of change in stock into equation (6) and subsequently equation (5), the contribution of type g to the application component of the enrollment rate change is (analogous equations for eligibility, award, entry, and exit in Appendix Section E):

$$
\frac{w^c_{t,g}}{P_{t,g}} \sum_{i=0}^{t} B^c_{t-i,g}(A^r_{t-i,g} - A^c_{t-i,g})E^c_{t-i,g}(P_{t-i,g} - S^c_{t-i,g})K^r_{g,i,t} \tag{10}
$$

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 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:

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

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:

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

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.

2.3 Partitioning application and award changes into subgroups

It may also be informative to understand which subgroups are driving changes in application rates, award rates, and overall entry rates. To do so, we partition the sample of applications into mutually exclusive subgroups (e.g., low-skilled men) given by g.

We partition the change in unconditional application rate ($\tilde{A}^r_t - \tilde{A}^c_t$) into subgroups:

$$
\begin{aligned}
\tilde{A}_t^r - \tilde{A}_t^c &= \sum_g A_{g,t}^r E_{g,t}^r w_{g,t}^r - A_{g,t}^c E_{g,t}^c w_{g,t}^c \\
&= \sum_g \underbrace{A_{g,t}^c E_{g,t}^c (w_{g,t}^r - w_{g,t}^c)}_{\text{Across group composition}} + \sum_g \underbrace{(A_{g,t}^r E_{g,t}^r - A_{g,t}^c E_{g,t}^c)(w_{g,t}^r - w_{g,t}^c)}_{\text{Within-across interaction}} + \sum_g (A_{g,t}^r E_{g,t}^r - A_{g,t}^c E_{g,t}^c) w_{g,t}^c \\
&= \sum_g \underbrace{A_{g,t}^c E_{g,t}^c (w_{g,t}^r - w_{g,t}^c)}_{\text{Across group composition}} + \sum_g \underbrace{(A_{g,t}^r E_{g,t}^r - A_{g,t}^c E_{g,t}^c)(w_{g,t}^r - w_{g,t}^c)}_{\text{Within-across interaction}} \\
&+ \sum_g \underbrace{(A_{g,t}^r - A_{g,t}^c) E_{g,t}^c w_{g,t}^c}_{\text{Application rate contribution}} + \sum_g \underbrace{A_{g,t}^c (E_{g,t}^r - E_{g,t}^c) w_{g,t}^c}_{\text{Eligibility rate contribution}} + \sum_g \underbrace{(A_{g,t}^r - A_{g,t}^c)(E_{g,t}^r - E_{g,t}^c) w_{g,t}^c}_{\text{Interaction within apply}}
\end{aligned} \tag{12}
$$

We partition the change in unconditional entry rate ($\tilde{N}_t^r - \tilde{N}_t^c$) into subgroups:

$$
\begin{aligned}
\tilde{N}_t^r - \tilde{N}_t^c &= \sum_g \underbrace{N_{g,t}^r}_{\text{Cond. entry rate}} w_{g,t}^r - N_{g,t}^c w_{g,t}^c \\
&= \sum_g \underbrace{N_{g,t}^c (w_{g,t}^r - w_{g,t}^c)}_{\text{Across group composition}} + \sum_g \underbrace{(N_{g,t}^r - N_{g,t}^c)(w_{g,t}^r - w_{g,t}^c)}_{\text{Within-across interaction}} + \sum_g \underbrace{(N_{g,t}^r - N_{g,t}^c) w_{g,t}^c}_{\text{entry rate contribution}} \\
\sum_g (N_{g,t}^r - N_{g,t}^c) w_{g,t}^c &= \sum_g (B_{g,t}^r A_{g,t}^r E_{g,t}^r - B_{g,t}^c A_{g,t}^c E_{g,t}^c) w_{g,t}^c \\
&= \sum_g \underbrace{(B_{g,t}^r - B_{g,t}^c) A_{g,t}^c E_{g,t}^c w_{g,t}^c}_{\text{Award rate contribution}} + \sum_g \underbrace{B_{g,t}^c (A_{g,t}^r - A_{g,t}^c) E_{g,t}^c w_{g,t}^c}_{\text{Application rate contribution}} \\
&+ \sum_g \underbrace{B_{g,t}^c A_{g,t}^c (E_{g,t}^r - E_{g,t}^c) w_{g,t}^c}_{\text{Eligibility rate contribution}} + \underbrace{\ldots}_{\text{Interaction within entry}}
\end{aligned} \tag{13}
$$

We partition the change in award rate conditional on application ($\tilde{B}_t^r - \tilde{B}_t^c$) into subgroups as follows, where $F_{g,t} \equiv \dfrac{\text{applicants}_{g,t}}{\sum_g \text{applicants}_{g,t}}$ is the fraction of total applicants that subgroup g makes up:

$$
\begin{aligned}
\tilde{B}_t^r - \tilde{B}_t^c &= \sum_g B_{g,t}^r F_{g,t}^r - B_{g,t}^c F_{g,t}^c \\
&= \sum_g \underbrace{(B_{g,t}^r - B_{g,t}^c) F_{g,t}^c}_{\text{Award rate contribution}} + \sum_g \underbrace{(F_{g,t}^r - F_{g,t}^c) B_{g,t}^c}_{\text{Applicant fraction contribution}} + \sum_g (B_{g,t}^r - B_{g,t}^c)(F_{g,t}^r - F_{g,t}^c)
\end{aligned} \tag{14}
$$

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 (55-58%) of the increase in the overall SSDI enrollment rate, but lower within-group exit rates (23-25%) are also an important part of the story. Changes in composition also play a nontrivial role (18-23%) in the SSDI enrollment rate increase. Table 1 shows that the bounds on the main components are relatively tight. Appendix Figure A.1 shows the decomposition results over time.

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

	Absolute contribution (pp)			As a share of total (%)		
	Minimum	Maximum	Used in graph	Minimum	Maximum	Used in graph
Across-group composition	**0.39**	**0.49**	**0.39**	**18.0**	**22.5**	**18.0**
Sex	-0.11	0.03	0.00	-5.3	1.3	0.1
Age	0.41	1.08	0.47	18.8	49.7	21.5
Earnings	-0.30	0.18	0.09	-13.7	8.3	4.3
Immigrant status	-0.32	-0.13	-0.19	-14.6	-5.9	-8.8
Within-group SSDI rates	**1.69**	**1.79**	**1.69**	**77.5**	**82.0**	**77.5**
Entry	1.20	1.26	1.20	54.8	57.6	54.8
Eligibility	*0.15*	*0.21*	*0.15*	*7.1*	*9.5*	*7.1*
Application	*0.64*	*0.80*	*0.80*	*29.5*	*36.6*	*36.6*
Award	*0.17*	*0.28*	*0.17*	*8.0*	*12.9*	*8.0*
Exit	0.51	0.55	0.51	23.3	25.0	23.3
Death	*0.32*	*0.38*	*0.32*	*14.9*	*17.6*	*14.9*
Recovery	*0.06*	*0.06*	*0.06*	*2.5*	*2.7*	*2.5*
Retirement	*0.12*	*0.13*	*0.13*	*5.4*	*6.0*	*6.0*
Other	*-0.01*	*-0.00*	*-0.00*	*-0.6*	*-0.2*	*-0.2*
Friction in population	-0.02	-0.02	-0.02	-1.0	-1.0	-1.0
Population discrepancies	0.01	0.01	0.01	0.4	0.4	0.4
Within-across interaction			**0.10**			**4.5**
Total to be explained	2.18	2.18	2.18	100.0	100.0	100.0

Notes: Table presents decomposition of the increase in SSDI enrollment rates from 1988 to 2010 into various components. The counterfactual SSDI enrollment rate in 2010 is 2.43 percent while the actual enrollment rate in 2010 is 4.61 percent, creating 2.18 pp of SSDI increase to be decomposed (see Appendix Table G.1). Across-group composition change, within-group change in SSDI enrollment rate, and the interaction between the two are calculated using equation (5). Across-group composition change is decomposed into specific characteristics using equation (11). Within-group SSDI rate is decomposed into entry, exit, friction in population, and population discrepancies using equation (6) and footnotes 13 and 15. Entry is decomposed 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) using equation (9). Exit is decomposed into death, retirement (defined as aging into the retirement program), recovery (defined as being found no longer eligible due to continuing disability review), and "other" (the residual) using equation (8). "Minimum" means the minimum bound, "Maximum" means the maximum bound, and "Used in graph" means the point estimate used in Figure A.1. See Section 2.1 for details on the decomposition method, and Appendix Section F for details on the construction of bounds.

The administrative panel data allow us to expand on the findings in Liebman (2015). In Figure 2 using equation (13), we find that the entry rate increase from 1988 to 2010 came disproportionately from low-skilled women (both younger and older), while men and higher-skilled individuals played a smaller role. This finding that women drove the vast majority of the entry from 1988 to 2010 contrasts with the conventional narrative about low-skilled men driving SSDI enrollment in the 1990s and 2000s.[17]

[17]See, e.g., Scott Winship, "Labor-Force Participation Among Men Is Declining As Disability Claims

Figure 2: Increase in SSDI entry (1988–2010) driven by low-skilled women

(a) Entry rate increase (b) Entrants in 1988

Notes: Left graph plots the fraction of the contribution of changes (in absolute terms) in entry rate that can be attributed to specific demographic groups, as given by equation (13). Negative numbers indicate that the group worked *against* the increase. The point estimates we report are the ones in which flows (e.g., B_t, A_t, E_t, X_t), when fixed, are held fixed at their counterfactual values. Right graph plots the composition of entrants in 1988 as a baseline comparison. The demographic groups are characterized by sex, average annual earnings between ages 25-34 (a measure of skill), and whether older or younger than 45 years old. See Appendix Table G.8 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 enrollment and avoid the unusual circumstances of the COVID-19 pandemic (when, e.g., Social Security field offices were closed).

Table 2 and Figure 3 present the main results. We find that virtually all of the decline in SSDI enrollment is attributable to decreases in within-group entry rates (90-97%), rather than changes in composition (1-5%) or changes in exit (1-4%). Within entry, most of the decrease comes from lower application rates (46-57%) and lower award rates (30-43%). The role of award rates is perhaps expected given that the decline in award rates at the appeals

Rise," Jan 13, 2015; Joint Economic Committee, "The Reward of Work, Incentives, and Upward Mobility," December 1, 2016.

level has been well-documented and attributed in part to retraining of administrative law judges (Hoynes et al., 2024). To our knowledge, however, there is no policy change that obviously explains the decline in applications. Moreover, as we discuss in more detail in Section 4.1, the decomposition is likely to underestimate the contribution from application rate changes (and overestimate the contribution from award rate changes) due to a shift in applicant composition. Once we adjust for changing applicant composition by severity, the share attributable to application increases 46-57% to 57-69%; the share attributable to award falls by the equivalent amount (see Appendix Table A.1).

Table 2: Decomposition results for the decrease in SSDI enrollment from 2010 to 2019

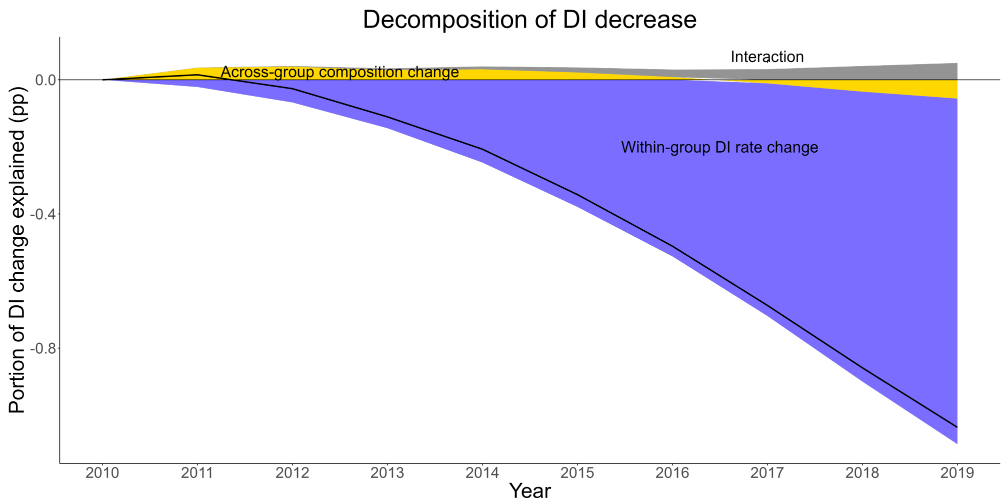
	Absolute contribution (pp)			As a share of total (%)		
	Minimum	Maximum	Used in graph	Minimum	Maximum	Used in graph
Across-group composition	**-0.01**	**-0.06**	**-0.06**	**0.6**	**5.4**	**5.4**
Sex	0.00	-0.02	0.00	-0.3	2.1	-0.0
Age	0.18	0.02	0.07	-17.6	-1.9	-6.7
Earnings	0.03	-0.11	-0.04	-3.1	10.4	3.5
Immigrant status	-0.06	-0.17	-0.11	5.9	15.9	10.6
Within-group SSDI rates	**-0.98**	**-1.03**	**-1.03**	**94.6**	**99.4**	**99.4**
Entry	-0.94	-1.00	-0.99	90.3	96.9	95.2
Eligibility	*-0.05*	*-0.09*	*-0.08*	*4.5*	*8.4*	*8.1*
Application	*-0.48*	*-0.59*	*-0.58*	*46.1*	*56.8*	*55.6*
Award	*-0.31*	*-0.45*	*-0.44*	*29.9*	*43.0*	*42.0*
Exit	-0.01	-0.04	-0.04	1.3	3.9	3.5
Death	*0.04*	*0.04*	*0.04*	*-4.2*	*-3.5*	*-4.1*
Recovery	*-0.06*	*-0.08*	*-0.08*	*5.6*	*7.4*	*7.3*
Retirement	*0.01*	*0.01*	*0.01*	*-1.0*	*-0.7*	*-0.8*
Other	*-0.01*	*-0.01*	*-0.01*	*0.6*	*1.1*	*1.1*
Friction in population	-0.01	-0.01	-0.01	0.9	1.1	0.9
Population discrepancies	0.00	0.00	0.00	-0.2	-0.1	-0.1
Within-across interaction			**0.05**			**-4.8**
Total to be explained	-1.04	-1.04	-1.04	100.0	100.0	100.0

Notes: Table presents decomposition of the decrease in SSDI enrollment rates from 2010 to 2019 into various components. The counterfactual SSDI enrollment rate in 2019 is 5.37 percent while the actual enrollment rate in 2019 is 4.33 percent, creating 1.04 pp of SSDI decline to be decomposed (see Appendix Table G.9). Across-group composition change, within-group change in SSDI enrollment rate, and the interaction between the two are calculated using equation (5). Across-group composition change is decomposed into specific characteristics using equation (11). Within-group SSDI rate is decomposed into entry, exit, friction in population, and population discrepancies using equation (6) and footnotes 13 and 15. Entry is decomposed 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) using equation (9). Exit is decomposed into death, retirement (defined as aging into the retirement program), recovery (defined as being found no longer eligible due to continuing disability review), and "other" (the residual) using equation (8). "Minimum" means the minimum bound, "Maximum" means the maximum bound, and "Used in graph" means the point estimate used in Figure 3. See Section 2.1 for details on the decomposition method, and Appendix Section F for details on the construction of bounds.

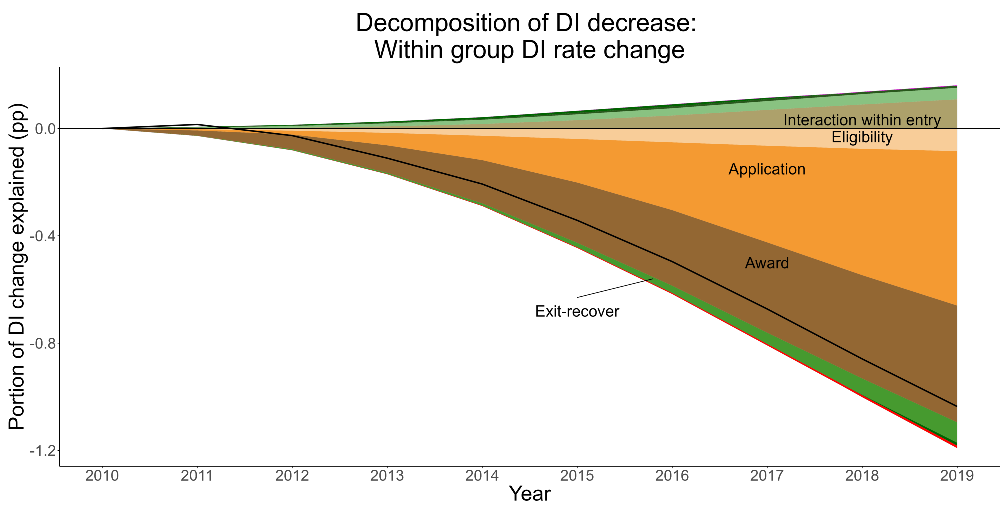
Which demographic groups drive the decline in application rates? In Figure 4 using equation (12), we find that men, especially younger men, contribute disproportionately to the decline in SSDI application rates. Older women contribute the least to the application decline, in both absolute terms and relative to their baseline shares. Looking across industries, the application rate decline comes from all industries, though construction and manufacturing are the largest contributors relative to their baseline shares (see Appendix Section G.4)—consistent with young lower-skilled men disproportionately driving the decline.

We do a similar exercise for award rates (conditional on applying) in Figure 5. The

Figure 3: SSDI decrease (2010–2019) attributable to lower application and award



(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 (5). 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 (9). 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 (8). "Friction in population" and "Population discrepancy" are described in footnotes 13 and 15. See Section 2.1 for details on the decomposition method. The point estimates we report are the ones in which flows (e.g., B_t, A_t, E_t, X_t), when fixed, are held fixed at their counterfactual values. See Table 2 for exact estimates.

decline in award rates is driven disproportionately by younger women; this pattern is likely explained by the ALJ retraining reducing award rates most for mental conditions, which younger women are more likely to apply with. Older men contribute the least to the award rate decline. The decline in entry rates (which is a combination of application rate and award rate) is driven disproportionately by younger people, both men and women (see Appendix Table G.22).

Figure 4: Application rate decline from 2010 to 2019 driven by men, disproportionately younger men

(a) Application rate decrease

(b) Applicants in 2010

Notes: Left graph plots the fraction of application rate decline that can be attributed to specific demographic groups, per equation (12). The point estimates we report are the ones in which flows (e.g., B_t, A_t, E_t, X_t), when fixed, are held fixed at their counterfactual values. Right graph plots the composition of applicants in 2010 as a baseline comparison. The demographic groups are characterized by sex, average annual earnings between ages 25-34 (a measure of skill), and whether older or younger than 45 years old. See Appendix Table G.16 for exact estimates.

Figure 5: Award rate decline from 2010 to 2019 driven disproportionately by younger women

(a) Award rate decrease

(b) Entrants in 2010

Notes: Left graph plots the fraction of award rate decline that can be attributed to specific demographic groups, per equation (14). The point estimates we report are the ones in which flows (e.g., B_t, A_t, E_t, X_t), when fixed, are held fixed at their counterfactual values. Right graph plots the composition of entrants in 2010 as a baseline comparison. The demographic groups are characterized by sex, average annual earnings between ages 25-34 (a measure of skill), and whether older or younger than 45 years old. See Appendix Table G.19 for exact estimates.

4 Characterizing the marginal (non-)applications and (non-)awards during the SSDI decline

In the previous section, we find that the largest share of the decline is attributable to a decline in within-group SSDI application rates, driven disproportionately by men and especially younger men. Most of the remainder of the SSDI enrollment decline is attributable to a decline in within-group award rates, driven disproportionately by younger women. In this section, we characterize the marginal (non-)applications and (non-)awards over this time period using additional characteristics.

4.1 Decomposing application and award rates using characteristics observed only for applicants

The SSA application data include detailed characteristics on applicants that are not observed for the full population, including severity, diagnosis, and geographic location. Since we do not observe these characteristics for the full population, we cannot incorporate them into the decomposition method outlined above. However, under certain assumptions, we can use them to characterize the applications (and awards) that would have taken place in the counterfactual world but did not in the real world.

We partition applications into mutually exclusive subgroups based on an applicant-specific characteristic d (e.g., for diagnosis, partition into mental, musculoskeletal, and other conditions). We write the difference between the counterfactual application rate for (population-level) group g at time t ($A^c_{t,g}$) and the real application rate ($A^r_{t,g}$) in terms of the d subgroups:

$$A^r_{t,g} - A^c_{t,g} = \sum_d \hat{A}^r_{t,g,d} - \sum_d \hat{A}^c_{t,g,d} = \sum_d (\hat{A}^r_{t,g,d} - \hat{A}^c_{t,g,d}) \tag{15}$$

where $\hat{A} \equiv \dfrac{applicant_{d,g,t}}{eligpop_{g,t}} \equiv P(A = 1, d|t, g, E = 1)$ is the joint conditional probability of applying and belonging to subgroup d, given year-group (t, g) and conditional on SSDI eligibility ($E = 1$). Changes in $\hat{A}_{t,g,d}$ could be driven by changes in the probability of applying conditional on belonging to subgroup d (e.g., having a musculoskeletal condition), or changes in the prevalence of subgroup d in the SSDI-eligible population (e.g., in the prevalence of musculoskeletal conditions for year-group t, g). If we assume that the subgroup composition in the SSDI-eligible population is stable over time, then changes we attribute to subgroup d using equation (15) are driven by changes in application rates among individuals in subgroup d (e.g., changes in application rates conditional on having a musculoskeletal condition). These assumptions appear to be plausible during the period of the SSDI decline: we find no changes in eligibility rates conditional on observables (see Section 3), and no improvements in population health (see Appendix Figures A.11 and A.12).[18]

We can similarly decompose the award rate $B_{t,g}$ using mutually exclusive subgroups:

$$\begin{aligned} B^r_{t,g} - B^c_{t,g} = & \underbrace{\sum_d (b^r_{t,g,d} - b^c_{t,g,d}) a^c_{t,g,d}}_{\text{change in } d\text{-specific award rates}} + \underbrace{\sum_d (a^r_{t,g,d} - a^c_{t,g,d}) b^c_{t,g,d}}_{\text{change in application composition}} \\ & + \underbrace{\sum_d (b^r_{t,g,d} - b^c_{t,g,d})(a^r_{t,g,d} - a^c_{t,g,d})}_{\text{interaction term}} \end{aligned} \tag{16}$$

since $B_{t,g} = \sum_d b_{d,g,t} a_{d,g,t}$ where $b_{t,g,d}$ is the subgroup-specific award rate (e.g., award rates for applications coming from mental, musculoskeletal, or other conditions) and $a_{t,g,d}$ is the share of applications belonging to subgroup d (e.g., the share of applications from year-group (t, g) coming from mental, musculoskeletal, or other conditions).

The "change in application composition" term could be driven by two different channels: changes in characteristics in the SSDI-eligible population, or changes in application behaviors conditional on subgroup. Interpreting the composition term in equation (16) as coming purely from changes in application behaviors requires the same assumptions we needed above to interpret equation (15)—specifically, that subgroup composition has not changed in the SSDI-eligible population. Under this assumption, the composition term represents how changes in applicant composition across subgroups mechanically affects award rates. In contrast, the "change in d-specific award rates" term reflects changes in award rates *within* subgroup, perhaps attributable to policy changes.

To decompose entry by applicant-specific characteristics, we start by writing the difference in real and counterfactual entry rates as follows using the definitions of $a_{d,g,t}$ and $b_{d,g,t}$ from above:

[18]Interpreting changes in application characteristics as changes in selection into application also requires the assumption that there have been no changes in how SSA measures the applicant characteristics. Some characteristics like geography are objective. For more subjective characteristics like diagnosis and severity, there have been no policy changes during the period of SSDI decline.

$$
\begin{aligned}
N^r_{g,t} - N^c_{g,t} &= B^r_{g,t}A^r_{g,t}E^r_{g,t} - B^c_{g,t}A^c_{g,t}E^c_{g,t} \\
&= \sum_d b^r_{d,g,t}a^r_{d,g,t}A^r_{g,t}E^r_{g,t} - b^c_{d,g,t}a^c_{d,g,t}A^c_{g,t}E^c_{g,t} \\
&= \sum_d (b^r_{d,g,t} - b^c_{d,g,t})a^c_{d,g,t}A^c_{g,t}E^c_{g,t} + \sum_d b^c_{d,g,t}(a^r_{d,g,t} - a^c_{d,g,t})A^c_{g,t}E^c_{g,t} \\
&+ \sum_d b^c_{d,g,t}a^c_{d,g,t}(A^r_{d,g,t} - A^c_{g,t})E^c_{g,t} + \sum_d b^c_{d,g,t}a^c_{d,g,t}A^c_{g,t}(E^r_{d,g,t} - E^c_{g,t}) + ...
\end{aligned}
\tag{17}
$$

If we plug this into the "entry rate contribution" part of equation (13) and sum over groups g, we can write:

$$
\begin{aligned}
\sum_g (N^r_{g,t} - N^c_{g,t})w^c_{g,t} &= \sum_g \underbrace{(B^r_{g,t} - B^c_{g,t})A^c_{g,t}E^c_{g,t}w^c_{g,t}}_{\text{Award rate contribution}} + \sum_g \underbrace{B^c_{g,t}(A^r_{g,t} - A^c_{g,t})E^c_{g,t}w^c_{g,t}}_{\text{Application rate contribution}} \\
&+ \sum_g \underbrace{B^c_{g,t}A^c_{g,t}(E^r_{g,t} - E^c_{g,t})w^c_{g,t}}_{\text{Eligibility rate contribution}} + \underbrace{...}_{\text{Interaction within entry}} \\
&= \sum_{gd} \underbrace{(b^r_{dgt} - b^c_{dgt})a^c_{dgt}A^c_{gt}E^c_{gt}w^c_{g,t}}_{\text{Award (by } d)} + \sum_{gd} \underbrace{(a^r_{gt} - a^c_{dgt})b^c_{dgt}A^c_{gt}E^c_{gt}w^c_{g,t}}_{\text{Applicant share (by } d)} \\
&+ \sum_{gd} \underbrace{(b^r_{dgt} - b^c_{dgt})(a^r_{dgt} - a^c_{dgt})A^c_{gt}E^c_{gt}w^c_{g,t}}_{\text{Interaction within award and apply (by d)}} \\
&+ \sum_{gd} \underbrace{b^c_{dgt}a^c_{dgt}(A^r_{gt} - A^c_{gt})E^c_{gt}w^c_{g,t}}_{\text{Application (by } d)} + \sum_g \underbrace{B^c_{g,t}A^c_{g,t}(E^r_{g,t} - E^c_{g,t})w^c_{g,t}}_{\text{Eligibility}} \\
&\underbrace{...}_{\text{Interaction terms}}
\end{aligned}
\tag{18}
$$

where the second equality uses equation (16) to decompose the "award rate contribution" term.

4.2 Characteristics of marginal non-applications

Using equation (15), we analyze heterogeneity in the decline in SSDI applications with respect to several different applicant characteristics. Figure 6 shows results with respect to three key characteristics for the decline from 2010 to 2019: severity, pre-application employment, and diagnosis. For each characteristic and time period, the top bar represents the actual breakdown of the change in application rate. The bottom bar represents what the breakdown *would have been hypothetically* if it had been proportional to the shares of applicant characteristics in 2007.

Perhaps the most striking finding is that with respect to applicant severity. The decline in applications during this period comes disproportionately from the moderately-severe and most-severe categories, as opposed to the least-severe. Marginal non-applicants are also more likely to be recently attached to the labor force. While the application decline comes from all disability types, applications for musculoskeletal conditions are underrepresented while applications with mental conditions and endocrine conditions (e.g., diabetes) are overrepresented.

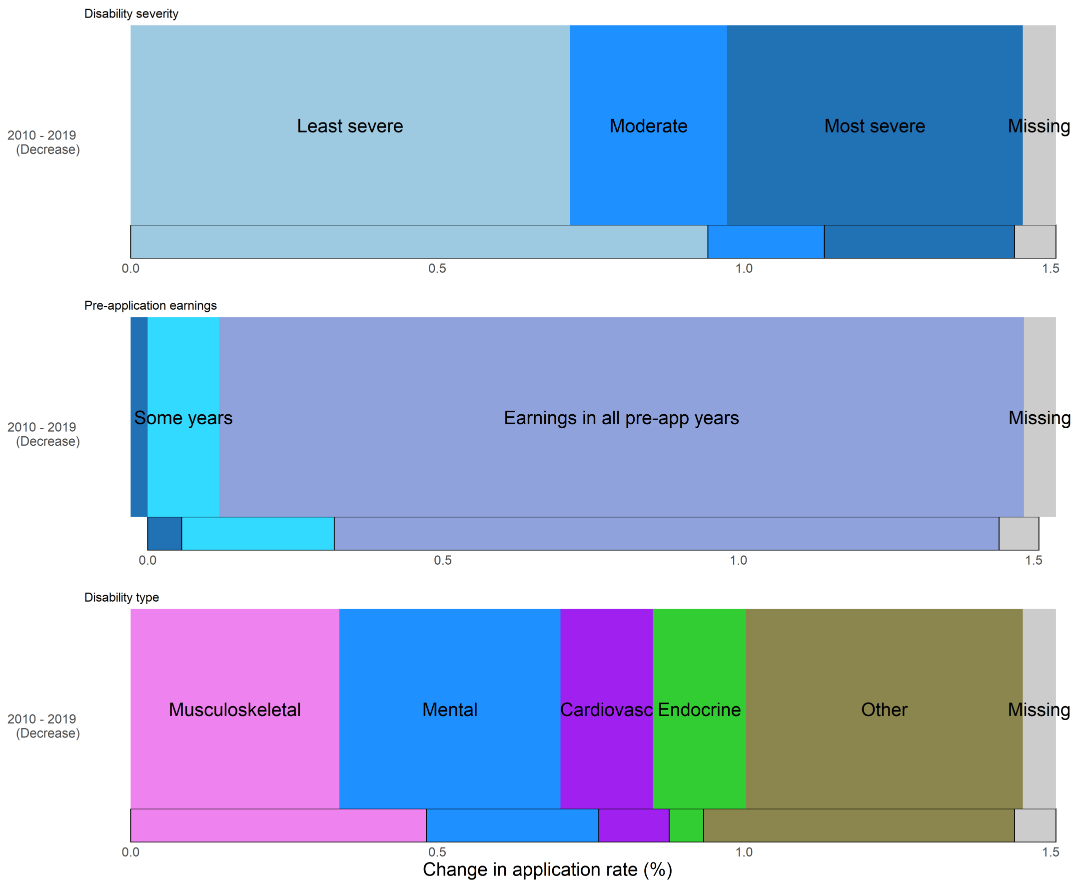
Diving deeper into these results, we find that applicant severity is positively correlated with recent applicant earnings: in 2019, the "most severe" applicants were more likely (71%) to have recently worked full-time than the "least severe" applicants (42%), and were more likely (38% vs 21%) to have early-career earnings in the top two earnings quintiles (see Appendix Figure A.2). The "least severe" appear more likely to apply primarily for economic reasons rather than health reasons, and are highly likely to be rejected. The most common diagnoses for the "most severe" are musculoskeletal (35%, mostly disorders of the back, arthropathies, and arthritis), cancer (15%), and neurological (13%); for the "least severe," they are musculoskeletal (39%), mental (22%), and neurological (8%). These facts suggest that middle- and high-severity applicants are the marginal workers, while low-severity applicants are much more disconnected from the labor market.[19]

We conduct heterogeneity analysis with respect to several other characteristics, with results in Appendix Section H.2. Marginal non-applicants are slightly more likely to come from areas with improving local labor market conditions (Appendix Table H.38). They are disproportionately from the construction and manufacturing industries (Appendix Table H.63), and less likely to be in industries with high work-from-home rates (Appendix Table H.68). However, we find no meaningful geographic heterogeneity with respect to state, urban/rural status, minimum wage changes, 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 (Appendix Tables H.18, H.28, H.33, H.43, H.48, and H.53). The composition of the decline in entry (i.e., approved applications) looks similar to the composition of the decline in applications, but less disproportionate for nearly all characteristics.

Finally, we compare the marginal applications during the Great Recession (2007-2014) period to the marginal non-applications during the post-recovery period (2014-2019). As shown in Appendix Figure A.3, we find that these two groups of marginal applicants are quite different. During the Great Recession period, the marginal applications are disproportionately from areas with declining labor market conditions, disproportionately in the

[19]This finding is consistent with Deshpande and Li (2019) and Deshpande and Lockwood (2022).

Figure 6: Marginal non-applicants disproportionately severe, labor-force-attached, and non-musculoskeletal



Notes: Figure characterizes the change in applicants by characteristics during 2010-2019. Each bar consists of a main bar and a sub-bar. The main bar gives the fraction of the decline from 2010-2019 represented by that characteristic, using equation (15). The sub-bar gives the hypothetical fractions that would have been proportional to applicant shares in 2007. "Least severe" means that the applicant was rejected at the disability examiner level (but could have been allowed on appeal). "Moderately severe" means that the disability examiner assigned a diary reason of "medical improvement expected" or "medical improvement possible." "Most severe" means that the disability examiner assigned a diary reason of "medical improvement not expected." "Earnings in all pre-app years" means the applicant worked for 4-5 years of the 5 years before application. "Earnings in some pre-app years" means the applicant worked for 1-3 years of the 5 years before application. "No earnings" means the applicant did not work in any of the 5 years before application. Diagnosis is recorded by the disability examiner assigned to the case. See Appendix Tables H.3, H.8, and H.73 for exact estimates.

least-severe category, and disproportionately representing musculoskeletal and mental conditions. These results are consistent with Maestas, Mullen and Strand (2015). In contrast, during the post-recession period, the marginal non-applications are disproportionately from areas with strong economic growth and in higher-severity categories, but are relatively proportional in the types of conditions they apply with. The Great Recession period appears to have pulled in applicants with less-severe conditions and musculoskeletal and mental conditions onto SSDI, while the post-recession period appears to have discouraged applicants with more-severe conditions and non-musculoskeletal conditions.

Adjusting the statistical decomposition results for changes in applicant composition. The change in applicant composition with respect to severity during the 2010-2019 decline means that the statistical decomposition is likely to underestimate the share of the decline in SSDI enrollment attributable to declining application rates. Since the applicant pool becomes less severe over time, award rates will mechanically fall. The statistical decomposition will attribute the entire decline in award rates causally to changes in award rates, when in fact some of the decline in award rates is the result of changing applicant composition. To account for differential selection into application over time, we further decompose the "Award rate contribution" term in equation (18) into the parts attributable to true changes in award rates versus changes arising from changing applicant composition. This adjustment increases the share of the SSDI enrollment decline attributable to lower application rates from 46-57% to 57-69%, and decreases the share attributable to lower award rates from 30-43% to 19-31% (see Appendix Table A.1).

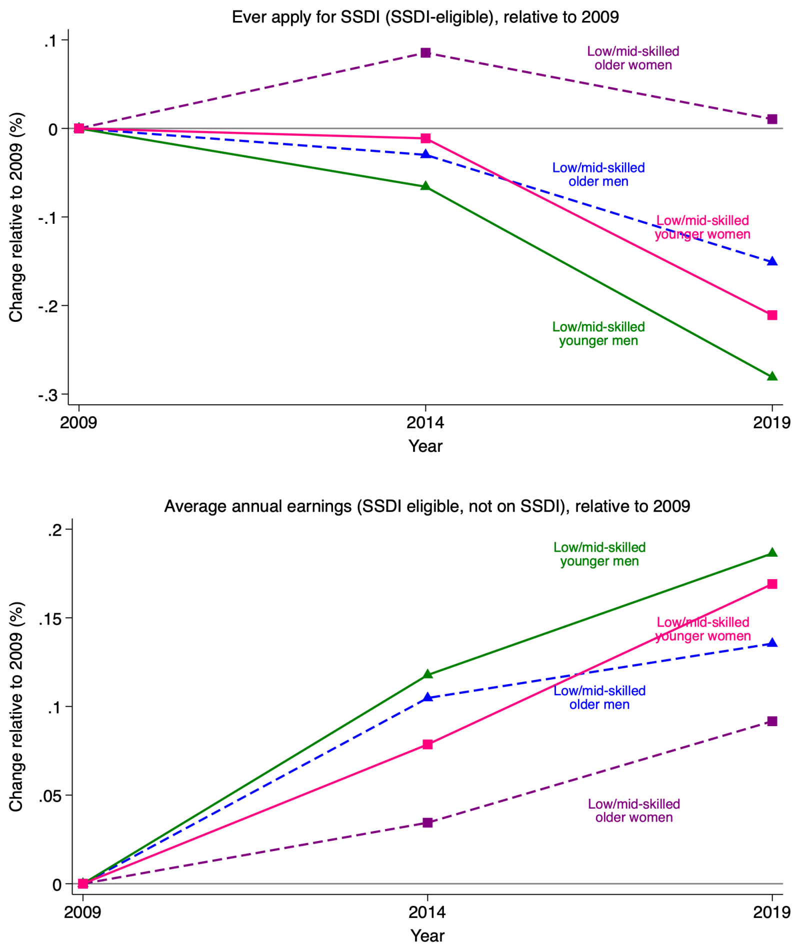
4.3 Characterizing the work behavior of marginal non-applicants

Figure 7 shows SSDI application rates and inflation-adjusted earnings for different (low-to-middle-skilled) demographic groups during the application decline period. Consistent with the results in Figure 4, younger men experience the largest declines in application rates, followed by younger women and older men, while older women experience no decline in application rates. The patterns in earnings gains almost perfectly mirror the application results: younger men experience the largest gains, followed by younger women and older men, with older women lagging behind. In Appendix Figure A.4, we find similar results by early-career industry: workers who started out in construction and manufacturing have the largest application declines and the largest earnings gains over this time.

How do we reconcile large earnings gains among younger men with previous findings on declining male labor force participation? In Appendix Figure A.5, we find that the SSA administrative data replicate the finding from previous work that non-employment rates have increased substantially for younger low-to-middle-skilled men. However, since SSDI requires a substantial work history, non-employed men are not on the margin for SSDI receipt. The large earnings gains in Figure 7 are driven by younger men who are attached to the labor market and therefore eligible for SSDI.[20]

[20] Other sources also document historic earnings growth at the bottom of the wage distribution following the Great Recession (Shambaugh and Strain, 2021; Aeppli and Wilmers, 2022; Dey, Handwerker, Piccone Jr

Figure 7: Low/mid-skilled younger men have largest SSDI application declines and largest earnings gains



Notes: Top figure plots the likelihood of ever applying for SSDI, relative to 2009. Bottom figure plots average annual earnings relative to 2009. "Low/mid-skilled" means average annual earnings of $1-$30,000 between the ages 25 to 34 years. "Younger/older" means age 35-39 and 50-54, respectively. The sample is derived from the Continuous Work History Sample linked to the Numident, F831 file, Payment History Update System, and Master Earnings File.

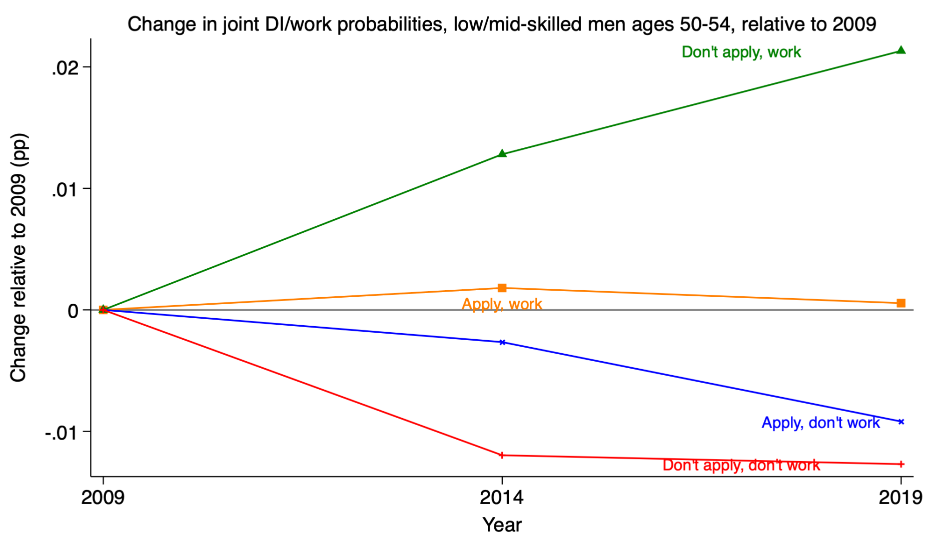
A key question is whether the workers with higher earnings are the *same* workers who are less likely to apply for SSDI. We conduct two exercises to shed light on this question. First, we test whether the increase in earnings and employment among low-skilled men applies to those with health conditions, 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. In Appendix Figure A.8, we present results from the same exercise as in Figure 7, but for individuals with

and Voorheis, 2022). More generally, the post-Great-Recession recovery has been the longest and strongest recovery in recent decades (see Appendix Figure A.7).

health conditions in the SIPP. We find similar patterns: among low-to-mid-skilled individuals with health conditions, younger men experience the largest application declines, followed by older men and younger women, and then by older women; the earnings gains mirror these patterns. The SIPP-SSA linked data also allow us to observe spouses, and we find that spouse earnings for low-to-middle-skilled men have grown rapidly since the Great Recession (Appendix Figure A.8). 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. Appendix Section B.1 provides more details on the SIPP analysis.

Second, we calculate the joint likelihood of employment and SSDI application across cohorts of low-to-middle-skilled men. Figure 8 shows that the likelihood of applying and not working has declined for older low-to-middle-skilled men in the post-recession period. At the same time, the likelihood of working and not applying has increased, while the likelihood of neither working nor applying has declined. Appendix Figure A.6 replicates the same result for older low-to-middle-skilled man with health conditions in the SIPP-SSA linked data. These results suggest that men who would have applied for SSDI instead work.

Figure 8: Low/mid-skilled men have become less likely to apply, more likely to work



Notes: Figure plots the joint probabilities of working and applying for SSDI benefits for low-to-middle-skilled men (defined as having average annual earnings of \$1-\$30,000 between the ages 25 to 34 years) ages 50 to 54 over time. Figure uses men from the Continuous Work History Sample linked to the Numident, F831 file, Payment History Update System, and Master Earnings File.

4.4 Characterizing marginal non-awards

Recall from the previous section that the decline in conditional award rates is driven disproportionately by younger women. We can additionally characterize the marginal non-awards by characteristics that are only observed for applicants using equation (16), with results in in Appendix Section H.2. We find that the award rate decline comes disproportionately from mental conditions (Appendix Table H.10). This result is consistent with administrative law judges reducing award rates more for less-verifiable conditions as a result of their re-training. Younger men and women are disproportionately likely to apply with mental conditions, which could explain why they disproportionately drive the award rate decline.

4.5 Implications of descriptive analysis

We find that the change in application behavior is driven disproportionately by the groups that experience the largest gains in earnings. This descriptive finding suggests some reasons for the decline in SSDI enrollment and rules out other reasons. One possibility is that improved labor market opportunities caused a reduction in SSDI applications. Another possibility is that a reduction in SSDI applications—caused by, e.g., higher administrative burden, lower award rates, or stigma—led to higher labor supply. A third possibility is that some third factor, like improvements in health, led to both higher employment rates and lower SSDI application rates.

The relationship between SSDI application and work behavior is at odds with other hypotheses for the decline in SSDI applications. For example, higher generosity of other benefits might reduce SSDI applications but likely would not increase employment. In the next section, we study in more detail hypotheses for the decline in SSDI applications.

5 Causal analysis of the decline in SSDI applications

We now evaluate the empirical relevance of several potential causes of the decline in SSDI applications. We first present a model of application behavior that we will use to guide and interpret this analysis. Next, we present a set of causal estimates on SSDI application of plausibly exogenous changes in a wide range of factors that could affect incentives to apply for SSDI. The factors we consider are summarized in Table 3. Lastly, we combine the causal estimates with the model to quantify the empirical importance of the various factors to the observed decline in SSDI applications since 2010.

5.1 Model of application behavior

The model serves three purposes. First, it clarifies the parameters that we need to recover to quantify the empirical importance of the various factors of the decline in SSDI applications. Second, it helps to make explicit the data, observable shifters, and assumptions that we need to identify and estimate these parameters. Lastly, it makes it possible to construct logically coherent predictions of counterfactual trends in SSDI applications in the absence of a particular factor. By comparing this counterfactual trend to the actual trend, we can draw inferences about the empirical importance of each factor.

Preferences. Consider a population of individuals of different types ν who vary in the characteristics that determine their capacity to work. The types are distributed across individuals according to the cumulative distribution function F_{ν_t} with support V. Let A and B be indicator variables for applying to and receiving benefits, respectively. The fixed cost of applying is given by the parameter $\kappa(\nu)$. The K-dimensional vectors z_t^b and z_t^w are shifters that affect utility when on benefits and working, respectively.

The state-specific utility function of a given individual of type ν is given by:

$$V_t(A,B) = \begin{cases} \sum_{k=1}^K \beta_k^b(\nu) z_{kt}^b + \xi_t^b - \kappa(\nu) & \text{if } A=1 \text{ and } B=1, \\ \sum_{k=1}^K \beta_k^w(\nu) z_{kt}^w + \xi_t^w - \kappa(\nu) & \text{if } A=1 \text{ and } B=0, \\ \sum_{k=1}^K \beta_k^w(\nu) z_{kt}^w + \xi_t^w & \text{if } A=0 \text{ and } B=0, \end{cases} \tag{19}$$

where ξ_t^b and ξ_t^w are drawn i.i.d. from a standard Gumbel distribution, capturing idiosyncratic variation across individuals in the utility of working relative to receiving benefits.

Before deriving the decision rule of the model, it is useful to note that we suppress the subscript for individuals to simplify the notation. However, z_t^b, z_t^w, ξ_t^b and ξ_t^w are allowed to vary across individuals of the same type ν, while the parameters κ, β_k^w, and β_k^w vary by ν but not between individuals with the same ν.

Decision rule and application rates. At the beginning of each period, the individual forms her (rational) expectations about the award function $G_t(v) \equiv \mathbb{P}(B_t = 1 | A_t = 1, \nu_t = v)$. The function captures the leniency of the SSDI system in the sense that a higher $G_t(v)$ means that a larger share of applicants of type v are awarded.[21] The individual then decides whether or not to apply for SSDI benefits to maximize their expected utility given the state-specific utility function in equation (19) and their beliefs.

The solution to this maximization problem leads to the following decision rule: An individual applies whenever the expected utility gain from applying is greater than the fixed cost:

[21]Eligibility can be built into G_t by, for example, putting $G_t(v) = 0$ for certain values of v, so only individuals with certain characteristics (e.g., age or work history) are eligible.

$$A_t = \mathbb{1}\left[G_t(v) \times \left(\sum_{k=1}^{K}(\beta_k^b(v)z_{kt}^b - \beta_k^w(v)z_{kt}^w) + \xi_t^b - \xi_t^w\right) \geq \kappa(v)\right].$$

The application rate of individuals of type v can then be expressed in terms of the model as:

$$p_t(v) \equiv \mathbb{P}(A_t = 1 \mid \nu_t = v) = \frac{\exp(m_t(v))}{1 + \exp(m_t(v))} \equiv H(m_t(v)).$$

where $m_t(v)$ captures the leniency-adjusted payoff to applying for SSDI for type v individuals:

$$m_t(v) \equiv \sum_{k=1}^{K}(\beta_k^b(v)z_{kt}^b - \beta_k^w(v)z_{kt}^w) - \frac{\kappa(v)}{G_t(v)}.$$

A model-based decomposition of changes in application rates. We are interested in understanding the causes of the long-run decline in application rates:

$$\begin{aligned}\mathbb{P}(A_{t_1} = 1) - \mathbb{P}(A_{t_0} = 1) &= \sum_{l=t_0}^{t_1-1}(\mathbb{P}(A_{l+1} = 1) - \mathbb{P}(A_l = 1)) \\ &= \sum_{l=t_0}^{t_1-1}(\underbrace{\int (f_{\nu_{l+1}}(v) - f_{\nu_l}(v))p_l(v)dv}_{\text{changes in composition}} + \underbrace{\int (p_{l+1}(v) - p_l(v))f_{\nu_{l+1}}(v)dv}_{\text{changes in application behavior}})\end{aligned}$$

where f_{ν_t} is the probability density function of ν_t. The first term after the second equality tells us the contribution from changes in the distribution of ν, keeping the application behavior fixed. The second term captures the contribution from changes in application behavior, keeping the distribution of ν fixed. This term can be further decomposed into three distinct components of changes in application behavior over time:

$$\int (p_{t+1}(v) - p_t(v))f_{\nu_{t+1}}(v)dv = \sum_{k=1}^{K}\Delta_{kt}^b + \sum_{k=1}^{K}\Delta_{kt}^w + \Delta_t^G$$

which (up to a first-order approximation) are defined as follows:

$$\Delta^b_{kt} = \int \underbrace{\underbrace{(f_{\nu_{t+1}}(v)h(m_t(v))}_{\text{share of } \nu \text{ type at the margin of applying}} \times \underbrace{\beta^b_k(v)}_{\text{effect on application incentives}} \times \underbrace{(z^b_{kt+1} - z^b_{kt})}_{\text{time shift in } k\text{'th benefit shifter}})dv}_{\text{aggregate change in application behavior due to time shift in the } k\text{'th benefit shifter}}$$

$$\Delta^w_{kt} = \int \underbrace{\underbrace{(f_{\nu_{t+1}}(v)h(m_t(v))}_{\text{share of } \nu \text{ type at the margin of applying}} \times \underbrace{-\beta^w_k(v)}_{\text{effect on application incentives}} \times \underbrace{(z^w_{kt+1} - z^w_{kt})}_{\text{time shift in } k\text{'th work shifter}})dv}_{\text{aggregate change in application behavior due to time shift in the } k\text{'th work shifter}}$$

$$\Delta^G_t = \int \underbrace{\underbrace{(f_{\nu_{t+1}}(v)h(m_t(v))}_{\text{share of } \nu \text{ type at the margin of applying}} \times \underbrace{\frac{\kappa(v)}{G_t(v)^2}}_{\text{effect on application incentives}} \times \underbrace{(G_{t+1}(v) - G_t(v))}_{\text{time shift in award function}})dv}_{\text{aggregate change in application behavior due to time shift in screening stringency}}$$

and $h(m) \equiv dH/dm$.

The contribution to $\mathbb{P}(A_{t_1} = 1) - \mathbb{P}(A_{t_0} = 1)$ of each component is increasing in the number of individuals that are close to the application margin, in the effect on application incentives of an increase in the component's shifter, and in the change over time in this shifter.

Taking the model-based decomposition to the data. In Section 6, we will use the model to construct logically coherent predictions of counterfactual trends in SSDI application rates in the absence of observed time changes in the k'th benefit shifter z^b_{kt}, in the k'th work shifter z^w_{kt}, or in the award function $G_t(v)$. To construct these counterfactual trends, we need to recover the parameters of Δ^b_{kt}, Δ^w_{kt}, or Δ^G_t.

In either case, the first step is to recover $f_{\nu_t}(v)$ and $h(m_t(v))$ for each year t. For this purpose, it is useful to observe that there is a tight link between the model-based decomposition above and the statistical decomposition of the time trend in the application rates. In fact, these decompositions coincide if one assumes that ν_t can be represented by the observed characteristics we use in the statistical decomposition. Under this assumption of selection on observables, we can directly measure $f_{\nu_t}(v)$ and $p_t(v)$ from the yearly micro data on SSDI applications. The quantity $h(m_t(v))$ can then be identified from the share of applicants by inverting this equation:

$$m_t(v) = \log\left(\frac{p_t(v)}{1 - p_t(v)}\right).$$

The next step is to recover the parameter $\beta_k^b(v)$, $\beta_k^w(v)$, or $\kappa(v)$. To do so, we will use a research design that isolates plausibly exogenous variation in observable shifters. However, for notational simplicity, suppose for now that the shifter z_{kt}^b, z_{kt}^w, or Δ_t^G is randomly assigned across individuals in at least one year. We can then recover $\beta_k^w(v)$ by estimating the effect of a marginal increase in z_{kt}^w on individuals of each type ν, since

$$\underbrace{\frac{\partial \mathbb{P}(A_t = 1 \mid \nu_t = v)}{\partial z_{kt}^w}}_{\text{Identified from (quasi)-experiment}} = \underbrace{h(m_t(v))}_{\text{Identified from application data}} \times \underbrace{\beta_k^w(v)}_{\text{Unobserved}}.$$

The same logic allows us to identify $\beta_b^b(v)$ by estimating the effect of a marginal increase in z_{kt}^b and recovering $h(m_t(v))$ from application data. By comparison, to recover $\kappa(v)$, we need to estimate the effect of a marginal increase in G_t on individuals of each type ν, since

$$\underbrace{\frac{\partial \mathbb{P}(A_t = 1 \mid \nu_t = v)}{\partial G_t(v)}}_{\text{Identified from (quasi)-experiment}} = \underbrace{h(m_t(v))}_{\text{\# Identified from application data}} \times \frac{\kappa(v)}{G_t(v)^2},$$

and $G_t(v)$ is observed from our data on applications and recipients.

Once we have identified $f_{\nu_t}(v)$, $h(m_t(v))$, and $\beta_k^b(v)$, $\beta_k^w(v)$, or $\kappa(v)$, we can quantify Δ_{kt}^b, Δ_{kt}^w, or Δ_t^G from the observed time changes in the k'th benefit shifter z_{kt}^b, in the k'th work shifter z_{kt}^w, or in the award function $G_t(v)$. As shown in Section 6, this allows us to construct logically coherent predictions of counterfactual trends in SSDI application rates. But first, we present the quasi-experimental estimates that pin down $\beta_k^b(v)$, $\beta_k^w(v)$, or $\kappa(v)$.

5.2 Quasi-experimental estimates

We now present a set of quasi-experimental estimates on SSDI application of plausibly exogenous changes in a wide range of factors that could affect incentives to apply for SSDI (i.e., $\beta_k^b(v)$, $\beta_k^w(v)$, or $\kappa(v)$ from the model above). Table 3 summarizes the factors we consider.

The inverse relationship between SSDI application and employment found in Section 4 suggests the following possibilities:

1. **Higher labor demand → lower SSDI.** Higher demand for less-skilled workers could

have increased their employment rates and diverted them from SSDI.[22]

2. **Lower SSDI due to lower award rates → higher employment.** Lower SSDI award rates at the appeals level, attributed in part to the retraining of judges, may have discouraged applications.[23]

3. **Lower SSDI due to higher administrative burden → higher employment.** Changes in wait times, field office service, representative compensation, or information could have discouraged applications.[24] The political discussion around social welfare benefits in the run-up to the 2016 election could have also discouraged applications.

4. **Third factor (e.g., better health) → lower SSDI, higher employment.** Reductions in pollution and smoking could have improved public health and reduced SSDI application rates. More effective treatments for mental health conditions and more availability of treatment could have also reduced SSDI applications.

5. **Higher mortality of potential applicants → lower SSDI, higher employment.** By increasing the mortality of potential applicants, the opioid crisis could have both reduced demand for SSDI and mechanically increased employment rates (if those potential applicants would not have worked).

6. **More generous benefits (inconsistent with work patterns).** If other benefits became more generous, people may have substituted from SSDI to those benefits, but then we would not expect to see higher employment rates.[25]

7. **Population aging (inconsistent with work patterns).** The aging of the population could have moved people from the SSDI program to the retirement program, but then we would not expect to see higher employment rates.

Table 3 summarizes the quasi-experimental evidence on all of these factors. We first determine whether the relevant factor changed during the period of the application decline (2010–19). We then use either novel evidence or existing evidence to determine the responsiveness of SSDI applications to that factor. By combining the change in the factor with the responsiveness of applications to that factor, we determine to what extent that factor could have contributed to the decline in SSDI applications.

[22] Glenn and Goss (2018); Ruffing (2023); Center on Budget and Policy Priorities (2025); Liu and Quinby (2023).

[23] See Glenn and Goss (2018); Social Security Administration (2019); Ruffing (2020, 2023); Center on Budget and Policy Priorities (2025); Liu and Quinby (2023); Mohamed et al. (2024).

[24] See Glenn and Goss (2018); Armour (2018); Ruffing (2023); Center on Budget and Policy Priorities (2025); Mohamed et al. (2024).

[25] See Glenn and Goss (2018); Ruffing (2023); Center on Budget and Policy Priorities (2025).

Table 3: Evaluating hypotheses for the decline in SSDI applications from 2010 to 2019

	Change in factor 2010–19?	Empirical strategy for response of SSDI applications	Explanatory power?	See for details
Consistent with SSDI application and work patterns				
1) Labor market conditions				
Labor demand	Yes, long recovery	Use Autor and Duggan (2003) shift-share design	Likely large	Section 5.2.1
Remote work	Yes, more remote jobs	Heterogeneity based on Dingel and Neiman (2020)	Little, if any	Section 5.2.1
Minimum wage	Yes, state increases	Heterogeneity by local minimum wage	Little, if any	Section 5.2.1
2) Award rates				
Award rates	Yes, ALJ reform	DiD using baseline ALJ award rate	Little, if any	Section 5.2.2
3) Admin burden				
Field office closings	Yes, several closings	Existing evidence: Deshpande and Li (2019)	Little, if any	Section 5.2.3
Processing times	No		Little, if any	Section 5.2.3
Legal representation	Yes, ALJ reforms	DiD using baseline legal representation	Little, if any	Section 5.2.3
Social Security mailings	No, only stopped 2011–14		Little, if any	Section 5.2.3
Stigma	Possibly, political discussion	Heterogeneity by political leaning	Little, if any	Section 5.2.3
4) Health				
Pollution	Yes, 1970 Clean Air Act	Heterogeneity based on Isen et al. (2017)	Little, if any	Section 5.2.4
Smoking	No		Little, if any	Section 5.2.4
Mental health treatment	Yes, higher take-up	Existing evidence + heterogeneity by diagnosis	Potentially some	Section 5.2.4
5) Mortality				
Opioid crisis	Yes	Heterogeneity by opioid death rate	Little, if any	Section 5.2.5
Inconsistent with SSDI application and work patterns				
6) Other benefits				
SNAP/TANF/UI	No		Little, if any	Section 5.2.6
Other cash benefits	Yes, VA Disability	Heterogeneity by veteran status	Little, if any	Section 5.2.6
Health insurance	Yes, ACA	Existing evidence: many sources (see text)	Little, if any	Section 5.2.6
Health care access	Yes, CHCs	Existing evidence: Anstreicher and Strand (2025)	Little, if any	Section 5.2.6
7) Population aging				
Population aging	No, working-age population has shifted to highest-DI-receipt ages		Little, if any	Section 5.2.7

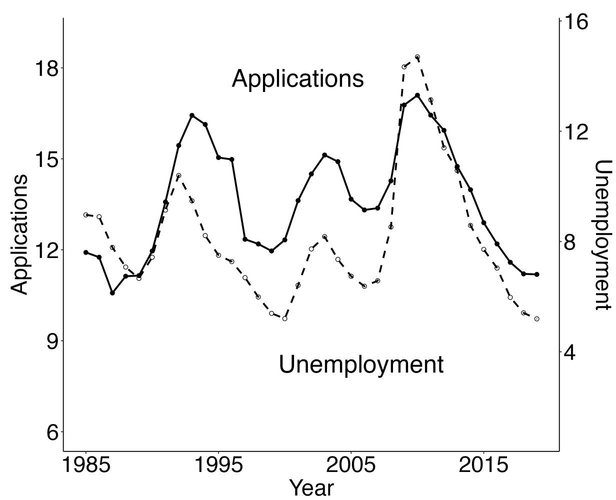
Notes: The first column lists various factors that could potentially have contributed to the decline in SSDI applications from 2010 to 2019. The second column summarizes the evidence on whether that factor changed during the period of the application decline (2010–19). The third column describes how we determine the responsiveness of SSDI applications to that factor, using either new evidence (either descriptive or quasi-experimental) or existing evidence. The fourth column describes, based on the combination of the second and third columns, whether the factor could potentially explain some part of the decline in SSDI applications, which previews our analysis in Section 6 about whether this factor is likely to be important in explaining the decline. See text for details.

5.2.1 Improvement in the labor market for less-skilled workers (Higher labor demand → lower SSDI)

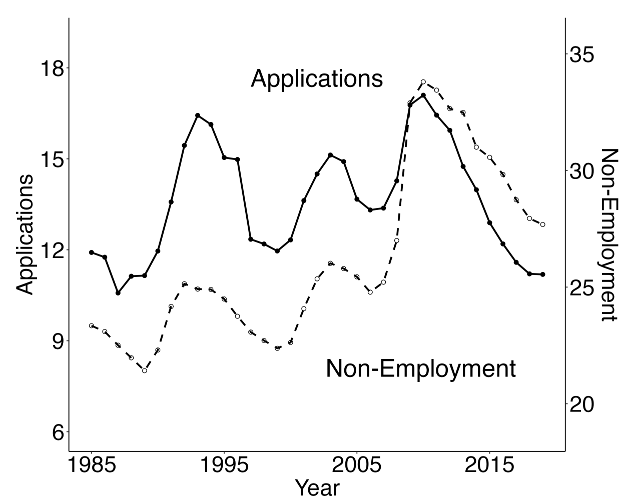
In a widely cited paper, Autor and Duggan (2003) conclude that SSDI application rates are sensitive to changes in demand for less-skilled workers, especially after the 1984 expansion of medical eligibility. Motivated and guided by their finding and research design, we examine whether improvements in the labor market conditions of less-skilled men (i.e., with no college education) from 2010 to 2019 could have reduced SSDI application rates.

The time series of unemployment and non-employment rates suggests that this could indeed be the case. As shown in Figure 9, both the unemployment rates and the employment-to-population ratio (the share of the working-age population who are currently working) track SSDI application rates closely over time for less-skilled men (see Appendix Figure A.9 for all adults). The steady and prolonged recovery from the Great Recession is no exception. As the labor market recovered, SSDI application rates fell. We also find in the cross-section that places with larger declines in local unemployment rates contributed disproportionately to declines in SSDI application rates from 2010 to 2019 (see Appendix Table H.38).

Figure 9: SSDI applications track unemployment and non-employment rates over time



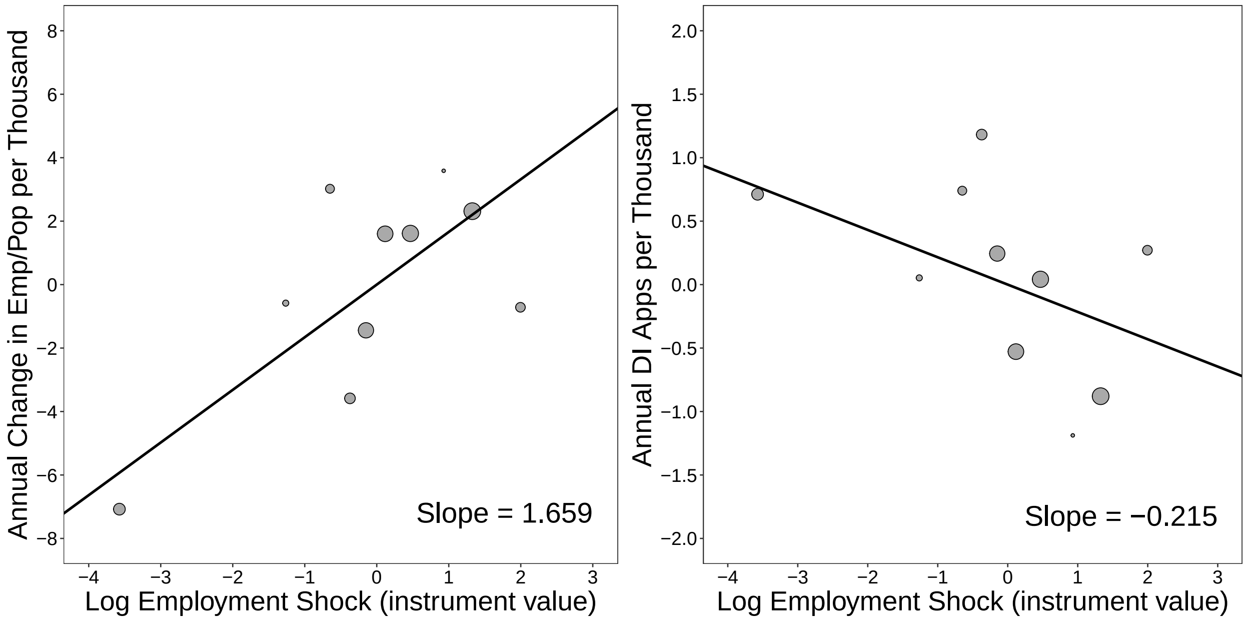
(a) Applications and unemployment, less-skilled men ages 18-66



(b) Applications and non-employment, less-skilled men ages 18-66

Notes: Figure plots SSDI applications, unemployment rates, and non-employment rates over time for men ages 18-66 years with no college education. SSDI applications are per thousand working-age adults. Employment measures (dashed lines) are plotted against the secondary axis in panel. Non-employment is reported as a percent of the working-age population, and unemployment as a percent of the labor force. Both are measured using monthly CPS data from IPUMS. Time series correlations of applications with non-employment and unemployment are 0.53 and 0.73, respectively. The correlation between non-employment and unemployment is 0.65. See Appendix Figure A.9 for analogous graphs using the full adult population.

Figure 10: Local labor market improvements positively correlated with employment and negatively correlated with SSDI application rates



(a) Employment and Log Employment Shock (b) Applications and Log Employment Shock

Notes: The data used to construct these plots is composed of non-overlapping three-year intervals for each state. Intervals used to construct the data are: (2013,2016], and (2016,2019]. All variables have been residualized with respect to the controls included in equation (20): time dummies and linear controls for annualized changes in population shares by age and gender, age being split into 3 bins: 18-39, 40-54, and 55-66. Both panels present bin scatter plots, constructed by assigning state-interval observations into 10 equally sized groups based on percentiles of the explanatory variable (log employment shock). Each circle shows the population-weighted average outcome (change in employment or SSDI applications) and average log employment shock within each bin. The size of each circle reflects the total population in that bin.

There is also a strong spatial association between SSDI application rates and changes in local employment and labor market conditions. To show this, we follow Autor and Duggan (2003). We first use CPS data to re-construct their measure of state-level labor demand shifts, defined as a weighted sum of national industry employment changes of less-skilled men (excluding own state employment) projected onto state industry composition. Next, Figure 10 plots these measures of labor demand shifts against changes in the employment of less-skilled men (10a) and the SSDI application rates (10b) of less-skilled men in each state. The key insight from Figure 10 is that the Autor and Duggan (2003) measures of labor market shifts continue to co-vary strongly with employment rates and SSDI application rates at the state level in more recent years.

To quantify and economically interpret the relationships in Figure 10, we follow Autor and Duggan (2003) in estimating the following 2SLS regression model:

$$(\text{Apps per Capita})_{j,\tau} = \alpha_0 + \lambda_{t(\tau)}\Delta(\text{Emp per Capita})_{j,\tau} + \beta_0' X_{j,\tau} + \varepsilon_{j,\tau} \tag{20}$$

with the corresponding first-stage equation:

$$\Delta(\text{Emp per Capita})_{j,\tau} = \alpha_1 + \gamma_{t(\tau)}\hat{\eta}_{j,\tau} + \beta_1' X_{j,\tau} + \vartheta_{j,\tau} \tag{21}$$

where X denotes a set of linear demographic controls (changes in population shares by sex and age group: 18-39, 40-54, 55-66), and τ represents an interval of three years. $(\text{Apps per Capita})_{j,\tau}$ is the average annual application rate of less-skilled men in state j over the three-year interval τ, and $\Delta(\text{Emp per Capita})_{j,\tau}$ is the change in the employment-to-population ratio for less-skilled men over the three-year interval τ (annualized by dividing this change by 3). Our instrument, $\hat{\eta}_{j,t}$, is the measure of state-level labor demand shifts.

Appendix Table C.1 presents the 2SLS estimates.[26] Our main 2SLS estimate for less-skilled men is -0.13 (with a standard error of 0.158): in a given three-year interval, an annualized 1 percentage point growth in the employment-to-population rate yielded a 0.13 percentage point decline in annual application rates. This average effect masks heterogeneity across individual types, especially with respect to age. For example, effects for older high school graduates (-0.33 with a standard error of 0.15) are several times larger than effects for younger high school graduates (-0.05 with a standard error of 0.07). In Section 6, we show that our estimates are large enough to explain much of the decline in SSDI applications from 2010 to 2019.

Contribution of other labor market factors, like remote work and minimum wage. Another labor-market-related explanation for the decline in SSDI applications is that improvements in technology enabled more workers to work remotely, which could have increased the labor *supply* of workers with disabilities and thereby reduced SSDI applications.[27] We find no heterogeneity in the decline in SSDI application by the Dingel and Neiman (2020) measure of feasibility of remote work across industries (see Appendix Table H.68).

Under some circumstances (like firm monopsony power), higher minimum wages could increase employment and reduce SSDI applications. However, we do not find a correlation between local minimum wage and SSDI application decline (see Appendix Table H.43).

[26] An implication of the model is that, conditional on type, a shift in the payoff of working will not change applicant award rates. Appendix Table C.2 shows that we find no evidence that the shifter affects award rates among applicants.

[27] Bloom et al. (2026) estimate that the work-from-home revolution accounts for 80% of the post-pandemic increase in employment among people with disabilities.

5.2.2 Decline in award rates on appeal (Lower SSDI → higher employment)

One of the leading hypotheses for the SSDI 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). Policy changes starting in 2008, including new training and guidelines for administrative law judges, reduced award rates at the appeals level (Hoynes et al., 2024), which could have subsequently discouraged applications and increased labor market earnings.[28]

We estimate the effect of award rates on SSDI applications. Since ALJs have specific geographic jurisdictions, we use geographic variation in award rates at the appeals level (specifically, the likelihood of award conditional on being rejected at the initial level) prior to 2008 to estimate the effect of a change in award rates on SSDI applications. We first establish that areas with higher allowance rates at the appeals level prior to 2008 experienced larger decreases in award rates after 2008, and then estimate the effect on SSDI applications in future years.

We estimate the following difference-in-differences specification:

$$Y_{it} = \alpha_i + \gamma_t + \sum_t \beta_t(\text{BaseAppealAllow}_i \times \text{D}_t) + \delta X_{it} + \epsilon_{it} \tag{22}$$

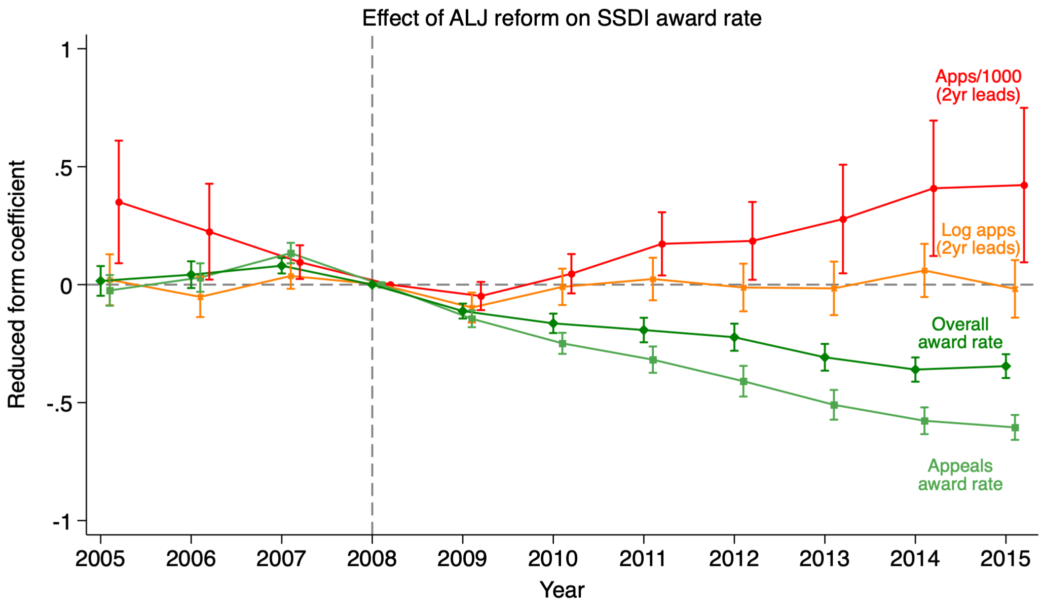
where Y_{it} is an outcome like appeals award rate (first stage) or future applications (reduced form) for county i in year t; BaseAppealAllow_i is the baseline appeals allowance rate (share of applications rejected at the initial level that are allowed on appeal in the three years prior to the reform); D_t are year indicators; 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.[29]

The main results are shown in Figure 11. We find that the ALJ reform reduces appeals award rates by 44 pp more, and overall allowance rates by 28 pp more, for (hypothetical) places with a 100% baseline allowance rate relative to (hypothetical) places with a 0% baseline allowance rate over the next 7 years. However, two-year application leads do not decline in areas with falling award rates (see Appendix Table A.2 for robustness checks).

[28] Papers from across the developed world show that DI denial or removal increases labor market earnings. See, e.g., Chen and van der Klaauw (2008); Von Wachter, Song and Manchester (2011); Maestas, Mullen and Strand (2013); Borghans, Gielen and Luttmer (2014); French and Song (2014); Moore (2015); Deshpande (2016); Autor, Kostøl, Mogstad and Setzler (2019); Haller, Staubli and Zweimüller (2024).

[29] We construct the number of SSDI applications in a county-year using the F831 file, which includes ZIP code. We construct one, two, and three year leads of applications since application responses to award rates may take time to manifest. To construct baseline appeals award rates (and overall award rates), we link the F831 file to payment data from the PHUS.

Figure 11: SSDI applications do not fall more in areas more affected by ALJ reform



Notes: Figure plots estimates of the effect of a county having a higher baseline appeals award rate in 2008 (i.e., β_t from equation (22)) 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.

5.2.3 Administrative burden of applying (Lower SSDI $\rightarrow$ higher employment)

We consider several potential explanations under the broad umbrella of administrative burden, but find that none can explain a large share of the decline in applications.

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 applications. See Appendix Section B.2.1 for details on the exact calculation.

Processing times. Processing times have not risen systematically in recent years.[30]

[30]The SSA reports average processing times for all cases nationwide only starting from 2014 (`https://www.ssa.gov/ssa-performance/disability-appeals-time`). Kearney, Price and Wilson (2021) find that, in areas where employment declined sharply during the Great Recession, areas assigned to SSA offices with longer appeals processing times experience lower SSDI enrollment, but the effect is modest.

Legal representation. Hoynes, Maestas and Strand (2026) document a decline in legal representation of SSDI applicants at the appeals level following the ALJ reforms discussed above, since lower appeals award rates reduced lawyer fees. They find that this change increased representation at the initial application level. We show in Figure 11 that the ALJ reforms had no effect on application by comparing areas with high versus low baseline appeals award rates. We also show in Appendix Figure A.10 that applications did not decline more for areas with high baseline levels of legal representation versus areas with low baseline levels following the ALJ reform.

End of Social Security statement mailings. SSA stopped mailing Social Security statements in 2011, restored the mailings in 2014, and then limited them again in 2017. These changes could have reduced worker awareness of SSDI benefits and their eligibility. However, the persistence of the decline in applications from 2010 to the present suggests that this change is not the primary explanation.

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 political leaning or by urban versus rural areas (see Appendix Tables H.18 and H.28).

5.2.4 Changes in health (Third factor → lower SSDI, higher employment)

Improvements in general health. Since our administrative data do not include health measures for the full population, we use the National Health Interview Survey to determine whether population health improved during the period of SSDI application decline. We find that neither overall health, nor rates of mental and musculoskeletal conditions specifically, has improved for low-to-middle-skilled men (see Appendix Figures A.11 and A.12).

Public health measures to reduce pollution and smoking. We examine whether public health measures to reduce pollution and smoking rates could have reduced SSDI applications.

- Pollution abatement: Isen et al. (2017) find that reductions in childhood pollution exposure due to the Clean Air Act of 1970 are associated with higher labor force participation in adulthood. Using data provided by Isen et al. (2017), we classify individuals by the pollution abatement requirements in the Clean Air Act for their place of birth. We find no heterogeneity in the decline in SSDI application based on this measure (see Appendix Section B.2.2 for more details on the analysis and Appendix Section G.3 for results).

- Decline in smoking: Smoking rates among men declined steadily from around 70% for the 1925 birth cohort to around 35% for the 1965 birth cohort, before plateauing for more recent birth cohorts (Holford, Levy, McKay, Clarke, Racine, Mez, Land, Jeon and Feuer, 2014). Men in birth cohorts between 1925 and 1965 would have turned 50 years old between 1975 and 2015. To the extent that lower smoking rates reduce SSDI applications, this effect would have started well before 2010. For this reason, lower smoking rates alone probably cannot explain the reversal of SSDI application growth in 2010, even though SSDI application levels may well have been higher in the absence of smoking reductions. We also find no heterogeneity in the application decline by county smoking rates (see Appendix Table H.58).[31]

Improvements in mental health treatment. Using data from the National Health and Nutrition Examination Survey (NHANES), we find that while rates of severe depression have not fallen in the working-age population or among low-skilled men, the use of antidepressants and antipsychotics has increased since 2010 (see Appendix Figures A.13 and A.14). Some papers estimate sizable increases in employment and/or reductions in disability benefits take-up from mental health treatment (Biasi, Dahl and Moser, 2027; Shapiro, 2022; Bütikofer, Cronin and Skira, 2020), while others estimate zero effects (Laird and Nielsen, 2016; Serena, 2024). Given the wide range of estimates, we cannot rule out improvements in mental health treatment as a driver of the decline in SSDI applications. It is unlikely to be the only or main driver, however, since the decline happens across all types of conditions, as shown in Figure 6.

5.2.5 Opioid crisis (Higher mortality → lower SSDI, higher employment)

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

[31] Using a sibling fixed effects model, Bengtsson and Nilsson (2018) find that smoking increases the likelihood of receiving disability benefits in Sweden by 4.2pp. Combining this estimate with the approximately 10pp reduction in male smoking rates between the 1955 and 1965 birth cohorts (Holford et al., 2014), we would expect smoking to reduce SSDI receipt rates among men by 0.4pp across these cohorts. This reduction is 20% of the actual reduction in SSDI receipt rates among men across these cohorts.

have applied for SSDI, it could explain some of the decline in SSDI application. We find no meaningful heterogeneity in the decline in SSDI applications across counties by the severity of the opioid crisis (see Appendix Table H.53).[32]

5.2.6 More generous other benefits (inconsistent with work patterns)

There was no increase in SNAP, TANF, or UI benefit amount or enrollment between 2010 and 2019 (see Appendix Figures B.1, B.2, and B.3). However, there were major changes in health insurance coverage and Veterans Disability Benefits during this period.

Affordable Care Act expansion of health insurance coverage. The Affordable Care Act of 2010 expanded access to health insurance to lower- and middle-income adults through Medicaid (in certain states) and the exchanges, starting in 2014. If potential SSDI applicants would have applied primarily to get health insurance coverage, then the ACA expansions could have contributed to the SSDI application decline. We investigate this hypothesis in several ways. First, we examine the correlation between increases in health insurance coverage and changes in SSDI applications (Appendix Figure B.4). We find that larger increases in health insurance coverage are associated with increases in SSDI applications, which is inconsistent with the hypothesis that health insurance coverage reduced demand for SSDI. Second, we study whether the decline in SSDI applications is concentrated in states that expanded Medicaid coverage (Appendix Table H.23). We find no heterogeneity in the SSDI application decline by state Medicaid expansion status. Finally, we review the large existing literature on the causal evidence on Medicaid expansions, with more details in Appendix Section B.2.3. Consistent with our correlational analysis, these papers find that Medicaid expansions had either no effect or a positive effect on SSDI and SSI applications.[33]

Veterans Disability Compensation. Enrollment in Veterans Disability Compensation (VDC) has increased from 3.2 million in 2010 to 5.7 million in 2023 (U.S. Department of Veterans Affairs, 2010, 2023). While there is no restriction on receiving both VDC and SSDI benefits, 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

[32] We use the CDC Wonder Database to measure deaths from opioids from 2010–2019, using the following ICD-10 codes: T40, T40.1, T40.2, T40.3, T40.4, T40.6. In the statistical decomposition, changes in mortality rates of SSDI recipients do not account for any of the decline in SSDI enrollment rates (Figure 3b).

[33] We review the following papers: Baicker, Finkelstein, Song and Taubman (2014); Maestas, Mullen and Strand (2014); Burns and Dague (2017); Soni, Burns, Dague and Simon (2017); Anand, Hyde, Colby and O'Leary (2019); Schmidt, Shore-Sheppard and Watson (2020); Heim, Lurie, Mullen and Simon (2021); Ne'eman and Maestas (2023a); Staiger, Helfer and Van Parys (2024). See Appendix Section B.2.3 for details.

on military EINs. However, we find that veterans have a disproportionately small decline in SSDI applications relative to their size (see Appendix Table G.30).

On the other hand, the share of older men who are veterans has decreased substantially from 2000 to 2020 (Chan, Duggan and Guo, 2021). We investigate whether a decline in the population share of veterans could have contributed to the decline in SSDI enrollment. We redo the decomposition exercise in Table 2 including veteran status (and thus the interaction between veteran status and age), with results in Appendix Table G.23. Including veteran status as a characteristic of the decomposition does not change the main results. See Appendix Section B.2.3 for more details.

5.2.7 Population aging (inconsistent with work patterns)

From Table 2, population aging does not play a major role in the decline in SSDI enrollment among the working-age population. This is likely for two reasons: First, population aging meant that the working-age population was on average older in 2019 than in 2010, and older workers have higher SSDI rates (see Appendix Figure A.15). Second, we analyze SSDI enrollment rates in the working-age population, which by definition does not include people above retirement age.

6 Counterfactual trends in SSDI applications

We now combine the causal estimates above with the model to construct predictions of counterfactual trends in SSDI applications.

6.1 Constructing counterfactual SSDI trends

To construct the counterfactual SSDI trend in the absence of, say, the observed time changes in the k'th work shifter z^w_{kt}, it could be tempting to simply set $\Delta^w_{kt} = 0$ for all $t_0 \leq t \leq t_1 - 1$. However, this would be misleading, as changes in z^w_{kt} from one period to another not only affect application shares directly through Δ^w_{kt}, but also change how many individuals are close to the margin of application in the future, as it changes future values of m_t. We show how to account for these considerations when constructing counterfactual application rates in the absence of observed changes in the labor demand shifter (z^w_{kt}) that we study in sub-section 5.2.1, and the award rate shifter (G_t) that we study in sub-section 5.2.2.

Changes in the work shifter. To account for both direct and indirect channels, we introduce the counterfactual leniency-adjusted benefit of applying, which is recursively defined by

$$\tilde{m}^w_{t+1}(v;k) = \tilde{m}^w_t(v;k) + m_{t+1}(v) - m_t(v) + \underbrace{\beta^w_k(v)\left(z^w_{k,t+1} - z^w_{k,t}\right)}_{\text{period } t\text{-effect of no change in } z^w_k}$$

with initial condition $\tilde{m}^w_{t_0}(v;k) = m_{t_0}(v)$. $\tilde{m}^w_{t+1}(v;k)$ measures the leniency-adjusted benefit of applying at time t had $z^w_{k,t}$ remained fixed from t_0 onwards. It is straightforward to solve the difference equation and obtain

$$\tilde{m}^w_t(v;k) = m_t(v) + \beta^w_k(v)\left(z^w_{k,t} - z^w_{k,t_0}\right). \tag{23}$$

This sequence also generates a sequence of counterfactual type-specific application rates $H(\tilde{m}^w_t(v;k))$ where we use skill groups as types.

The counterfactual *aggregate* trend in SSDI applications in the absence of the observed time changes in the k'th work shifter z^w_{kt} can then be defined by:

$$\mathbb{P}(A^w_{t_1}(k) = 1) = \int H(\tilde{m}^w_t(v;k)) f_{v_t}(v)dv \tag{24}$$

where $A^w_{t_1}(k)$ denotes application decision at time t_1 if z^w_{kl} is set equal to $z^w_{kt_0}$ from period t_0 to t_1. As explained in sub-section 5.1, we can compute this counterfactual by combining the quasi-experimental estimates in sub-section 5.2.1 with yearly micro data on SSDI applications to measure $m_t(v)$ and the observed time changes in z^w_{kt}.

Changes in the award function. We can consider the effect of turning off changes in the award function G_t in a similar manner. Define a counterfactual (setting $G_{t+1} = G_t$) sequence of leniency-adjusted benefits of applying by:

$$\tilde{m}^G_{t+1}(v) = \tilde{m}^G_t(v) + m_{t+1}(v) - m_t(v) + \underbrace{\left(\frac{\kappa(v)}{G_{t+1}(v)} - \frac{\kappa(v)}{G_t(v)}\right)}_{\text{period } t\text{-effect of no change in } G},$$

with initial condition $\tilde{m}^G_{t_0}(v) = m_{t_0}(v)$. This gives

$$\tilde{m}^G_t(v) = m_t(v) + \kappa(v)\left(\frac{1}{G_t(v)} - \frac{1}{G_{t_0}(v)}\right).$$

Again, we can write the counterfactual *aggregate* trend in SSDI applications as

$$\mathbb{P}(A_{t_1}^G = 1) = \int H(\tilde{m}_t^G(v)) f_{v_t}(v) dv,$$

where A_t^G denotes application decision at time t if G_t remained constant from t_0 to t_1. As explained in sub-section 5.1, we can compute this counterfactual by combining the quasi-experimental estimates in sub-section 5.2.2 with yearly micro data on SSDI applications to measure $m_t(v)$ and the observed time changes in G_t.

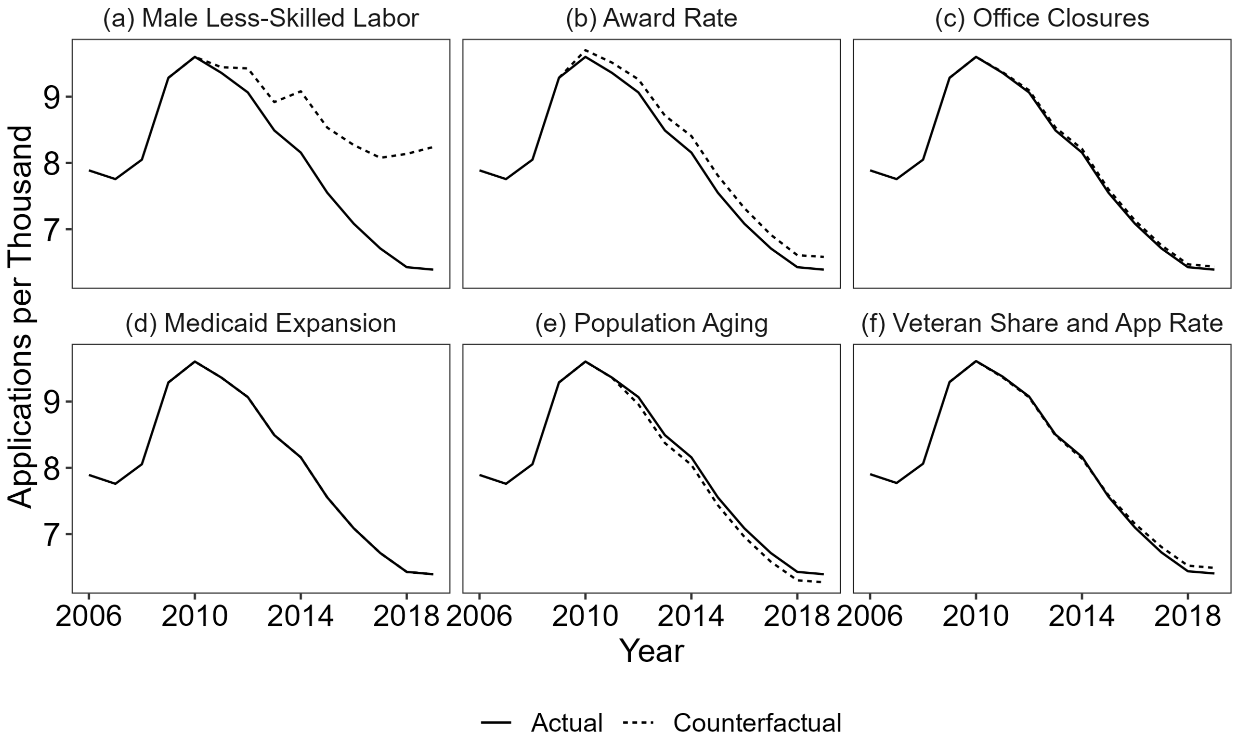
6.2 Counterfactual results

In Figure 12, we apply equations (23) and (24) to compute application rates under six counterfactual scenarios: (a) the employment-to-population ratio for less-skilled men had remained at its 2010 value, (b) the SSDI award rate had been fixed at pre-recession levels, (c) the number of SSA field offices had been fixed at pre-recession levels, (d) Medicaid access had not been expanded under the ACA, (e) the population had not aged relatively to pre-recession levels, and (f) the veteran population share and application rate had been fixed at pre-recession levels. Appendix Section C includes details on the calculations of these counterfactuals.

Fixing male less-skilled labor market conditions—allowing all else to vary over time—produces a counterfactual application rate in 2019 that is close to its baseline 2010 value. This exercise suggests that in 2019, rising employment among less-skilled men can explain 57 percent of the decline in the application rate relative to 2010. Appendix Figure C.1 shows that labor market conditions for less-skilled men entirely explain the decline in application rates among men in particular. In contrast, the other counterfactuals in Figure 12 suggest that award rates, office closures, Medicaid expansions, population aging, and changes in veteran composition or benefits cannot explain much of the decline.

We translate these SSDI application counterfactuals into counterfactual changes in enrollment, using back-of-the-envelope calculations with actual award rates by type and over time. Cumulatively from 2010 to 2019, improvements in labor market conditions for less-skilled men reduced SSDI enrollment by 781,000, or 0.39 percent of the 2019 working-age population. By comparison, the total decline in SSDI enrollment rate in the working-age population, relative to the counterfactual, is 1.04 pp (Table 2).

Figure 12: Labor demand for less-skilled men explains substantial share of SSDI application decline



Notes: Figure presents counterfactuals based on the method discussed in Section 6. When the "counterfactual" line is not visible, it is on top of the "actual" line. For panel (d) type is state of residence. For panel (e), type is age (18-24, 25-30, 31-40, 41-50, 51-64, 65-66). For panel (f), type is veteran status. For all other panels, type is defined by a combination of sex, educational attainment, and age (18-40 vs. 41-66). In panel (e) we fix the population age composition as observed in 2010. In panel (f), we fix both the veteran population share and application rates among veterans. For more details on estimation, see Appendix Section C.

7 Conclusion

The increase in SSDI enrollment in the 1990s and 2000s sparked significant policy debate and concern about the fairness of the social safety net and the consequences of a declining workforce. Yet the subsequent drop in SSDI applications and enrollment starting in 2010 has received much less attention and prompted little reconsideration about those previous concerns.

We find that the recent decline in SSDI enrollment is driven primarily by declines in applications, and secondarily by declines in awards, with minimal contribution from population composition, financial eligibility, or exit. The decline in SSDI applications comes disproportionately from older low-to-middle skilled men and disproportionately from applicants who have relatively severe conditions and are strongly attached to the labor force. Potential applicants appear to switch from applying for SSDI to working. Low- and middle-skilled men with health limitations during this time have historically high earnings levels and live with spouses with historically high earnings levels. In this population, income from SSDI is replaced with income from work.

We find that the most likely explanation for the decline in applications is improved work opportunities for low- and middle-skilled men with health limitations. Strong economic opportunities at the bottom of the earnings distribution appear to have pulled these men into the labor force and diverted them, at least temporarily, from SSDI. We find evidence that is inconsistent with other explanations for the decline in SSDI applications, including lower award rates at the appeals level, higher administrative burden of applying, improved population health, and increased generosity of other programs.

The evidence that better employment opportunities drive the SSDI decline prompts two questions. First, will the marginal non-applicants apply for SSDI benefits in the event of an economic downturn? Perhaps so, but the prolonged economic recovery from 2010 to the present means that many potential applicants have already hit retirement age and have therefore been permanently diverted from SSDI. Second, can policies that improve employment opportunities divert more people from SSDI? It is unclear whether temporary jobs or training programs can provide the same opportunities to low- and middle-skilled workers that the economic recovery in the 2010s did. To the extent that they can, however, successful efforts to divert individuals from SSDI could amount to substantial cost savings and higher long-term labor force participation rates.

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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	Princeton

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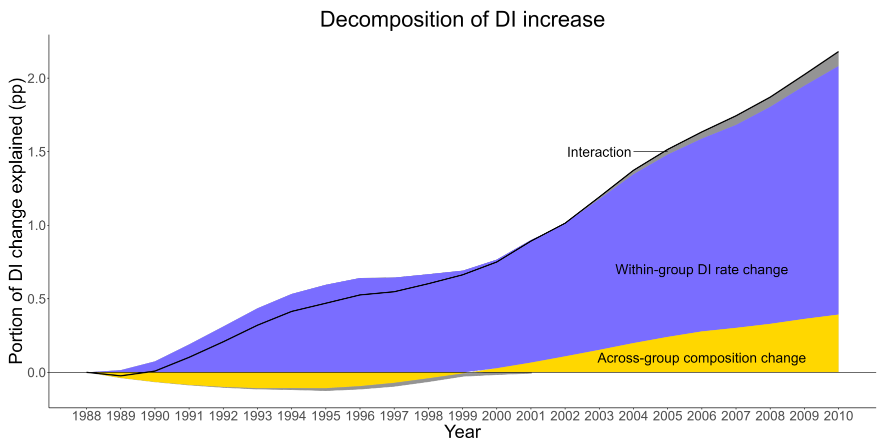
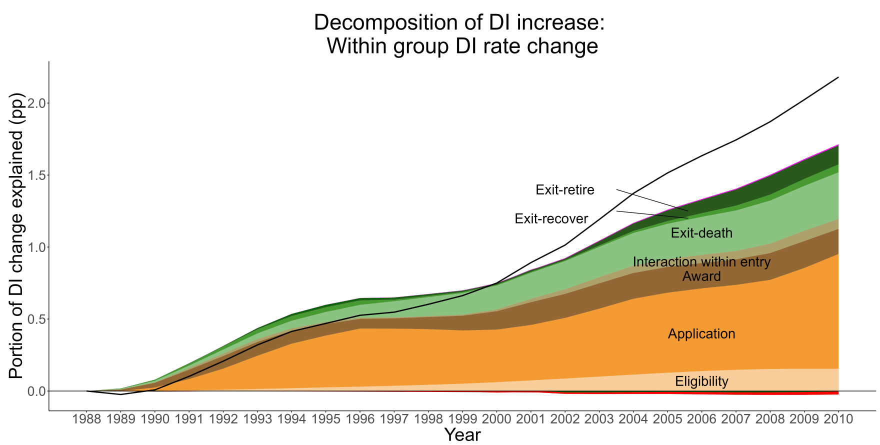
A Appendix Figures and Tables

Appendix Figure A.1: SSDI increase (1988–2010) attributable to higher application/award, lower exit



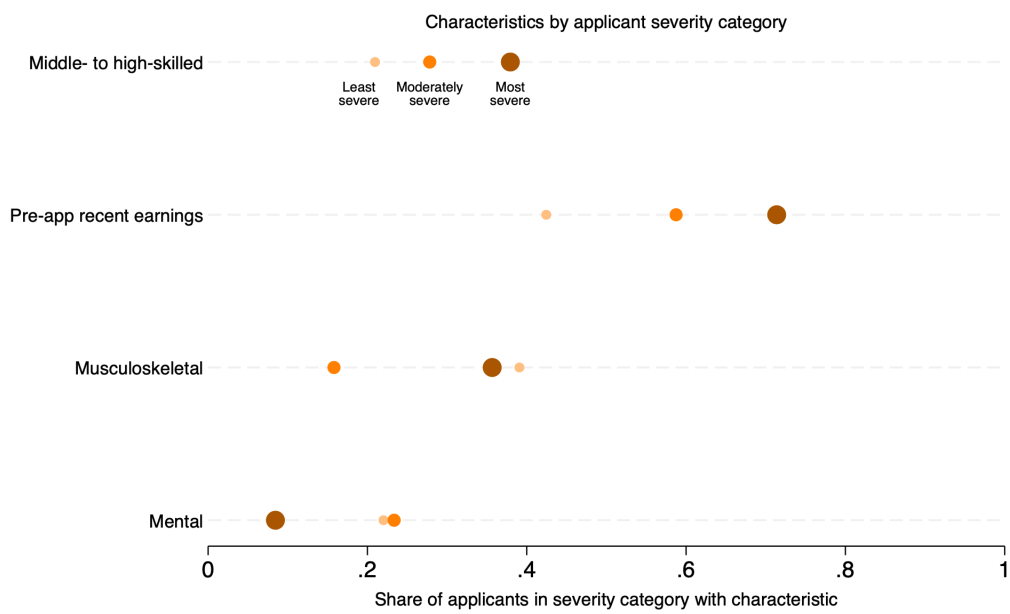
(a) Across-group versus within-group changes



(b) Within-group changes in behavior

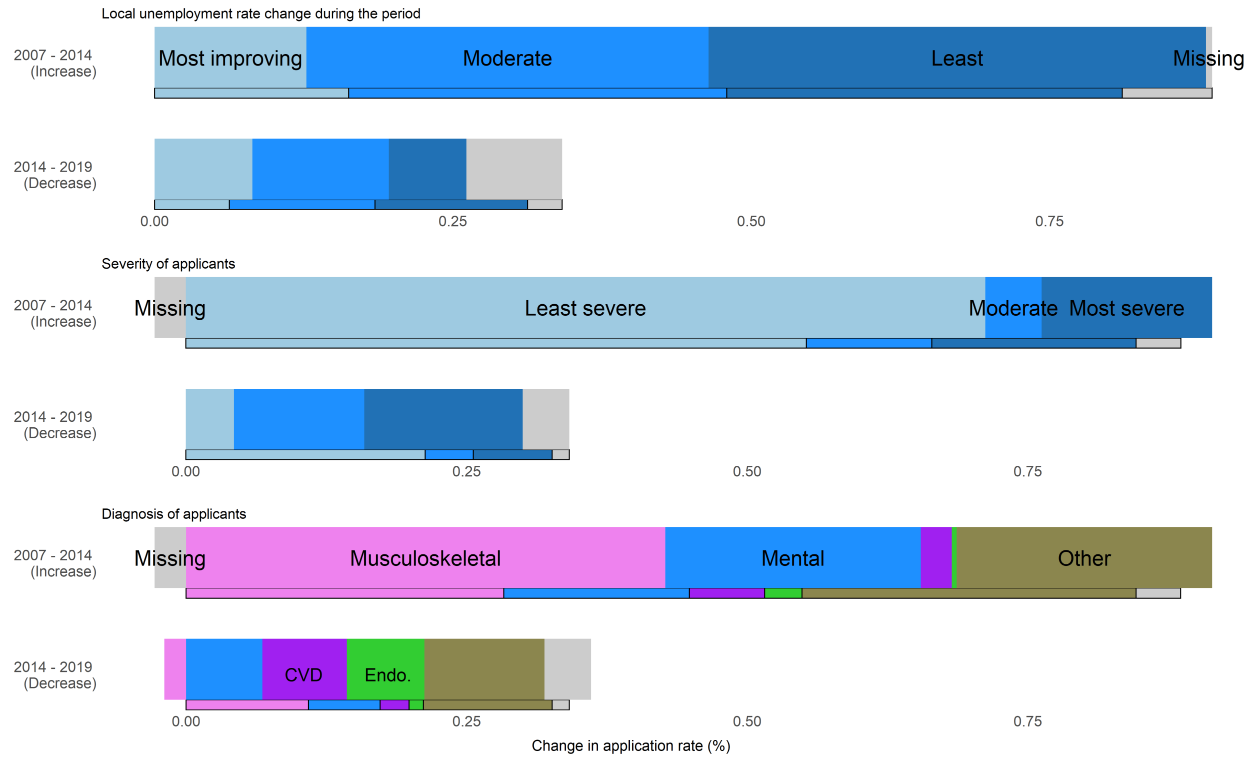
Notes: Top figure plots the decomposition of the increase in SSDI enrollment rates from 1988 to 2010 into across-group composition change, within-group change in SSDI enrollment rate, and the interaction between the two, as given by equation (5). Bottom figure plots the decomposition of the within-group 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 by equation (9). 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 (8). "Friction in population" and "Population discrepancy" are described in footnotes 13 and 15. The point estimates we report are the ones in which flows (e.g., B_t, A_t, E_t, X_t), when fixed, are held fixed at their counterfactual values. See Section 2.1 for details on the decomposition method. See Table 1 for exact estimates.

Appendix Figure A.2: Higher-severity applicants are higher-skilled and have higher labor force attachment



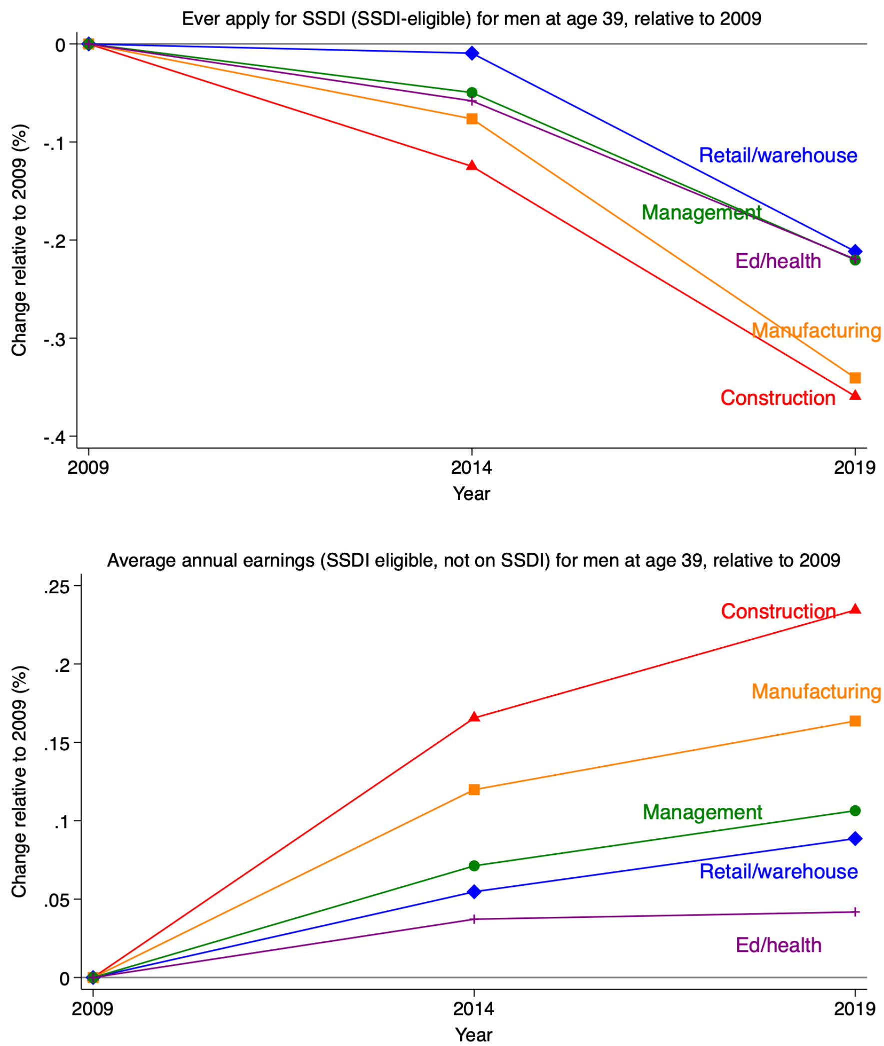
Notes: Figure shows share of SSDI applicants in 2019 in a given severity category who have a particular characteristic. "Middle- to high-skilled" means in top two earnings quintile in one's birth cohort between ages 25 to 35. "Pre-app recent earnings" means earning at least $15,000 in at least three of the five years preceding application. "Least severe" means that the applicant was rejected at the disability examiner level (but could have been allowed on appeal). "Moderately severe" means that the disability examiner assigned a diary reason of "medical improvement expected" or "medical improvement possible." "Most severe" means that the disability examiner assigned a diary reason of "medical improvement not expected." The sample is constructed from the F831 file.

Appendix Figure A.3: Marginal (non-)applicants during Great Recession (2007-2014) and post-recession period (2014-2019) are different



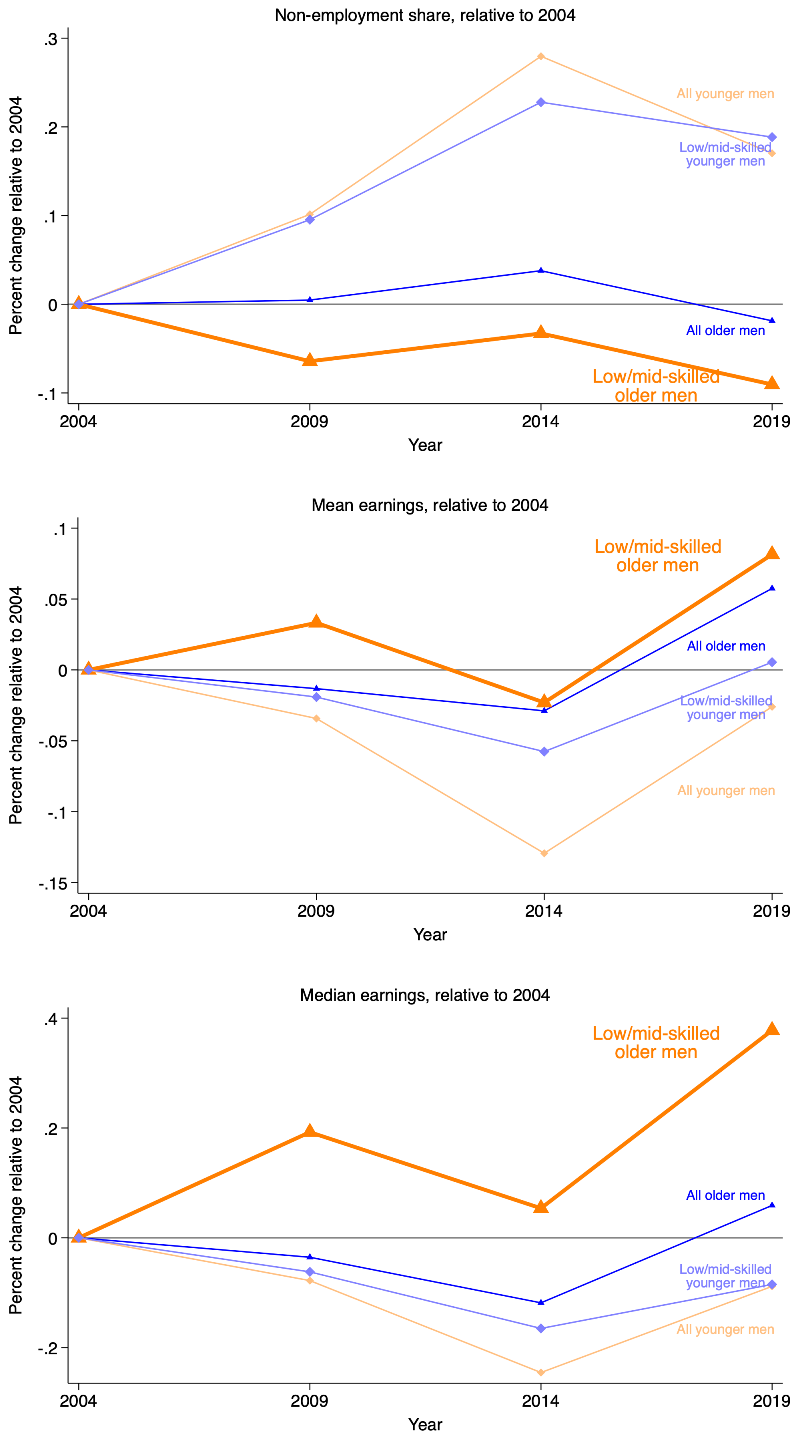
Notes: Figure characterizes the change in applicants by characteristics during 2007-2014 ("Great Recession," when there was an increase in applications) and during 2014-2019 ("post-recession," when there was a decrease in applications). Each bar consists of a main bar and a sub-bar. The main bar gives the fraction of the decline from that period represented by that characteristic, using equation (15). The sub-bar gives the hypothetical fractions that would have been proportional to applicant shares in 2007. We link ZIP code to Bureau of Labor Statistics Local Area Unemployment Statistics. "Most improving labor market" means that the change in the unemployment rate from 2007-14 (or 2014-19) is in the top tercile. "Moderately improving" means in the middle tercile. "Least improving" means the bottom tercile. "Least severe" means that the applicant was rejected at the disability examiner level (but could have been allowed on appeal). "Moderately severe" means that the disability examiner assigned a diary reason of "medical improvement expected" or "medical improvement possible." "Most severe" means that the disability examiner assigned a diary reason of "medical improvement not expected." Diagnosis is recorded by the disability examiner assigned to the case. See Appendix Section H.3 for exact estimates.

Appendix Figure A.4: Men working in construction and manufacturing have largest SSDI application declines and largest earnings gains



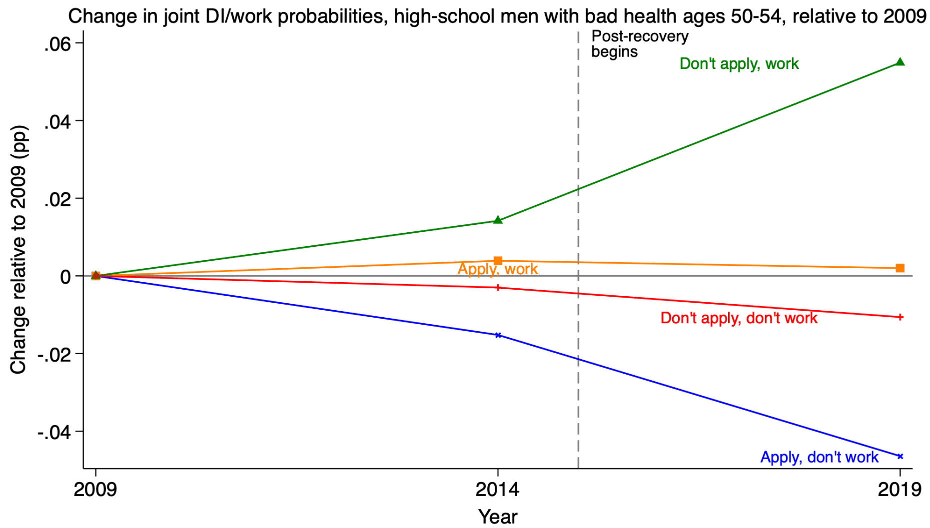
Notes: Top figure plots the the likelihood of ever applying for SSDI, relative to 2009. Bottom figure plots average annual earnings relative to 2009. Sample is men working in that industry between ages 25 to 34 years with average annual earnings of \$1-\$30,000 during that time. The sample is derived from the Continuous Work History Sample linked to the Numident, F831 file, Payment History Update System, and Master Earnings File.

Appendix Figure A.5: Non-employment has risen for younger men, but declined for older low/mid-skilled men



Notes: Figures plot non-employment likelihood, mean earnings, and median earnings for low-to-middle-skilled men and all men at ages 40 and 55, over time. Low-to-middle-skilled men are defined as having average earnings between $1 and $30,000 between ages 25 to 34 years old. The sample is derived from the Continuous Work History Sample linked to the Numident and Master Earnings File.

Appendix Figure A.6: Low/mid-skilled men with health conditions have become less likely to apply, more likely to work (and not apply)

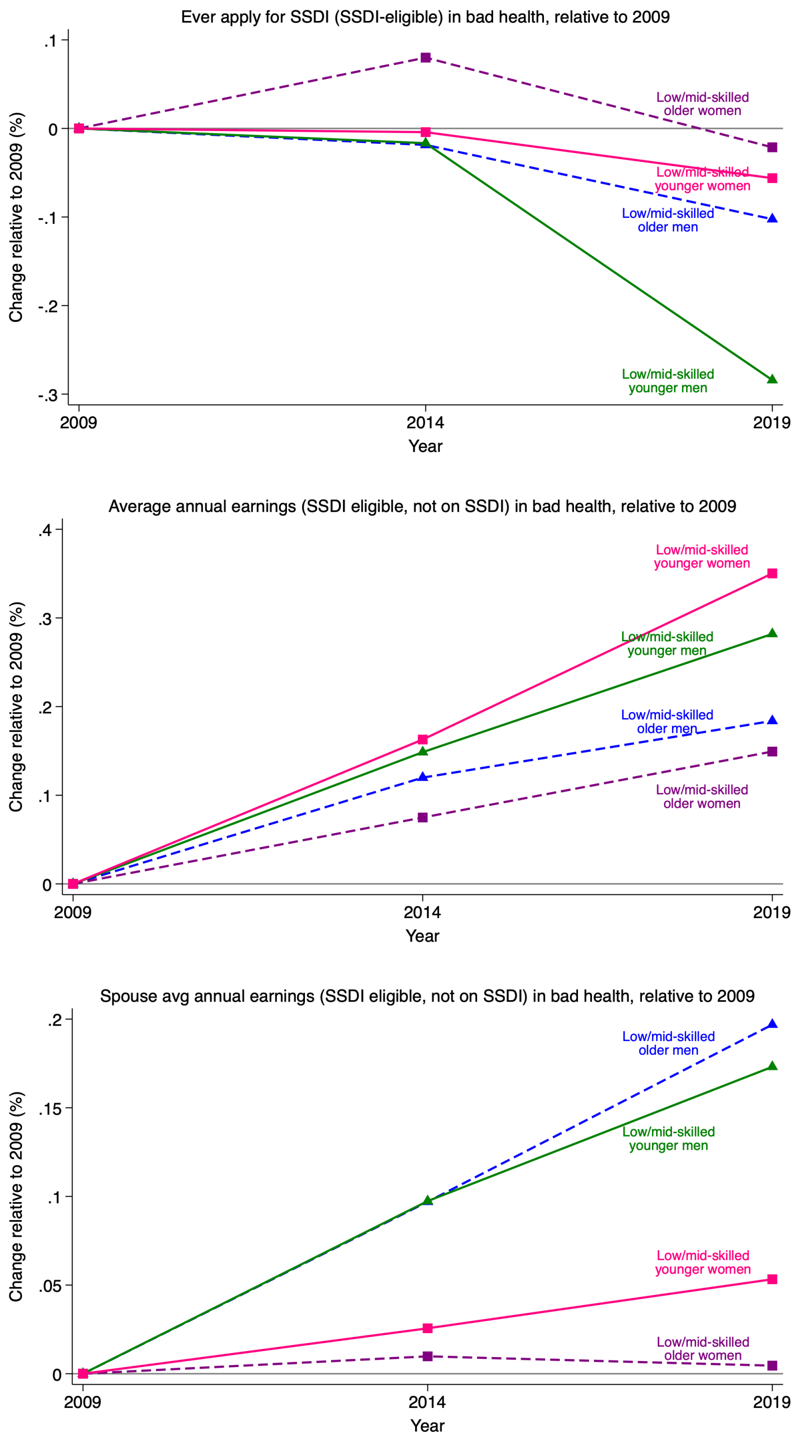


Notes: Figure plots the joint probabilities of working and applying for SSDI benefits for men with a high school degree or less over time. Figure uses men from the SIPP who have a high school degree or less and report being in "fair" or "poor" health; the sample is derived from the 1996, 2001, 2004, 2008, and 2014 panels of the SIPP linked to the Numident, F831 file, Payment History Update System, and Master Earnings File.

Appendix Figure A.7: Prolonged economic recovery following Great Recession

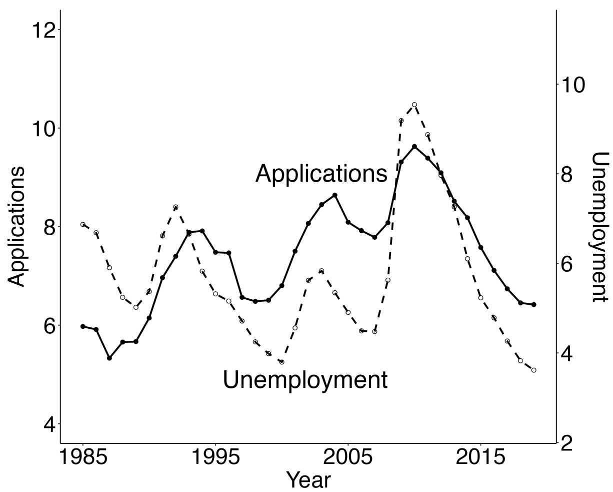
Notes: Figure plots US unemployment rate over time. Gray areas indicate recession periods as determined by the National Bureau of Economic Statistics. Source: U.S. Bureau of Labor Statistics, Unemployment Rate [UNRATE], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/UNRATE, July 18, 2025.

Appendix Figure A.8: Among low-to-middle-skilled people *with poor health*, falling SSDI application/receipt and rising earnings

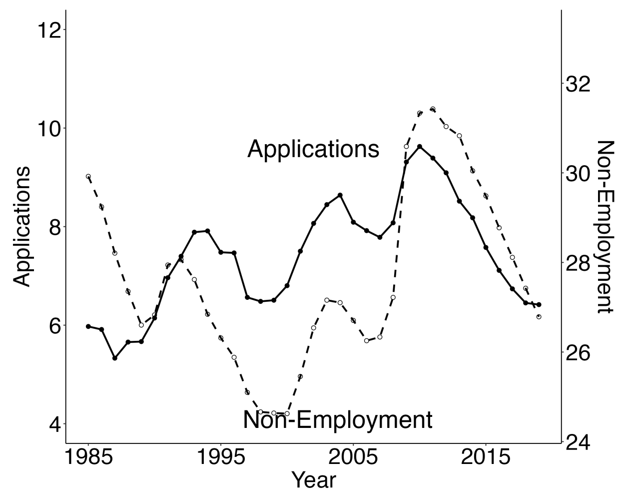


Notes: Figure plots the following outcomes over time, relative to 2009, for individuals in poor health: ever applied for SSDI, average annual earnings, and average annual spouse earnings conditional on having a spouse. The sample is derived from the 1996, 2001, 2004, 2008, and 2014 panels of the SIPP linked to the Numident, F831 file, Payment History Update System, and Master Earnings File. "Bad health" is defined as self-reported "fair" or "poor" health. Low/mid-skilled is defined as having a high school degree. See Appendix Section B.1 for more details on the SIPP analysis.

Appendix Figure A.9: SSDI application, unemployment, and non-employment rates for all adults age 18-66



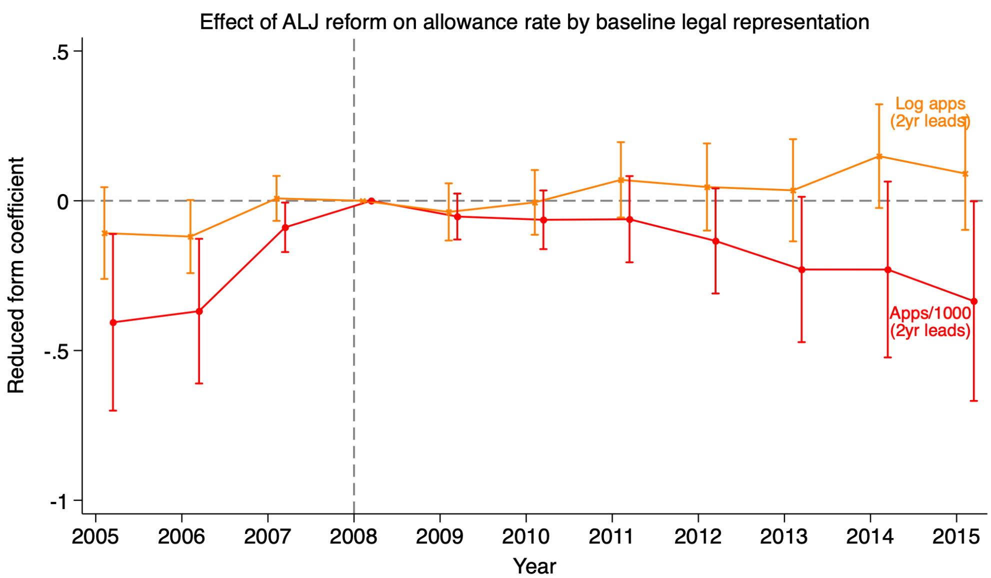
(a) Applications and unemployment, all adults ages 18-66



(b) Applications and non-employment, all adults ages 18-66

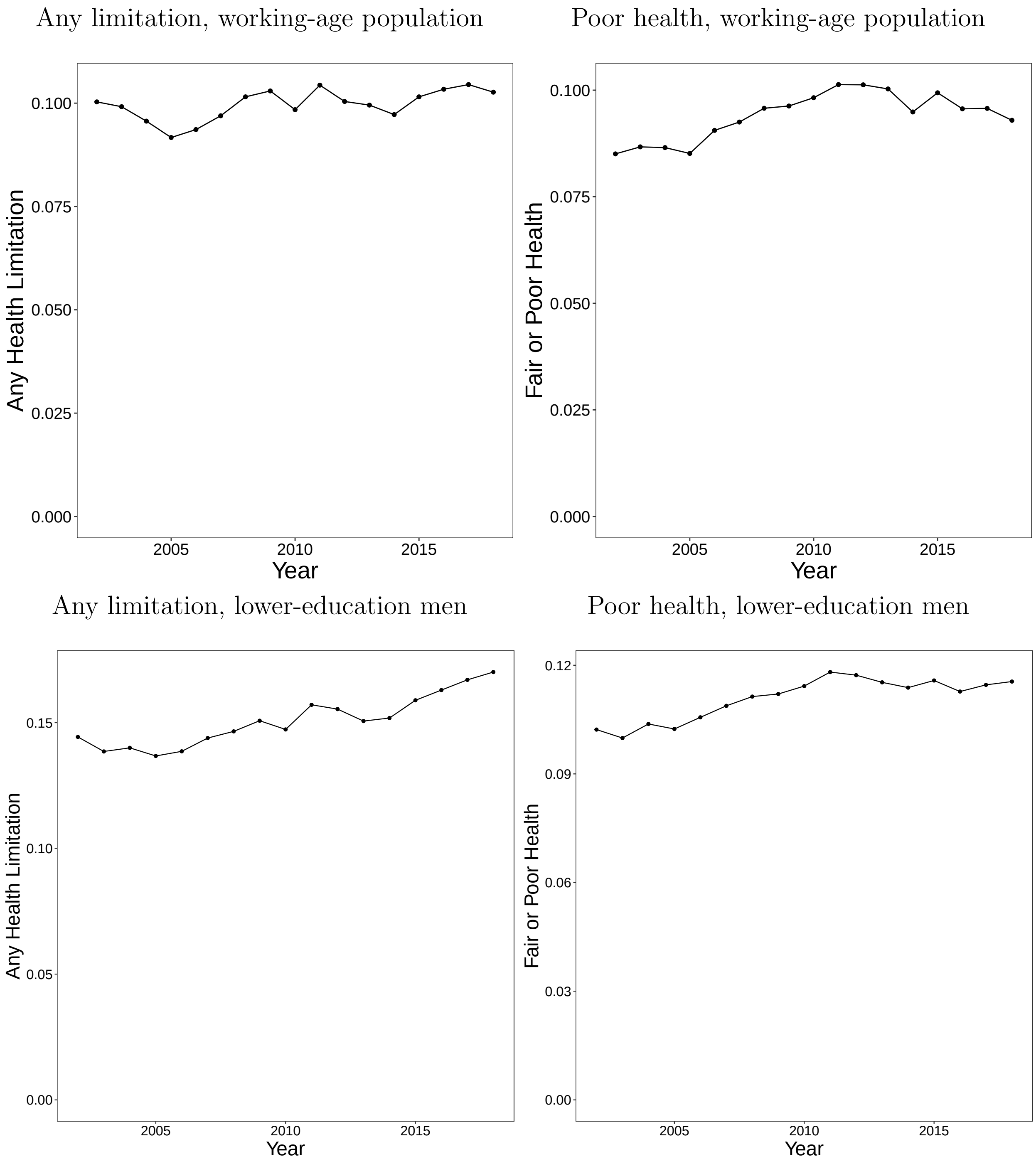
Notes: Figure plots SSDI applications, unemployment rates, and non-employment rates over time for all adults ages 18-66. SSDI applications are per thousand working-age adults. Employment measures (dashed lines) are plotted against the secondary axis in panel. Non-employment is reported as a percent of the working-age population, and unemployment as a percent of the labor force. Both are measured using monthly CPS data from IPUMS for individuals age 18 to 66. Overall time series correlations of applications with non-employment and unemployment are 0.45 and 0.58, respectively. The correlation between non-employment and unemployment is 0.81.

Appendix Figure A.10: No differential effect of ALJ reform on future applications by baseline legal representation



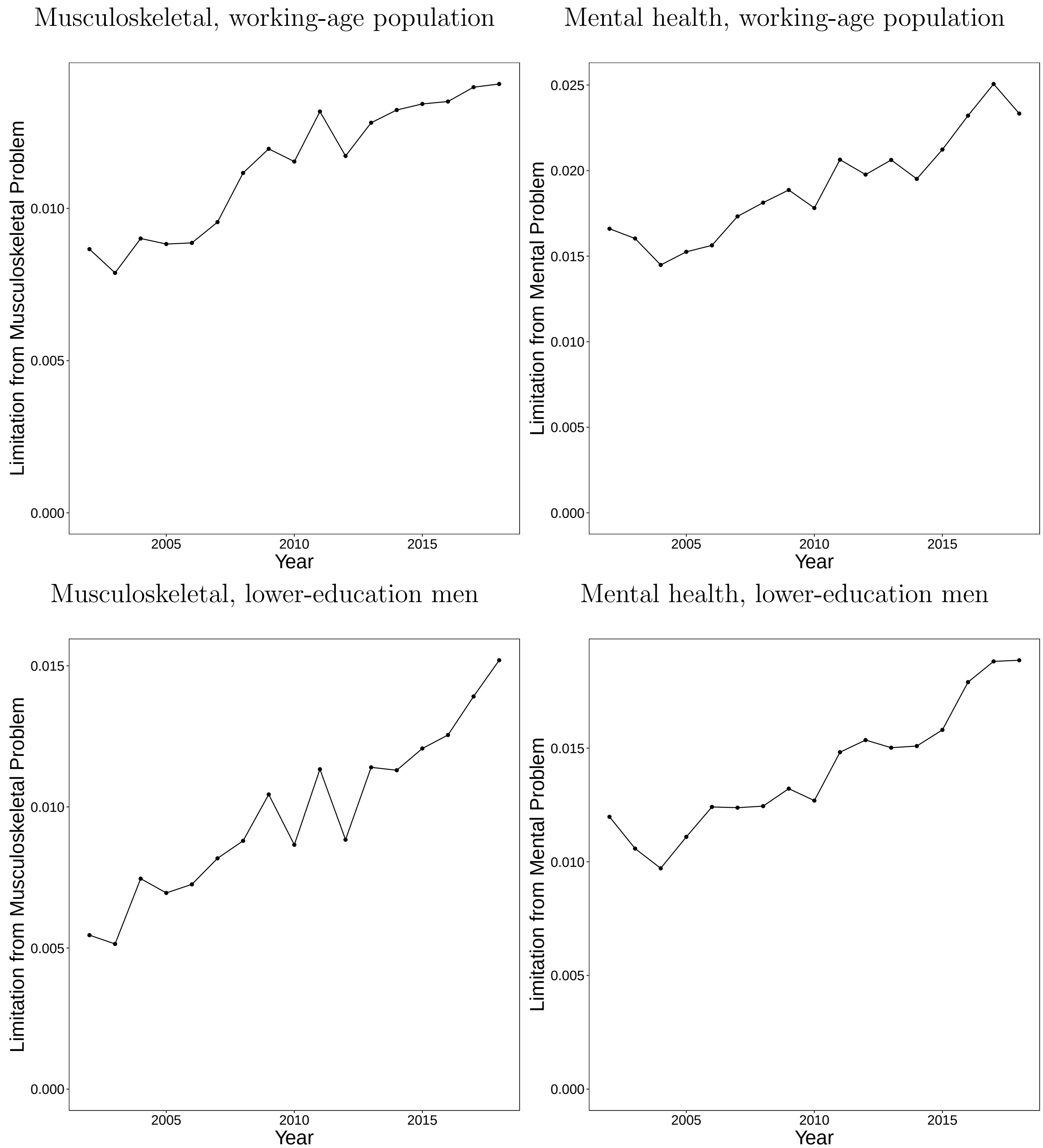
Notes: Figure plots estimates of the effect of a county having a higher baseline SSDI legal representation rate in 2007 (i.e., β_t from equation (22), where baseline ALJ award rate is replaced by baseline SSDI legal representation rate) on the number of SSDI applications two years later (divided by 100) 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 MEDIB.

Appendix Figure A.11: Population health did not improve substantially from 2010–2018



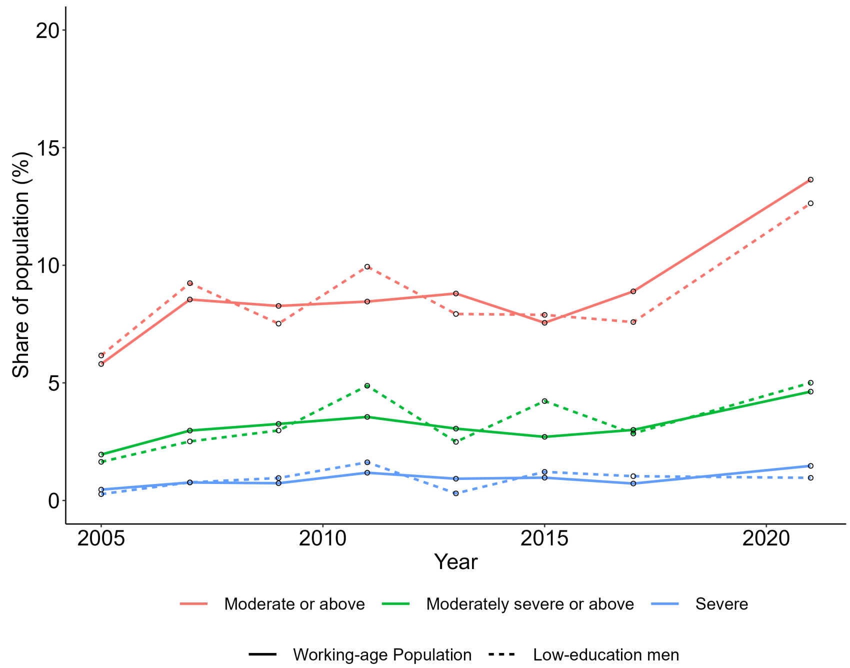
Notes: Figures plot self-reported health in the National Health Interview Survey among the overall working-age population (top) and lower-education men (without a college degree; bottom). "Any limitation" means individuals who report being "limited in any way in any activities because of physical, mental, or emotional problems." "Poor health" means those reporting "fair" or "poor" overall health (as opposed to "good," "very good," or "excellent.")

Appendix Figure A.12: Mental and musculoskeletal health did not improve substantially from 2010–2018



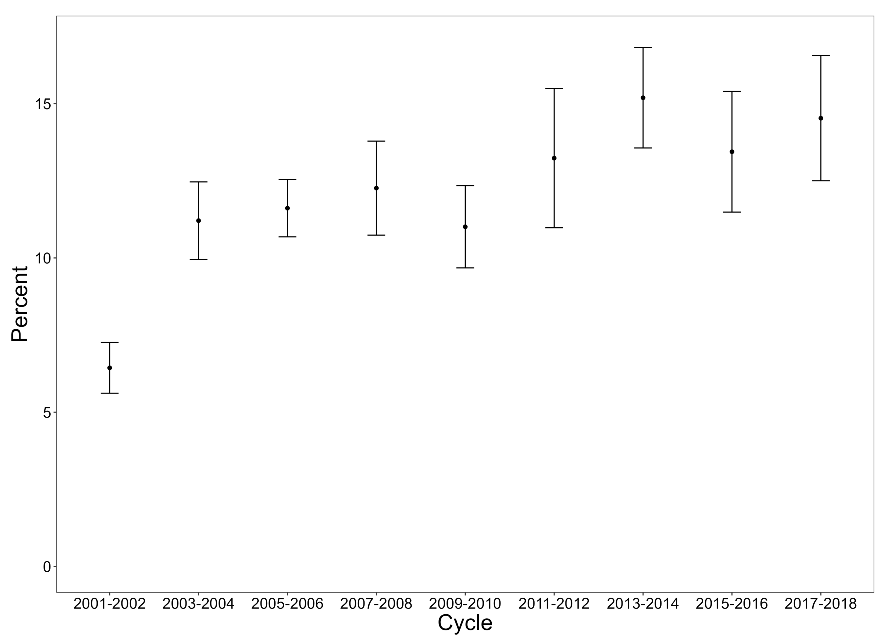
Notes: Figures plot self-reported health in the National Health Interview Survey among the overall working-age population (top) and lower-education men (without a college degree; bottom). Each graph reports the share of respondents who indicate having a work or functional limitation caused by musculoskeletal issues (left panels) or depression, anxiety, and emotional problems (right panels).

Appendix Figure A.13: Severe depression rates did not fall from 2010–2019



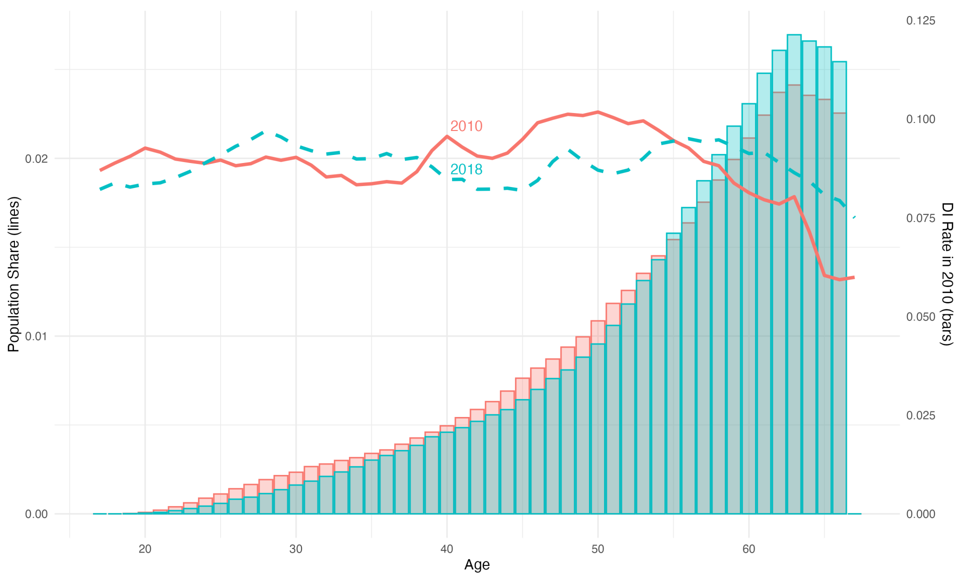
Notes: Figure plots depression rates among the working-age population (solid lines) and low-education men (dashed lines) estimated from the PHQ-9 depression screener in the National Health and Nutrition Examination Survey (NHANES). We use the standard PHQ-9 thresholds for "moderate," "moderately severe," and "severe" depression. Markers indicate the years in which the NHANES was administered; there is no NHANES data available between 2017 and 2021.

Appendix Figure A.14: Use of antidepressants and antipsychotics increased around 2011



Notes: Figure plots fraction of US adults using antidepressants or antipsychotics. Source: National Center for Health Statistics, National Health and Nutrition Examination Survey 2001–2018.

Appendix Figure A.15: From 2010 to 2018, working-age population became older on average, and older working-age people have higher SSDI rates



Notes: Figure plots age distribution of working-age population in 2010 and 2018 (left axis), plus SSDI enrollment rates by age in the same years (right axis). The sample is constructed from the Continuous Work History Sample (CWHS) linked to the Payment History Update System (PHUS) and the Numident.

Appendix Table A.1: Decomposition results for the decrease in SSDI enrollment from 2010 to 2019: adjustment for change in applicant severity composition

	Absolute contribution (pp)			As a share of total (%)		
	Minimum	Maximum	Used in graph	Minimum	Maximum	Used in graph
Original						
Entry	**-0.94**	**-1.00**	**-0.99**	**90.3**	**96.9**	**95.2**
Eligibility	-0.05	-0.09	-0.08	4.5	8.4	8.1
Application	-0.48	-0.59	-0.58	46.1	56.8	55.6
Award	-0.31	-0.45	-0.44	29.9	43.0	42.0
Adjusted						
Entry	**-0.94**	**-1.00**	**-0.99**	**90.3**	**96.9**	**95.2**
Eligibility	-0.05	-0.09	-0.08	4.5	8.4	8.1
Application + Applicant share	-0.59	-0.72	-0.61	57.1	69.1	59.2
Application	-0.48	-0.59	-0.58	46.2	56.7	55.6
Applicant share	-0.10	-0.15	-0.15	9.4	14.7	14.4
Award	-0.19	-0.32	-0.31	18.6	31.0	30.3

Notes: Table presents decomposition of the decrease in SSDI enrollment rates from 2010 to 2019 into the components of Entry. "Original" reproduces the results from Table 2. "Adjusted" presents results using equation (18) to adjust for changes in applicant severity. Since applicants became less severe over this period, the award shares in Table 2 reflect a mechanical effect of lower award rates due to less-severe applicants. The "adjusted" numbers correct for this issue. In the adjusted numbers, "Award" represents the first term in equation (18) and "Applicant share" represents the second term in equation (18). "Minimum" means the minimum bound, "Maximum" means the maximum bound, and "Used in graph" means the point estimate used in Figure 3. See Section 2.1 for details on the decomposition method, and Appendix Section F for details on the construction of bounds.

Appendix Table A.2: Robustness Checks for Sensitivity of Applications to ALJ Reform

	Specification of Controls					
Outcome Specification	(1)	(2)	(3)	(4)	(5)	(6)
Level Applications	4.3	-9.7	19.6	9.8	42.3	-37.3
	(45.4)	(44.2)	(47.8)	(48.4)	(51.8)	(59.2)
	Pre-Reform Mean Applications:				*986*	
Log Applications	-0.09	-0.10	-0.06	-0.04	-0.01	-0.10
	(0.06)	(0.05)	(0.05)	(0.06)	(0.05)	(0.06)
Additional Controls						
Unemp. Rate	-	X	X	X	X	X
Initial (DDS) Allowance Rate	-	-	X	-	X	X
SSDI Application Rate	-	-	-	X	X	X
2006 Avg Applicant Earnings	-	-	-	-	-	X
Mental/Musculoskeletal Applicant Share	-	-	-	-	-	X

Notes: Table reports estimates of the effect of the ALJ reform on SSDI applications using a pre-post version of equation (22): i.e., β_t from $Y_{it} = \alpha_i + \gamma_t + \beta_t(\text{BaseAppealAllow}_i \times \text{Post2008}_t) + \delta X_{it} + \epsilon_{it}$. Y_{it} is either level applications or log applications. See Section 5.2.2 for details. Columns denote alternative model specifications, using different sets of controls in the regression models.

B Details of empirical analysis

B.1 SIPP analysis

We use the 1996, 2001, 2004, 2008, and 2014 panels of the Survey of Income and Program Participation linked to SSA administrative data, including the Numident, F831 files, Payment History Update System, and Summary Earnings Record. For the 1996, 2001, 2004, and 2008, we use the core files and the topical module on adult disability, which includes questions about health conditions, self-reported health status, and activities of daily living and other questions about daily function. For the reengineered 2014 panel, we use the SSA supplement which asks many of the health questions previously asked in the adult disability topical modules.

We append all five panels together. In order to study the subgroup that drives the decline in SSDI applications, we limit sample to men with a high-school degree or less. We classify individuals by birth cohort in 5-year intervals (1940–44, 1945–1950, 1950–54, 1955–1960, 1960–64, 1965–1970). We also create groups for different measures of health in the SIPP; our main classification is reporting "fair" or "poor" health (EHSTAT in the 1996, 2001, 2004, and 2008 panels; EHLTSTAT in the 2014 SSA supplement). We identify spouses using the SIPP family relationship variables.

For each year, we create variables for cumulative SSDI application (ever apply up to that year), cumulative SSDI receipt (ever receive SSDI up to that year), own earnings and employment (average annual), and spouse earnings and spouse employment (average annual, conditional on having a spouse and unconditional on having a spouse). Earnings variables are inflation-adjusted using 2000 as the base year (as in our CWHS analysis). We condition the earnings and employment variables on being financially eligible for SSDI (calculated using individual earnings history) and not receiving SSDI at that age.

We use SIPP survey weights. The SIPP survey weights are consistent across panels for the 1996, 2001, 2004, and 2008 panels. However, the scale of the weights changes by several orders of magnitude for the reengineered 2014 panel, so we normalize the average 2014 panel weight to equal the average 2008 panel weight.

B.2 Evidence on potential explanations for decline in SSDI applications

B.2.1 Details on Social Security field office closing calculations

Deshpande and Li (2019) estimate large declines in applications and awards resulting from

Social Security field office closings. We use estimates from Deshpande and Li (2019) to determine how much of the decline in SSDI applications can be explained by Social Security field office closings.

For each office closing, there is an average annual decline of 157 SSDI applications and 298 SSDI awards. We assume that effects of office closings are persistent and linear, meaning an office closing in a given year results in a sustained decline in all subsequent years. We calculate the counterfactual number of applications and awards in the absence of any office closings. Comparing actual applications (or awards), counterfactual applications (or awards), and applications (or awards) in 2010, we estimate that field office closings account for 3–6% of the decline in applications and 8–17% of the decline in awards between 2010 and 2019. The variation in estimates depends on assumptions about persistence: assuming that all office closings since 2000 have had lasting effects through 2019 gives the estimates on the higher end of the range, while assuming that only closings after 2010 had an effect through 2019 gives the estimate on the lower end of the range.

B.2.2 Details on pollution abatement analysis

We estimate the effect of local pollution on SSDI enrollment using variation from the Clean Air Act as in Isen et al. (2017). Following Isen et al. (2017), we construct a crosswalk between Numident place of birth 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.

We follow the matching procedure developed by 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 procedures: 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. Taking individuals from the Numident file who were working-age adults between 2010 and 2019, we can match place of birth for nearly one-half of individuals.

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)

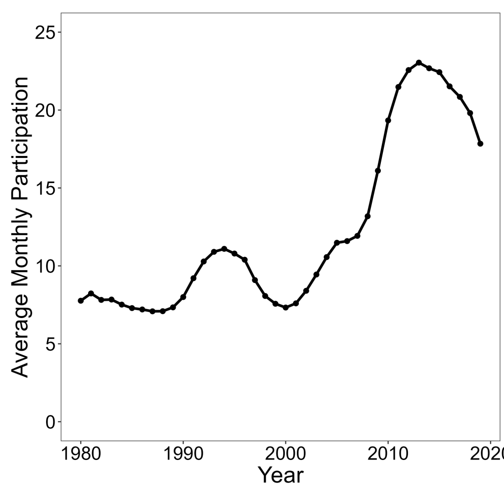
(data provided by the authors). We determine if the decline in applications is disproportionately concentrated among individuals born in non-attainment counties, in which Clean Air Act regulations imposed improvements in air quality over time. We report our results in Appendix Section G.3. We find that the SSDI application decline is disproportionately concentrated in these counties.

B.2.3 Generosity of other social welfare benefits

The explanation of higher generosity of other social welfare programs is inconsistent with the patterns we observe in SSDI applications and employment. Still, we consider how the enrollment and generosity of other social safety programs have changed since 2010.

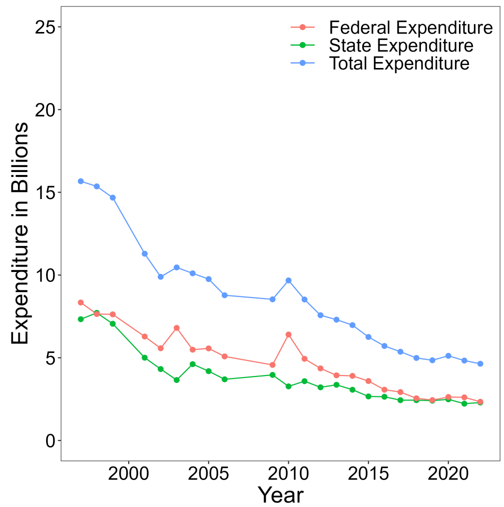
SNAP, TANF, and UI. There was no increase in SNAP, TANF, or UI benefit amount or enrollment between 2010 and 2019 (see Appendix Figures B.1, B.2, and B.3).

Appendix Figure B.1: SNAP program participation did not increase from 2010–2019



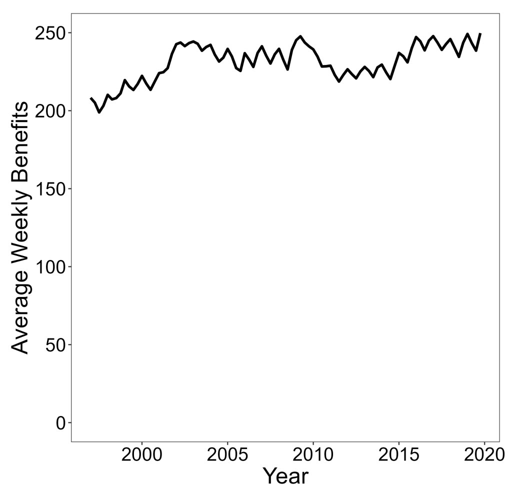
Notes: Figure plots average monthly SNAP participation from 1980 to 2020, in millions. Source: United States Department of Agriculture, "Persons, Households, Benefits, and Average Monthly Benefit per Person & Household."

Appendix Figure B.2: TANF spending did not increase from 2010–2019



Notes: Figure plots federal, state, and total expenditures on TANF (all direct assistance expenditures) over time, in 2000 dollars. Source: United States Department of Health and Human Services, Office of Family Assistance. FY 1997-2022 Federal TANF & State MOE Financial Data.

Appendix Figure B.3: UI benefit amount did not increase substantially from 2010–2019



Notes: Figure plots average weekly UI benefits in each quarter averaged across states and adjusted for inflation to 2000 dollars. Source: United States Department of Labor, Unemployment Insurance Data Base (`https://oui.doleta.gov/unemploy/data_summary/DataSum.asp`).

Health insurance. The Affordable Care Act of 2010 expanded Medicaid to more low-income adults and subsidized health insurance for lower- and middle-income adults through the exchanges. If some potential SSDI applicants would have applied primarily to get health insurance coverage, these health insurance expansions could have contributed to the decline in SSDI applicants.

We investigate this hypothesis in several ways. First, we determine whether states that experienced larger increases in health care coverage over this period have larger SSDI application declines. Appendix Figure B.4 shows this is not the case; if anything, states with greater enrollment in Medicaid and health insurance exchanges (left graph) or changes in health insurance coverage in general (right graph) had smaller declines in SSDI application rates.

Second, we study whether the decline in SSDI applications is concentrated in states that expanded Medicaid coverage (Appendix Table H.23). We find no heterogeneity in the SSDI application decline by state Medicaid expansion status.

Finally, we review the large existing literature on the effect of Medicaid expansion on SSDI and SSI applications. Appendix Table B.1 summarizes the population, outcome, and estimated effect for each of six papers (Baicker et al., 2014; Maestas et al., 2014; Burns and Dague, 2017; Anand et al., 2019; Schmidt et al., 2020).[34] It then presents our calculation extrapolating the effect size to SSDI applications from all adults.

Two papers (Staiger et al., 2024; Ne'eman and Maestas, 2023a) estimate the effects of Medicaid expansion on SSDI enrollment. Both find expansion increased enrollment. We infer effects on SSDI applications by assuming Medicaid expansion has no effect on rejected applications, and then converting the excess pool of SSDI recipients over the study period into annualized excess SSDI applications.[35]

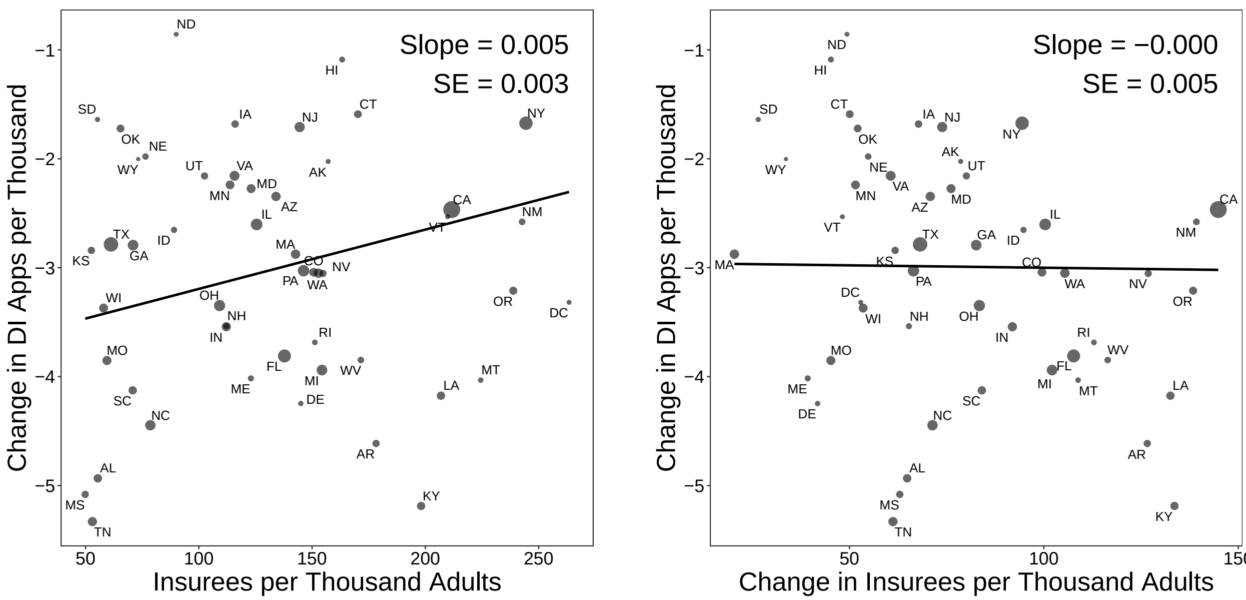
Two other papers (Maestas et al., 2014; Baicker et al., 2014) estimate effects for specific states (Massachusetts and Oregon respectively) from pre-expansion variation. For these, we assume that these state-specific effects are representative of effects in Medicaid-expanding states more generally. For Maestas et al. (2014), we also scale their quarterly estimates into annual ones.

Finally, two papers (Anand et al., 2019; Schmidt et al., 2020) directly estimate the impact of Medicaid expansion on SSDI applications. We report their estimates as-is.

[34]Burns and Dague (2017) and Soni et al. (2017) additionally examine effects on SSI applications. (Heim et al., 2021) tests for effects of Medicaid expansion by looking for changes in beneficiary composition.

[35]Staiger et al. (2024) specifically estimates effects on enrollment for disabled individuals, who they estimate to represent 11.4 percent of the total working-age population. For this estimate, we further assume no effect of Medicaid expansion on SSDI applications from non-disabled individuals.

Appendix Figure B.4: State-level changes in SSDI application rates vs changes in health insurance coverage



(a) Expanded Medicaid and Exchanges

(b) All Health Insurance

Notes: Panel (a) plots, for each state, the number of insurees enrolled in either expanded Medicaid or the exchanges through the Affordable Care Act in 2019 (relative to the adult population in 2019) (x-axis) against the change in SSDI application rates from 2010 to 2019 (y-axis). On the x-axis, we count insurees from Medicaid Group 8 (adult enrollees eligible for Medicaid under Affordable Care Act expansions) and state health insurance exchanges. Data on Medicaid Group 8 enrollment comes from the Medicaid Budget and Expenditure System. Data on enrollment in exchanges and basic health plans is taken from the Kaiser Family Foundation, originally published in Health Insurance Marketplace Open Enrollment Reports by the Office of the Assistant Secretary for Planning and Evaluation (2014-2016) and the Marketplace Open Enrollment Period Public Use Files by the Centers for Medicare and Medicaid Services (2017-2019). Panel (b) repeats the exercise using growth in *all* health insurance coverage, as measured in the American Community Survey.

	Staiger et al. (2024)	Ne'eman and Maestas (2023)	Maestas et al. (2014)	Baicker et al. (2014)	Anand et al. (2019)	Schmidt et al. (2020)
Population:	Disabled Adults	All Adults	Adults in MA	Adults in OR	All adults	All adults
Outcome:	Enrollment Stock	Enrollment Stock	Quarterly Apps	Applications	Applications	Applications
Effect Estimate (per Thousand):	20.20	8.00	0.05	0.07	0.04	0.00
Extrapolating effect estimate to:						
All Adults:	2.30	8.00	0.05	0.07	0.04	0.00
Translating effect estimate into:						
Annual Apps from All Adults:	0.77	2.67	0.19	0.07	0.04	0.00

Notes: Table reports our calculations of the effects of Medicaid expansion on annual SSDI application rates implied by each of the six papers presented. The second to last row reports the effect actually appearing in the given paper (which, per the row before it, is not necessarily the effect of Medicaid expansion on annual SSDI application rates). The last row converts this estimate into an effect on annual application rates. For papers reporting effects on enrollment, we assume Medicaid expansion has *no* effect on rejected applications, and then translate the excess pool of SSDI beneficiaries over the study period into annualized excess SSDI applications. For Ne'eman and Maestas (2023a), we further scale by the share of the working-age population that reports a disability (11.23 percent).

Appendix Table B.1: Estimating the effect of Medicaid expansion on SSDI applications

Health care access. Anstreicher (2021) and Anstreicher and Strand (2025) find that community health center (CHC) expansions starting in 2000 reduced SSDI applications in surrounding areas. However, CHC expansions begin well before the decline in SSDI enrollment, and Anstreicher and Strand (2025) find that they can only account for about 3% of the total decline in SSDI applications.

Veterans Disability Compensation. We consider two major changes to Veterans Disability Compensation that could have affected SSDI application rates, with complete results in Appendix Section G.2. First, 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,[36] 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; in fact, veterans have a disproportionately small decline in SSDI applications relative to their size (see Appendix Table G.30).

Second, from 2000 to 2020, the fraction of men ages 45 to 64 who report in the CPS that they are veterans fell from 34 percent to 12 percent (Chan et al., 2021). To the extent that VDC enrollment increases SSDI enrollment, a decline in the population share of veterans could contribute to the decline in SSDI enrollment, especially among men. To investigate this hypothesis, we redo the decomposition exercise in Table 2 including veteran status (and thus the interaction between veteran status and age). The results are shown in Appendix Table G.23. Including veteran status as a characteristic of the decomposition does not change the main results: the application contribution is similar at 46–58% (vs 46–57%), the award contribution is identical at 30–43%, and the composition (including veteran status) contribution is similar at -1 to 6% (vs 1–5%). These results indicate that the declining veteran share among older men is not a large enough phenomenon to explain a large part of the SSDI enrollment or application decline.

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

C Details of application counterfactuals

To take to data our model of application behaviors from Section 5, we let $p_t(v) \equiv \mathbb{P}(A_t|v_t = v)$ denote the application rate among those of type v regardless of eligibility status (i.e., the application-to-population ratio). This aligns with the measures used in our empirical evidence in Section 5 and Appendix Section B, and it is necessary because determinants of one's type (e.g., education for our exercise fixing labor market conditions) can only be observed for applicants in our administrative data sources. We find no meaningful trends in eligibility rates, so we expect trends in the application-to-population ratio to roughly map into trends in application rates among the eligible.

Except where otherwise specified, we define one's type v by a combination of age (older than 40 versus 40 and younger), educational attainment, and sex. Around 5% of SSDI applications are missing information on the applicant's education. To address this, we assume education is missing at random conditional on the other determinants of type and the year of applying for SSDI.

Homogeneity assumption. For our baseline results, we assume homogeneity across types in utility parameters. This means that, for example, the type-specific condition pinning down the labor market shifter, β_k^w, using the following equality:

$$\underbrace{\frac{\partial \mathbb{P}(A_t = 1 \mid \nu_t = v)}{\partial z_{kt}^w}}_{\text{Identified from (quasi)-experiment}} = \underbrace{h(m_t(v))}_{\text{Identified from application data}} \times \underbrace{\beta_k^w(v)}_{\text{Unobserved}},$$

implies a condition that must also hold in expectation across types and time periods:

$$\mathbb{E}\left[\frac{\partial \mathbb{P}(A_t = 1|\nu_t = v)}{\partial z_{kt}^w}\right] = \mathbb{E}[h(m_t(v))]\beta_k^w \tag{25}$$

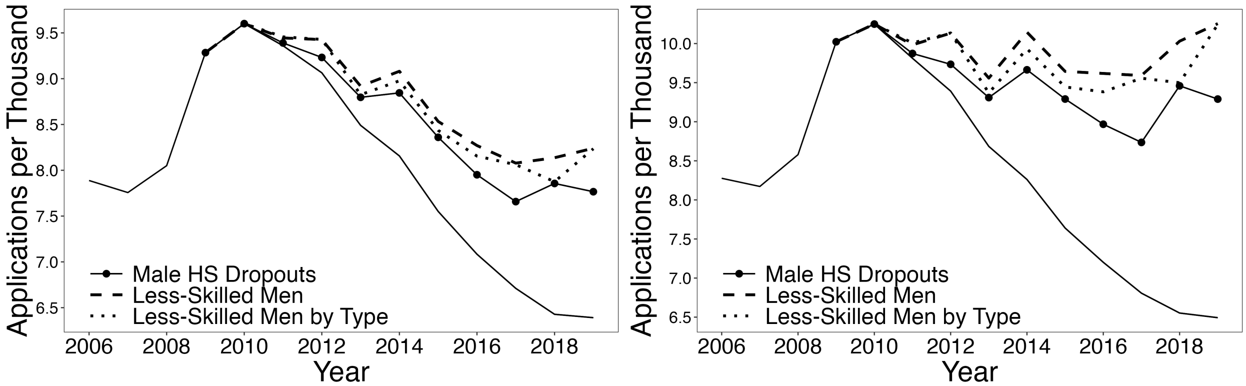
To actually estimate β_k^w, we take an estimate of the quasi-experimental effect of the shifter z_k^w on application behaviors to be an estimate of the left-hand side term. We divide this by an estimate for $\mathbb{E}[h(m_t(v))]$, which we get by averaging over type and period-specific densities at the margin of applying, as implied by their application rates. Our estimates for parameters governing the utility of applying for SSDI follow from this homogeneity assumption in a similar way.

C.1 Counterfactuals fixing less-skilled labor market conditions

Appendix Figure C.1 presents alternative counterfactual application rates, fixing labor market conditions for less-skilled men (i.e., men with no college education). Panel (a) reports overall application rates, averaging counterfactuals for less-skilled men with application rates for other (unaffected) subpopulations, and panel (b) reports application rates specifically among men. These panels both report three counterfactuals which point to the same conclusion: fixing labor market conditions for less-skilled men can explain a substantial share of the recent decline in overall application rates because they can entirely explain the recent decline for men in particular.

The first counterfactual we report (the dashed line) is derived from the causal estimate in the first panel of Appendix Table C.1. This is the counterfactual appearing also in Figure 12. We next relax the homogeneity assumption underlying that counterfactual, using type-specific causal estimates from the second panel of Appendix Table C.1 to estimate type-specific sensitivities to labor market conditions. This can only be done for types with an existing first stage, so in this counterfactual (the dotted line), we do not fix labor market conditions for the one type that has a low first stage F-statistic (older male high school dropouts). In our last counterfactual, we fix labor market conditions for male high school dropouts in particular (echoing the choice of Autor and Duggan (2003) to focus on dropouts). This counterfactual (the connected line) is based on a sensitivity estimate for male dropouts, derived from causal estimates for that group: an estimate of -0.21 (standard error 0.42) with a first stage of 1.20 (standard error 1.10).

Appendix Figure C.1: Application counterfactuals fixing labor market conditions



(a) Application rate among working-age adults (b) Application rate among working-age men

Notes: Graphs present counterfactuals fixing labor market conditions for less-skilled men. "Less-Skilled Men" uses the effect estimates from the first panel of Appendix Table C.1. "Less-Skilled Men by Type" uses estimates from the second panel of Appendix Table C.1, for the three types with a strong first stage. "Male HS Dropouts" uses the TSLS estimate for high school dropouts (-0.21 standard error: 0.42) (variance-weighted average of "HS dropout" rows in Appendix Table C.1).

Appendix Table C.1: Estimates of the effects of labor market conditions on SSDI applications

		First Stage		2SLS	
		Coef	F	Coef	S.E.
(a) Overall Estimates for Less-Skilled Men					
		1.659	15.024	-0.130	0.158
(b) Less-Skilled Men, by Type (Education × Age)					
Education	Age				
HS Dropouts	41-66	0.425	0.069	-0.906	1.788
HS Dropouts	18-40	1.611	2.398	-0.146	0.167
Only HS	41-66	1.441	6.219	-0.329	0.146
Only HS	18-40	1.889	32.401	-0.049	0.065

Notes: These models include the controls in equation (20): time dummies and linear controls for annualized changes in population shares by age and gender, age being split into 3 bins: 18-39, 40-54, and 55-66.

Appendix Table C.2: Estimates of the effects of labor market conditions on SSDI award rates

		First Stage		2SLS	
		Coef	F	Coef	S.E.
(a) Overall Estimates for Less-Skilled Men					
		1.659	15.024	-0.036	0.076
(b) Less-Skilled Men, by Type (Education × Age)					
Education	Age				
HS Dropouts	41-66	0.425	0.069	-0.361	0.906
HS Dropouts	18-40	1.611	2.398	-0.015	0.016
Only High School	41-66	1.441	6.219	-0.164	0.100
Only High School	18-40	1.889	32.401	-0.004	0.016

Notes: This table reports 2SLS effects of labor market conditions on award rates among applicants–a check on the exclusion restriction of the instrument. These models include the controls in equation (20): time dummies and linear controls for annualized changes in population shares by age and gender, age being split into 3 bins: 18-39, 40-54, and 55-66.

C.2 Counterfactuals fixing award rates

Appendix Table A.2 reports the estimated effects of ALJ reform on SSDI applications, which we will translate into effects of *award rates* on application rates for the purpose of simulating counterfactuals. To do so, we scale the reform's estimated effects on log applications by the application-to-population ratio to convert them into effects on application probabilities. We then divide this by the reform's "first stage" effect on award rates, consistent with the following identity:

$$\frac{\partial \mathbb{P}(A_t = 1)}{\partial \mathbb{P}(\text{Award}_t = 1 | A_t = 1)} = \left[\frac{\partial \log(\text{Apps}_t)}{\partial z_t^b} \Big/ \frac{\partial \mathbb{P}(\text{Award}_t = 1 | A_t = 1)}{\partial z_t^b} \right] \times \frac{\text{Apps}_t}{\text{Pop}_t}$$

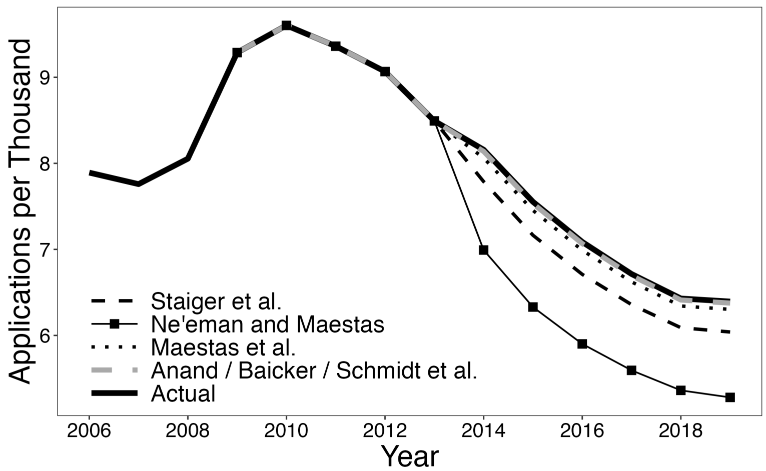
We then translate effects of award rates on application probabilities into effects on the utility cost of applying by adjusting for the density at the margin of applying and the probability of award, based on average application and award rates over the period surrounding ALJ reforms (2009-2015).

We report in Figure 12 the most extreme counterfactual from taking the largest effect estimate reported in Appendix Table A.2.

C.3 Counterfactuals fixing office closures

The quasi-experimental effect of office closures on SSDI applications comes from Deshpande and Li (2019) and is reported in Section B.2.1. We take the estimate of 157 fewer SSDI

Appendix Figure C.2: Application counterfactuals fixing Medicaid access



Notes: Counterfactuals use effect estimates reported in the final row of Appendix Table B.1. The counterfactual line using Baicker et al. (2014); Anand et al. (2019); Schmidt et al. (2020) is on top of the "actual" line.

applications per office closing and translate it into an effect on application rates by dividing by population counts each year. Averaging this and densities at the margin of applying over calendar years 2000 to 2019 (the years analyzed by Deshpande and Li, 2019) provides the inputs to solve for β_k^b using a version of equation (25).

C.4 Counterfactuals fixing Medicaid access

Appendix Figure C.2 plots counterfactual SSDI rates in the absence of the ACA Medicaid expansions, based on the alternative effect estimates reported in Appendix Table B.1. For this exercise, we take a person's type (v) to be state of residence, since some states expanded Medicaid and others did not. The results of Appendix Figure C.2 come from averaging the counterfactuals for Medicaid-expanding states with (unaffected) states that never expanded Medicaid. Because application responses to Medicaid are all positive or close to zero, these counterfactual application rates lie weakly below the actual application rates observed in the data. In Figure 12, we plot the counterfactual implied by estimates from Schmidt et al. (2020), which is indistinguishable from actual application rates.

C.5 Counterfactuals fixing the age distribution

When counterfactually fixing the age distribution, we do not rely on a model of application behaviors. Instead, we hold fixed the population density across ages while allowing age-specific application rates to freely vary over time per the data. Letting type ν be defined only by age alone, the counterfactual in t_1 having fixed the age distribution at its year-t value is:

$$P(A_{t_1}^{\text{aging}}) = \int P(A_{t_1}|\nu_{t_1} = v) f_{\nu_t}(v) dv$$

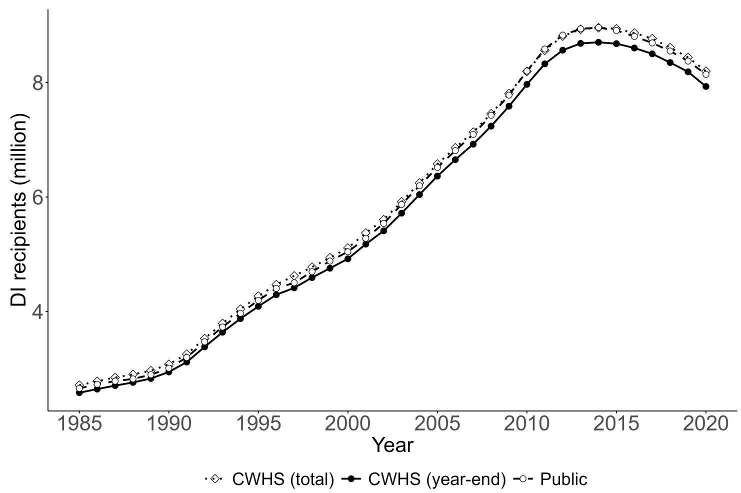
C.6 Counterfactuals fixing veteran shares and application rates

To gauge how much veterans contribute to the decline, we define type by veteran status alone and counterfactually fix two objects. First, we fix the density of veteran status in the population, in the same way we fixed the age distribution above. Second, we also fully shut down changes over time in the application rates of veterans. This leaves only one channel driving counterfactual declines in overall application rates: changes in the application behaviors of non-veterans.

D Data Appendix

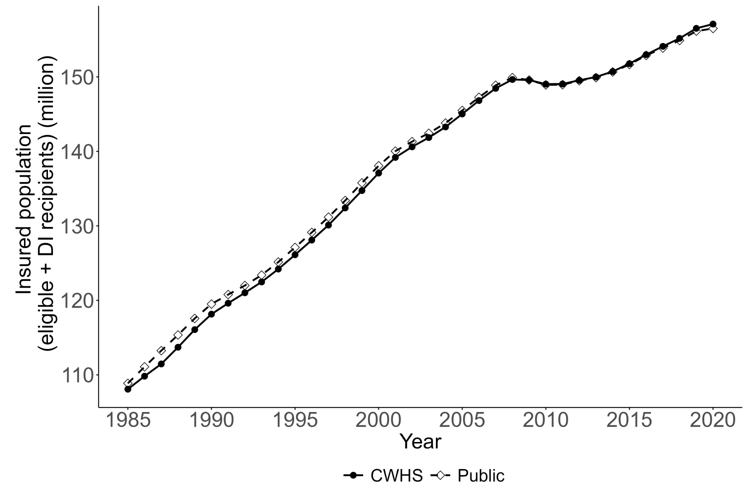
D.1 Matching public data on SSDI

Appendix Figure D.1: CWHS vs public data: SSDI recipients



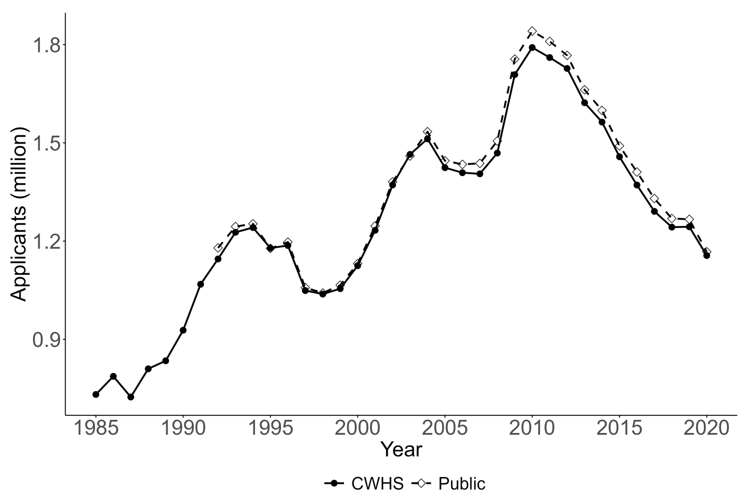
Notes: Figure plots the number of SSDI recipients over time from different data sources: authors' tabulations from the Continuous Work History Sample (CWHS) and publicly available data from the Social Security Administration. We identify SSDI recipients in the CWHS by determining whether they receive transfers in the Payment History Update System (PHUS) before retirement age. The solid line plots CWHS year-end SSDI recipients, which excludes SSDI recipients that died or terminated their status at each calendar year-end. The dotted line plots all recipients in the CWHS who were on SSDI in the calendar year. The dashed line plots the SSDI recipients reported in the first column of Table 49 in Social Security Administration (2024).

Appendix Figure D.2: CWHS vs public data: SSDI-insured population



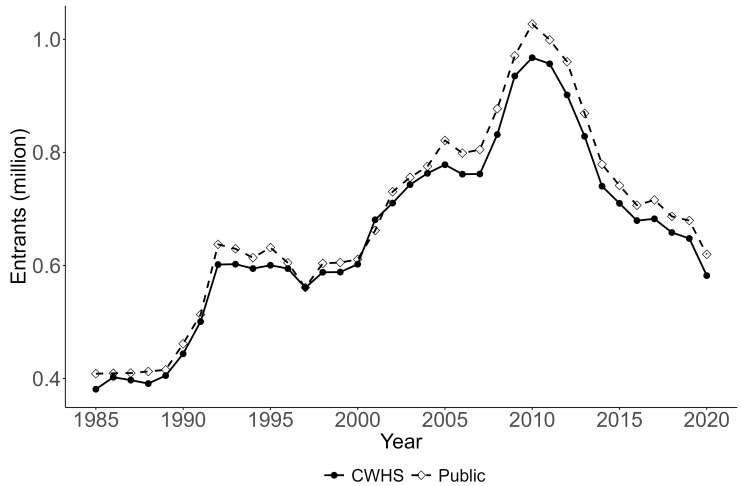
Notes: Figure plots the number of SSDI "insured" individuals—i.e., those who are financially eligible for SSDI—over time from different data sources: authors' tabulations from the Continuous Work History Sample (CWHS) and publicly available data from the Social Security Administration. We identify the insured population not on SSDI in the CWHS by calculating financial eligibility from the Master Earnings File; we then add this number to the number of SSDI recipients to get the total insured population. The solid line plots insured population in the CWHS. The dashed line plots SSDI recipients reported by the Social Security Administration in 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 D.3: CWHS vs public data: SSDI applicants



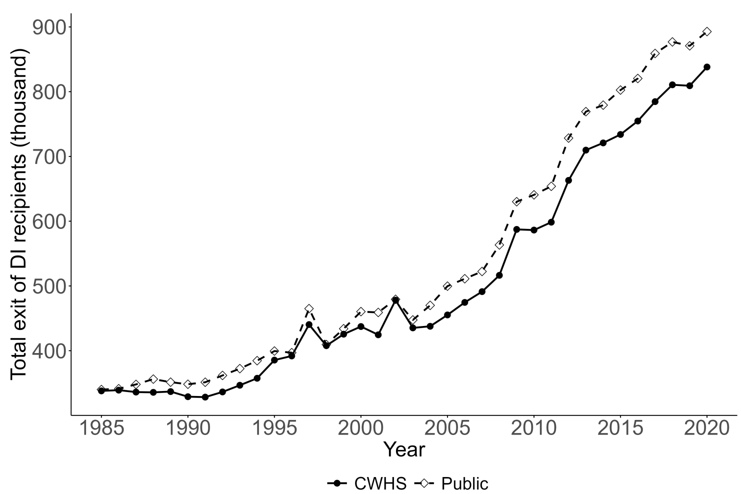
Notes: Figure plots number of SSDI applicants over time from different data sources: authors' tabulations from the Continuous Work History Sample (CWHS) and publicly available data from the Social Security Administration. We identify applicants in the CWHS by linking them to the F831 file. The solid line plots number of applicants based on the CWHS. The dashed line plots number of applicants in Table 60 from the 2023 Annual Statistical Report (Social Security Administration, 2024), where we sum the number of pending applications and all four columns in medical decisions and exclude technical denials.

Appendix Figure D.4: CWHS vs public data: SSDI entrants



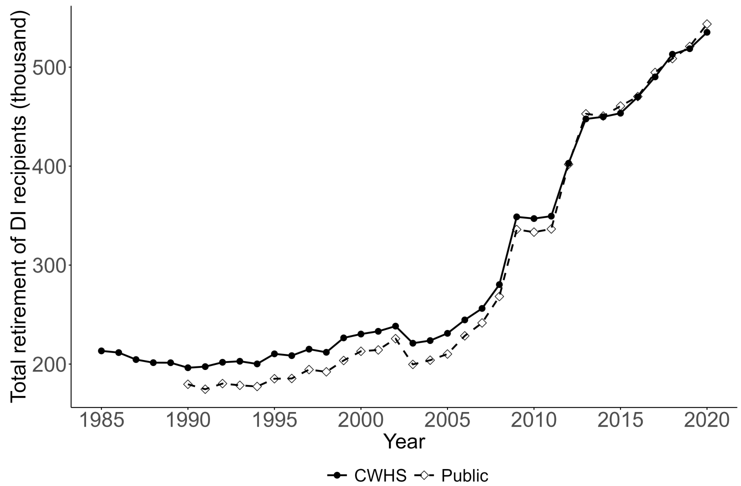
Notes: Figure plots number of SSDI entrants over time from different data sources: authors' tabulations from the Continuous Work History Sample (CWHS) and publicly available data from the Social Security Administration. We identify entrants in the CWHS by linking them to the Payment History Update System (PHUS) and the Master Beneficiary Record. The solid line plots number of entrants based on the CWHS. The dashed line plots number of entrants in Table 39 from the 2023 Annual Statistical Report (Social Security Administration, 2024).

Appendix Figure D.5: CWHS vs public data: SSDI exits



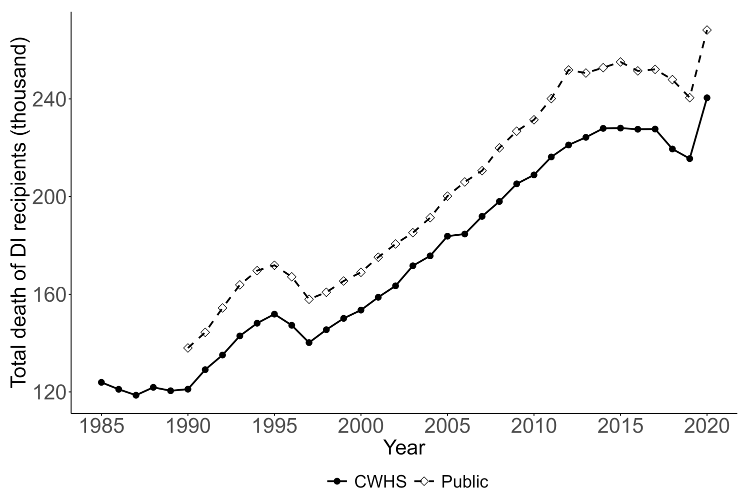
Notes: Figure plots number of SSDI exits over time from different data sources: authors' tabulations from the Continuous Work History Sample (CWHS) and publicly available data from the Social Security Administration. We identify exits in the CWHS by linking them to the Payment History Update System (PHUS) and the Master Beneficiary Record, or by determining from the Numident that they had either died. The solid line plots the number of exits based on the CWHS. The dashed line plots number of exits from the SSA Annual Statistical Report in each year.

Appendix Figure D.6: CWHS vs public data: SSDI exits from retirement



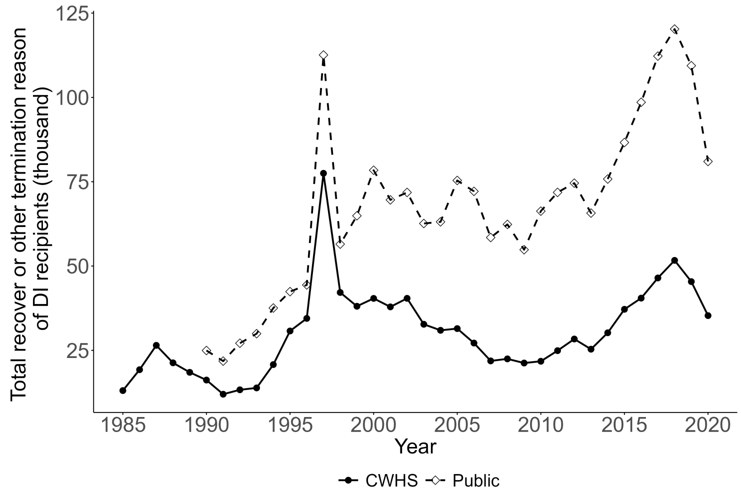
Notes: Figure plots number of SSDI exits due to retirement over time from different data sources: authors' tabulations from the Continuous Work History Sample (CWHS) and publicly available data from the Social Security Administration. We identify exits due to retirement in the CWHS by linking them to the Payment History Update System (PHUS) and the Master Beneficiary Record. The solid line plots the number of exits due to retirement based on the CWHS. The dashed line plots the number of exits due to retirement from the SSA Annual Statistical Report in each year.

Appendix Figure D.7: CWHS vs public data: SSDI exits from death



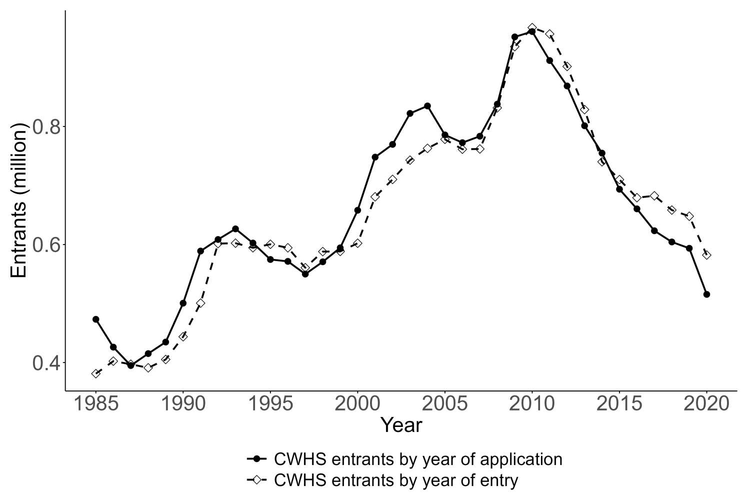
Notes: Figure plots number of SSDI exits due to death over time from different data sources: authors' tabulations from the Continuous Work History Sample (CWHS) and publicly available data from the Social Security Administration. We identify exits due to death in the CWHS by linking them to date of death in the Numident. The solid line plots number of exits due to death based on the CWHS. The dashed line plots number of exits due to death from the SSA Annual Statistical Report in each year.

Appendix Figure D.8: CWHS vs public data: SSDI exits from recovery



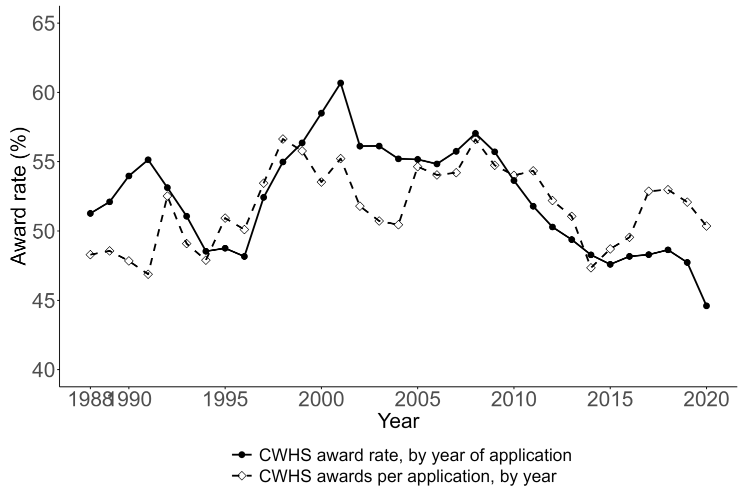
Notes: Figure plots number of SSDI exits due to recovery over time from different data sources: authors' tabulations from the Continuous Work History Sample (CWHS) and publicly available data from the Social Security Administration. We identify exits due to death in the CWHS by linking them by linking them to the Payment History Update System (PHUS) and the Master Beneficiary Record. The solid line plots the number of exits due to medical recovery or other reasons based on the CWHS. The dashed line plots the number of exits due to all non-retirement and death reason from the SSA Annual Statistical Report in each year.

Appendix Figure D.9: CWHS SSDI entrants, by year of entry vs year of application



Notes: The dashed line plots the number of people who enter SSDI in each year, regardless of when the application was submitted. The solid line plots the number of SSDI applications submitted in each year that ultimately lead to SSDI receipt. These differ because applications may not receive an allowance decision in the same calendar year in which they are submitted. Both series are calculated using the Continuous Work History Sample (CWHS) linked to the F831, PHUS, and MBR.

Appendix Figure D.10: CWHS SSDI annual awards per application vs. annual award rates



Notes: The dashed line plots the number of SSDI awards granted in each year (regardless of when the application was submitted), divided by the number of applications received in that year. The solid line plots the eventual award rate for applications submitted in each year. These differ because applications may not receive an allowance decision in the same calendar year in which they are submitted. Both series are calculated using the Continuous Work History Sample (CWHS) linked to the F831, PHUS, and MBR.

E Decomposition details

In this section, we walk through the decomposition exercise in more detail. The exact specifications outlined here form the basis of the point estimates reported in the "Used in graph" column in Tables 1 and 2 and Figures A.1 and 3.

Recursive structure of SSDI enrollment rates

DI enrollment rate ("on DI") O is defined to be SSDI stock S divided by population P.

$$O_{t,g} = \frac{S_{t,g}}{P_{t,g}}$$

DI stock is a recursive process that depends on past SSDI stock, past population, entry rates (N), and exit rates (X) and SSDI entrants that are immigrants (α):

$$S_{t,g} = S_{t-1,g} + \alpha_{t,g} + N_{t,g}(P_{t-1,g} - S_{t-1,g}) - X_{t,g}S_{t-1,g} \tag{26}$$

Population is also a recursive process that depends on past population, past SSDI stock, immigration (α SSDI-entering immigrants; β non-SSDI-entering immigrants), and death rates (γ, for non-DI beneficiaries; δ, for SSDI beneficiaries).[37]

$$P_{t,g} = P_{t-1,g} + (\alpha_{t,g} + \beta_{t,g}) - \underbrace{\gamma_t(P_{t-1,g} - S_{t-1,g})}_{\text{death of non-DI beneficiaries}} - \underbrace{\delta_{t,g}S_{t-1,g}}_{\text{death of SSDI beneficiaries}} \tag{27}$$

We compute the actual SSDI stock using the recursive accounting equation (26) and (27) with contemporaneous entry and exit rates. The counterfactual SSDI stock is obtained by applying the base-year entry and exit rates to the same equations.[38] For both series, we initialize the recursion by setting $S^c_{0,g} = S^r_{0,g} =$ SSDI stock in the base year and $P^c_{0,g} = P^r_{0,g} =$ base-year population.

$$S^r_{t,g} = S^r_{t-1,g} + \alpha^r_{t,g} + N^r_{t,g}(P^r_{t-1,g} - S^r_{t-1,g}) - X^r_{t,g}S^r_{t-1,g}$$
$$S^c_{t,g} = S^c_{t-1,g} + \alpha^r_{t,g} + N^c_{t,g}(P^c_{t-1,g} - S^c_{t-1,g}) - X^c_{t,g}S^c_{t-1,g}$$

[37] In equation (8), we refer to $\delta_{t,g}$ as Mortality Rate$_{t,g}$. We change notation here for brevity.

[38] We set α to be the contemporaneous value in both series to simplify the calculation. The actual value of α is minimal.

We compute the actual population by using contemporaneous immigration and death rates. For the counterfactual population series, since population dynamics are not the focus of this analysis, we hold fixed only the SSDI stock S and the death rate for SSDI beneficiaries δ at their base-year levels while allowing all other components to follow their actual contemporaneous values.[39] Since the number of SSDI beneficiary deaths is minimal, $P^c_{t,g} \approx P^r_{t,g}$.

$$P^r_{t,g} = P^r_{t-1,g} + \underbrace{(\alpha^r_{t,g} + \beta^r_{t,g})}_{\text{Immigrants}} - \underbrace{\gamma^r_t(P^r_{t-1,g} - S^r_{t-1,g})}_{\text{death of non-DI beneficiaries}} - \underbrace{\delta^r_{t,g} S^r_{t-1,g}}_{\text{death of SSDI beneficiaries}}$$
$$P^c_{t,g} = P^c_{t-1,g} + \underbrace{(\alpha^r_{t,g} + \beta^r_{t,g})}_{\text{Immigrants}} - \underbrace{\gamma^r_t(P^c_{t-1,g} - S^c_{t-1,g})}_{\text{death of non-DI beneficiaries}} - \underbrace{\delta^c_{t,g} S^c_{t-1,g}}_{\text{death of SSDI beneficiaries}}$$

Step 1: Breaking down overall SSDI enrollment rate

Overall SSDI rate O_t can be written as

$$O_t = \frac{S_t}{P_t} = \frac{\sum_g S_{t,g}}{P_t} = \sum_g \underbrace{\frac{S_{t,g}}{P_{t,g}}}_{O_{t,g}} \underbrace{\frac{P_{t,g}}{P_t}}_{w_{t,g}} = \sum_g O_{t,g} w_{t,g}$$

We decompose the difference between the actual and counterfactual overall SSDI rate into three components: the change in characteristics, the change in conditional SSDI rates, and their interaction.

$$\begin{aligned} O^r_t - O^c_t = & \underbrace{\sum_g O^c_{t,g}(w^r_{t,g} - w^c_{t,g})}_{\text{change in characteristics}} + \underbrace{\sum_g (O^r_{t,g} - O^c_{t,g}) w^c_{t,g}}_{\text{change from conditional SSDI rates}} \\ & + \underbrace{\sum_g (O^r_{t,g} - O^c_{t,g})(w^r_{t,g} - w^c_{t,g})}_{\text{characteristics } \times \text{SSDI rate interaction}} \end{aligned} \tag{28}$$

[39] For both series, we initialize the recursion by setting $S^c_{0,g} = S^r_{0,g}$ = SSDI stock in the base year and $P^c_{0,g} = P^r_{0,g}$ = base-year population.

Step 2: Breaking down group-specific SSDI enrollment rate

For the first period,

$$
\begin{aligned}
O^r_{1,g} - O^c_{1,g} &= \frac{S^r_{1,g}}{P^r_{1,g}} - \frac{S^c_{1,g}}{P^c_{1,g}} \\
&= \frac{S^r_{1,g} - S^c_{1,g}}{P^c_{1,g}} + \underbrace{S^r_{1,g}(\frac{1}{P^r_{1,g}} - \frac{1}{P^c_{1,g}})}_{\text{Friction in population}} \\
&= \underbrace{\frac{S^r_{0,g} - S^c_{0,g}}{P^c_{1,g}}}_{0} + \underbrace{(N^r_{1,g} - N^c_{1,g})\frac{(P_{0,g} - S_{0,g})}{P^c_{1,g}}}_{\text{change from conditional entry rate}} \underbrace{-(X^r_{1,g} - X^c_{1,g})\frac{S_{0,g}}{P^c_{1,g}}}_{\text{change from conditional exit rate}} + \underbrace{S^r_{1,g}(\frac{1}{P^r_{1,g}} - \frac{1}{P^c_{1,g}})}_{\text{Friction in population}} \\
&\approx \underbrace{(N^r_{1,g} - N^c_{1,g})\frac{(P_{0,g} - S_{0,g})}{P^c_{1,g}}}_{\text{change from conditional entry rate}} \underbrace{-(X^r_{1,g} - X^c_{1,g})\frac{S_{0,g}}{P^c_{1,g}}}_{\text{change from conditional exit rate}}
\end{aligned}
$$

For other periods,

$$
\begin{aligned}
O^r_{t,g} - O^c_{t,g} =& \frac{S^r_{t,g}}{P^r_{t,g}} - \frac{S^c_{t,g}}{P^c_{t,g}} \\
=& \frac{S^r_{t,g} - S^c_{t,g}}{P^c_{t,g}} + \underbrace{S^r_{t,g}(\frac{1}{P^r_{t,g}} - \frac{1}{P^c_{t,g}})}_{\text{Friction in population}}
\end{aligned} \tag{29}
$$

Where

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

The approximation comes from the fact that $P^c_{t,g} \approx P^r_{t,g}$. If we ignore the approximation and aggregate all of the interaction terms together, we get:

$$
\begin{aligned}
S^r_{t+1,g} - S^c_{t+1,g} =& \underbrace{(N^r_{t,g} - N^c_{t,g})(P^c_{t-1,g} - S^c_{t-1,g})}_{\text{change from conditional entry rate}} \\
& \underbrace{-(X^r_{t,g} - X^c_{t,g})S^c_{t-1,g}}_{\text{change from conditional exit rate}} \\
& \underbrace{+N^r_{t,g}(P^r_{t-1,g} - P^c_{t-1,g})}_{\text{change from population discrepancy}} \\
& \underbrace{+(1 - N^r_{t,g} - X^r_{t,g})}_{\equiv K^r_{g,t}}(S^c_{t-1,g} - S^c_{t-1,g}) \\
=& \underbrace{\sum_{i=0}^{t}(N^r_{t-i,g} - N^c_{t-i,g})(P^c_{t-i,g} - S^c_{t-i,g})K^r_{g,i,t}}_{\text{cumulative change from conditional entry rate}} \\
& \underbrace{-\sum_{i=0}^{t}(X^r_{t-i,g} - X^c_{t-i,g})S^c_{t-i,g}K^r_{g,i,t}}_{\text{cumulative change from conditional exit rate}} \\
& \underbrace{+\sum_{i=0}^{t}\left[N^r_{t-i,g}(P^r_{t-i,g} - P^c_{t-i,g})\right]K^r_{g,i,t}}_{\text{cumulative change from pop. discrepancies} \approx 0}
\end{aligned}
\tag{30}
$$

Step 3: Further decompose entry and exit

The entry rate (N) is the product of award rate (B), application rate (A) and eligibility rate (E). Thus we can decompose the differnce betweeen the actual and counterfactual entry rate:

$$
\begin{aligned}
N^r_{t,g} - N^c_{t,g} =& B^r_{t,g}A^r_{t,g}E^r_{t,g} - B^c_{t,g}A^c_{t,g}E^c_{t,g} \\
=& \underbrace{(B^r_{t,g} - B^c_{t,g})A^c_{t,g}E^c_{t,g}}_{\text{partial award}} + \underbrace{B^c_{t,g}(A^r_{t,g} - A^c_{t,g})E^c_{t,g}}_{\text{partial apply}} + \underbrace{B^c_{t,g}A^c_{t,g}(E^r_{t,g} - E^c_{t,g})}_{\text{partial elig}} \\
&+ \underbrace{B^c_{t,g}(A^r_{t,g} - A^c_{t,g})(E^r_{t,g} - E^c_{t,g})}_{\text{apply} \times \text{elig}} \\
&+ \underbrace{(B^r_{t,g} - B^c_{t,g})A^c_{t,g}(E^r_{t,g} - E^c_{t,g})}_{\text{award} \times \text{elig}} \\
&+ \underbrace{(B^r_{t,g} - B^c_{t,g})(A^r_{t,g} - A^c_{t,g})E^c_{t,g}}_{\text{award} \times \text{apply}} \\
&+ \underbrace{(B^r_{t,g} - B^c_{t,g})(A^r_{t,g} - A^c_{t,g})(E^r_{t,g} - E^c_{t,g})}_{\text{award} \times \text{apply} \times \text{elig}}
\end{aligned} \tag{31}
$$

where the last four terms sum up to the interaction within entry. The exit rate (X) is the aggregation of exit rates arising from different reasons (retirement, death, recovery, and other exits). Therefore, these components are additively separable.

Substituting equation (31) into (30), (29) and (28), we can calculate the absolute contribution we report in the "Used in graph" column in Tables 1 and 2 and Figures A.1 and 3. For instance, the contribution from applications is defined to be:

$$
w^c_{g,t}\left[\frac{1}{P^c_{t,g}}\sum_{i=0}^{t} B^c_{t-i,g}(A^r_{t-i,g} - A^c_{t-i,g})E^c_{t-i,g}(P^c_{t-i,g} - S^c_{t-i,g})K^r_{g,i,t}\right] \tag{32}
$$

Similarly, the contribution from award is:

$$
w^c_{g,t}\left[\frac{1}{P^c_{t,g}}\sum_{i=0}^{t} (B^r_{t-i,g} - B^c_{t-i,g})A^c_{t-i,g}E^c_{t-i,g}(P^c_{t-i,g} - S^c_{t-i,g})K^r_{g,i,t}\right] \tag{33}
$$

The contribution from eligibility is:

$$
w^c_{g,t}\left[\frac{1}{P^c_{t,g}}\sum_{i=0}^{t} B^c_{t-i,g}A^c_{t-i,g}(E^r_{t-i,g} - E^c_{t-i,g})(P^c_{t-i,g} - S^c_{t-i,g})K^r_{g,i,t}\right] \tag{34}
$$

The contribution from entry is:

$$w^c_{g,t}\left[\frac{1}{P^c_{t,g}}\sum_{i=0}^{t}(N^r_{t-i,g}-N^c_{t-i,g})(P^c_{t-i,g}-S^c_{t-i,g})K^r_{g,i,t}\right] \tag{35}$$

The contribution from exit due to death is:

$$w^c_{g,t}\left[\frac{1}{P^c_{t,g}}\sum_{i=0}^{t}(\delta^r_{t-i,g}-\delta^c_{t-i,g})S^c_{t-i,g}K^r_{g,i,t}\right] \tag{36}$$

F Bounds for the decomposition estimates

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

As we break down $O^r_{t,g} - O^c_{t,g}$, we make several choices about how to allocate interaction terms. These choices shape the definition of our "partial effects" of interest (e.g., the cumulative impact of changes in entry on SSDI rates), both directly and indirectly through the way stocks are allowed to accumulate over time (as determined by K). To account for potential differences arising from these choices, we construct bounds that encompass all possible formulations of partial effects and discounting. The resulting bounds are reported in Tables 1 and 2.

Bounds on Components of Entry

Recall we defined in equation (10) the cumulative impact of changes in application rates, according to a specific variant of our decomposition that fixes everything else at its counterfactual (c). The general expression for the cumulative impacts of awards, applications, and entry–accounting for how interaction terms can be differently allocated–are as follows:

$$\Delta O_{B_{t,g}}(\Theta) = \frac{1}{P^{s_P}} \sum_{i=0}^{t} \underbrace{(B^r_{t-i,g} - B^c_{t-i,g}) A^{s^A_B}_{t-i,g} E^{s^E_B}_{t-i,g}}_{\Delta B_{t-i,g}(\Theta)} (P^{s^B_B}_{t-i,g} - S^{s^B_B}_{t-i,g}) K_{g,i,t}(\Theta)$$

$$\Delta O_{A_{t,g}}(\Theta) = \frac{1}{P^{s_P}} \sum_{i=0}^{t} \underbrace{B^{s^B_A}_{t-i,g} (A^r_{t-i,g} - A^c_{t-i,g}) E^{s^E_A}_{t-i,g}}_{\Delta A_{t-i,g}(\Theta)} (P^{s^A_A}_{t-i,g} - S^{s^A_A}_{t-i,g}) K_{g,i,t}(\Theta)$$

$$\Delta O_{E_{t,g}}(\Theta) = \frac{1}{P^{s_P}} \sum_{i=0}^{t} \underbrace{B^{s^B_E}_{t-i,g} A^{s^A_E}_{t-i,g} (E^r_{t-i,g} - E^c_{t-i,g})}_{\Delta E_{t-i,g}(\Theta)} (P^{s^E_E}_{t-i,g} - S^{s^E_E}_{t-i,g}) K_{g,i,t}(\Theta)$$

where Θ denotes a vector containing a total of 15 elements describing how different components of the stock process are held fixed (i.e., how interaction terms are allocated). Each of these elements can take on counterfactual (c) or actually observed (r) values, implying a total of 2^{15} different ways to define these cumulative impacts.

The first element of Θ (s_P) represents how we fix the population in the denominator of the enrollment rate (e.g., in equation (29)). The next 9 elements (s^y_x for x and $y \in \{B, A, E\}$) represent how the other determinants of entry are being fixed when measuring the impact of changes in eligibility, applications, and awards. For each measure, there are three such determinants: the SSDI stock and the remaining two steps of the entry process (e.g., to measure the impact of changes in application rates, we must decide how to fix existing SSDI stocks, eligibility rates, and award rates).[40] The 11th element (s_I) represents how we fix SSDI stocks and population counts when measuring the impact of interactions between the three steps of the entry process . The final 4 elements represent how we fix SSDI stocks when measuring the impact of the 4 alternative causes of exits (retirement, mortality, recovery, and other exits).

Because entry is a non-linear function of awards, applications, and eligibility, aggregating up to measure the impact of changing *entry* requires summing up these three terms along with the *interaction term* which describes the impact of their joint changes. This interaction term can be expressed as:

$$\begin{aligned}\Delta O_{(B\times A\times E)_{t,g}}(\Theta) =& \frac{1}{P^{s_P}}\sum_{i=0}^{t}\left[(N^r_{t-i,g}-N^c_{t-i,g})\right](P^{s_I}_{t-i,g}-S^{s_I}_{t-i,g})K_{g,i,t}(\Theta)\\ &-\frac{1}{P^{s_P}}\sum_{i=0}^{t}\left[\Delta B_{t-i,g}(\Theta)+\Delta A_{t-i,g}(\Theta)+\Delta E_{t-i,g}(\Theta)\right](P^{s_I}_{t-i,g}-S^{s_I}_{t-i,g})K_{g,i,t}(\Theta)\end{aligned} \tag{37}$$

For a given choice of Θ, aggregating up $\Delta O_{(B\times A\times E)_{t,g}}+\Delta O_{B_{t,g}}+\Delta O_{A_{t,g}}+\Delta O_{E_{t,g}}$ gives a measure of the cumulative impact of SSDI entry. With total exits being a sum of cause-specific exits per equation (8), expressions for the cumulative impacts of cause-specific exits are:

$$\begin{aligned}\Delta O_{\text{Ret. Rate}_{t,g}}(\Theta) =& \frac{1}{P^{s_P}}\sum_{i=0}^{t}(\text{Ret. Rate}^r_{t,g}-\text{Ret. Rate}^c_{t,g})S^{s_R}_{t-i,g}K_{g,i,t}(\Theta)\\ \Delta O_{\text{Mort. Rate}_{t,g}}(\Theta) =& \frac{1}{P^{s_P}}\sum_{i=0}^{t}(\text{Mort. Rate}^r_{t,g}-\text{Mort. Rate}^c_{t,g})S^{s_M}_{t-i,g}K_{g,i,t}(\Theta)\\ \Delta O_{\text{Recov. Rate}_{t,g}}(\Theta) =& \frac{1}{P^{s_P}}\sum_{i=0}^{t}(\text{Recov. Rate}^r_{t,g}-\text{Recov. Rate}^c_{t,g})S^{s_H}_{t-i,g}K_{g,i,t}(\Theta)\\ \Delta O_{\text{Other Rate}_{t,g}}(\Theta) =& \frac{1}{P^{s_P}}\sum_{i=0}^{t}(\text{Other Rate}^r_{t,g}-\text{Other Rate}^c_{t,g})S^{s_O}_{t-i,g}K_{g,i,t}(\Theta)\end{aligned}$$

Each of the 15 binary choices available when deciding how to fix determinants of the

[40] The elements s^y_x for which $x=y$ control how the SSDI stock and population count are fixed when measuring the cumulative impact of changes in x.

stock accounting equation will affect the specification of $K_{g,i,t}$, which can we can write as:

$$K_{g,i,t}(\Theta) \equiv \begin{cases} \prod_{j=1}^{i} k_{t-j+1,g}(\Theta) & \text{if } i \geq 1 \\ 1 & \text{if } i = 0 \end{cases}$$

where $k_{t,g}(\Theta)$ is the value which makes the following accounting identity hold:

$$\begin{aligned} S^r_{t+1,g} - S^c_{t+1,g} =& \Delta B_{t,g}(\Theta)(P^{s^B_B}_{t,g} - S^{s^B_B}_{t,g}) + \Delta A_{t,g}(\Theta)(P^{s^A_A}_{t,g} - S^{s^A_A}_{t,g}) + \Delta E_{t,g}(\Theta)(P^{s^E_E}_{t,g} - S^{s^E_E}_{t,g}) \\ &+ [(N^r_{t,g} - N^c_{t,g}) - \Delta B_{t,g}(\Theta) - \Delta A_{t,g}(\Theta) - \Delta E_{t,g}(\Theta)](P^{s_I}_{t,g} - S^{s_I}_{t,g}) \\ &- \Delta \text{Ret. Rate}_{t,g}(\Theta) S^{s_R}_{t,g} - \Delta \text{Mort. Rate}_{t,g}(\Theta) S^{s_M}_{t,g} \\ &- \Delta \text{Recov. Rate}_{t,g}(\Theta) S^{s_H}_{t,g} - \Delta \text{Other Rate}_{t,g}(\Theta) S^{s_O}_{t,g} \\ &+ \text{Population Discrepancy}_{t,g}(\Theta) \\ &+ k_{t,g}(\Theta)(S^r_{t,g} - S^c_{t,g}) \end{aligned} \tag{38}$$

where Population Discrepancy$_{t,g}(\Theta)$ is the gap between actually observed and counterfactual application counts not accounted for by changes we attribute to awards, applications, eligibility, or the interactions within entry:

$$\begin{aligned} N^r_{t,g} P^r_{t,g} - N^c_{t,g} P^c_{t,g} =& \Delta B_{t,g}(\Theta) P^{s^B_B}_{t,g} + \Delta A_{t,g}(\Theta) P^{s^A_A}_{t,g} + \Delta E_{t,g}(\Theta) P^{s^E_E}_{t,g} \\ &+ [(N^r_{t,g} - N^c_{t,g}) - \Delta B_{t,g}(\Theta) - A_{t,g}(\Theta) - E_{t,g}(\Theta)] P^{s_I}_{t,g} \\ &+ \text{Population Discrepancy}_{t,g}(\Theta) \end{aligned}$$

To illustrate the exact expression for K and the population discrepancy and how they depend on the choice of Θ, consider the examples at the end of this section. Note that we add some notation to our labels for the "partial effects" in these decompositions, to make clearer how determinants of the decomposition are being held fixed in each example.

Example 1: Our baseline specification, used for reporting point estimates, fixing everything at counterfactual (c) values.

$$
\begin{aligned}
S^r_{g,t+1} - S^c_{g,t+1} = & \underbrace{(N^r_{g,t} - N^c_{g,t})(P^c_{g,t} - S^c_{g,t})}_{\text{Partial Entry}} \underbrace{-(X^r_{g,t} - X^c_{g,t})S^c_{g,t}}_{\text{Partial Exit}} \\
& + \underbrace{N^r_{g,t}(P^r_{g,t} - P^c_{g,t})}_{\text{Population Discrepancy}} + \underbrace{(1 - N^r_{g,t} - X^r_{g,t})}_{k^r}(S^r_{g,t} - S^c_{g,t}) \\
= & \underbrace{(B^r_{g,t} - B^c_{g,t})A^c_{g,t}E^c_{g,t}(P^c_{g,t} - S^c_{g,t})}_{\text{Partial Award (c,c,c)}} \\
& + \underbrace{B^c_{g,t}(A^r_{g,t} - A^c_{g,t})E^c_{g,t}(P^c_{g,t} - S^c_{g,t})}_{\text{Partial Apply (c,c,c)}} \\
& + \underbrace{B^c_{g,t}A^c_{g,t}(E^r_{g,t} - E^c_{g,t})(P^c_{g,t} - S^c_{g,t})}_{\text{Partial Elig (c,c,c)}} \\
& + \underbrace{((N^r_{g,t} - N^c_{g,t}) - (B^r_{g,t} - B^c_{g,t})A^c_{g,t}E^c_{g,t} - B^c_{g,t}(A^r_{g,t} - A^c_{g,t})E^c_{g,t} - B^c_{g,t}A^c_{g,t}(E^r_{g,t} - E^c_{g,t}))(P^c_{g,t} - S^c_{g,t})}_{\text{Interaction (c)}} \\
& \underbrace{-(X^r_{g,t} - X^c_{g,t})S^c_{g,t}}_{\text{Partial Exit (c,c,c,c)}} \\
& + \underbrace{N^r_{g,t}(P^r_{g,t} - P^c_{g,t})}_{\text{Population Discrepancy}} + \underbrace{(1 - N^r_{g,t} - X^r_{g,t})}_{k^r}(S^r_{g,t} - S^c_{g,t})
\end{aligned}
$$

Example 2: Fixing SSDI stocks at actual (r) values when measuring impacts of entry or exit. Relative to our baseline specification, fixing SSDI stocks (in blue text) at actual values requires that K fix entry and exit rates at *counterfactual* values.

$$
\begin{aligned}
S^r_{g,t+1} - S^c_{g,t+1} = & \underbrace{(N^r_{g,t} - N^c_{g,t})(P^r_{g,t} - S^r_{g,t})}_{\text{Partial Entry}} \underbrace{-(X^r_{g,t} - X^c_{g,t})S^r_{g,t}}_{\text{Partial Exit}} \\
& + \underbrace{N^c_{g,t}(P^r_{g,t} - P^c_{g,t})}_{\text{Population Discrepancy}} + \underbrace{(1 - N^c_{g,t} - X^c_{g,t})}_{k^c}(S^r_{g,t} - S^c_{g,t}) \\
= & \underbrace{(B^r_{g,t} - B^c_{g,t})A^c_{g,t}E^c_{g,t}(P^r_{g,t} - S^r_{g,t})}_{\text{Partial Award (c,c,r)}} \\
& + \underbrace{B^c_{g,t}(A^r_{g,t} - A^c_{g,t})E^c_{g,t}(P^r_{g,t} - S^r_{g,t})}_{\text{Partial Apply (c,c,r)}} \\
& + \underbrace{B^c_{g,t}A^c_{g,t}(E^r_{g,t} - E^c_{g,t})(P^r_{g,t} - S^r_{g,t})}_{\text{Partial Elig (c,c,r)}} \\
& + \underbrace{((N^r_{g,t} - N^c_{g,t}) - (B^r_{g,t} - B^c_{g,t})A^c_{g,t}E^c_{g,t} - B^c_{g,t}(A^r_{g,t} - A^c_{g,t})E^c_{g,t} - B^c_{g,t}A^c_{g,t}(E^r_{g,t} - E^c_{g,t}))(P^r_{g,t} - S^r_{g,t})}_{\text{Interaction (r)}} \\
& \underbrace{-(X^r_{g,t} - X^c_{g,t})S^r_{g,t}}_{\text{Partial Exit (c,c,c,r)}} \\
& + \underbrace{N^c_{g,t}(P^r_{g,t} - P^c_{g,t})}_{\text{Population Discrepancy}} + \underbrace{(1 - N^c_{g,t} - X^c_{g,t})}_{k^c}(S^r_{g,t} - S^c_{g,t})
\end{aligned}
$$

Example 3: Fixing SSDI stocks at counterfactual (c) values when measuring impacts of exit, actual values (r) when measuring impacts of entry. Relative to the baseline specification, fixing SSDI stocks at actual values for measuring the partial effect of entry rates implies that K' must fix entry rates at *counterfactual* values.

$$
\begin{aligned}
S^r_{g,t+1} - S^c_{g,t+1} = & \underbrace{(N^r_{g,t} - N^c_{g,t})(P^r_{g,t} - S^r_{g,t})}_{\text{Partial Entry}} \underbrace{-(X^r_{g,t} - X^c_{g,t})S^r_{g,t}}_{\text{Partial Exit}} \\
& + \underbrace{N^c_{g,t}(P^r_{g,t} - P^c_{g,t})}_{\text{Population Discrepancy}} + \underbrace{(1 - N^c_{g,t} - X^c_{g,t})}_{k^c}(S^r_{g,t} - S^c_{g,t}) \\
& = \underbrace{(B^r_{g,t} - B^c_{g,t})A^c_{g,t}E^c_{g,t}(P^r_{g,t} - S^r_{g,t})}_{\text{Partial Award (c,c,r)}} \\
& + \underbrace{B^c_{g,t}(A^r_{g,t} - A^c_{g,t})E^c_{g,t}(P^r_{g,t} - S^r_{g,t})}_{\text{Partial Apply (c,c,r)}} \\
& + \underbrace{B^c_{g,t}A^c_{g,t}(E^r_{g,t} - E^c_{g,t})(P^r_{g,t} - S^r_{g,t})}_{\text{Partial Elig (c,c,r)}} \\
& + \underbrace{((N^r_{g,t} - N^c_{g,t}) - (B^r_{g,t} - B^c_{g,t})A^c_{g,t}E^c_{g,t} - B^c_{g,t}(A^r_{g,t} - A^c_{g,t})E^c_{g,t} - B^c_{g,t}A^c_{g,t}(E^r_{g,t} - E^c_{g,t}))(P^r_{g,t} - S^r_{g,t})}_{\text{Interaction (r)}} \\
& \underbrace{-(X^r_{g,t} - X^c_{g,t})S^c_{g,t}}_{\text{Partial Exit (c,c,c,c)}} \\
& + \underbrace{N^c_{g,t}(P^r_{g,t} - P^c_{g,t})}_{\text{Population Discrepancy}} + \underbrace{(1 - N^c_{g,t} - X^r_{g,t})}_{k'}(S^r_{g,t} - S^c_{g,t})
\end{aligned}
$$

Example 4: Fixing SSDI stocks at counterfactual (c) values when measuring impacts of exit, apply, and interaction within entry, actual values (r) when measuring impacts of award and eligibility. Using equation (38), allowing these differences in defining partial effects within entry leads to some interaction terms appearing in k.

$$
\begin{aligned}
S^r_{g,t+1} - S^c_{g,t+1} = {} & \underbrace{(N^r_{g,t} - N^c_{g,t})(P^r_{g,t} - S^r_{g,t})}_{\text{Partial Entry}} \underbrace{-(X^r_{g,t} - X^c_{g,t})S^r_{g,t}}_{\text{Partial Exit}} \\
& + \underbrace{N^c_{g,t}(P^r_{g,t} - P^c_{g,t})}_{\text{Population Discrepancy}} + \underbrace{(1 - N^c_{g,t} - X^c_{g,t})}_{k^c}(S^r_{g,t} - S^c_{g,t}) \\
& = \underbrace{(B^r_{g,t} - B^c_{g,t})A^c_{g,t}E^c_{g,t}(P^r_{g,t} - S^r_{g,t})}_{\text{Partial Award (c,c,r)}} \\
& + \underbrace{B^c_{g,t}(A^r_{g,t} - A^c_{g,t})E^c_{g,t}(P^c_{g,t} - S^c_{g,t})}_{\text{Partial Apply (c,c,c)}} \\
& + \underbrace{B^c_{g,t}A^c_{g,t}(E^r_{g,t} - E^c_{g,t})(P^r_{g,t} - S^r_{g,t})}_{\text{Partial Elig (c,c,r)}} \\
& + \underbrace{((N^r_{g,t} - N^c_{g,t}) - (B^r_{g,t} - B^c_{g,t})A^c_{g,t}E^c_{g,t} - B^c_{g,t}(A^r_{g,t} - A^c_{g,t})E^c_{g,t} - B^c_{g,t}A^c_{g,t}(E^r_{g,t} - E^c_{g,t}))(P^c_{g,t} - S^c_{g,t})}_{\text{Interaction (c)}} \\
& \underbrace{-(X^r_{g,t} - X^c_{g,t})S^c_{g,t}}_{\text{Partial Exit (c,c,c,c)}} \\
& + \underbrace{N^r_{g,t}(P^r_{g,t} - P^c_{g,t})}_{\text{Population Discrepancy}} + \underbrace{(1 - N^r_{g,t} - X^r_{g,t})}_{k^r}(S^r_{g,t} - S^c_{g,t}) \\
& + \underbrace{(B^r_{g,t} - B^c_{g,t})A^c_{g,t}E^c_{g,t}[(P^c_{g,t} - S^c_{g,t}) - (P^r_{g,t} - S^r_{g,t})]}_{\text{Partial Award (c,c,c) - Partial Award (c,c,r)}} \\
& + \underbrace{B^c_{g,t}A^c_{g,t}(E^r_{g,t} - E^c_{g,t})[(P^c_{g,t} - S^c_{g,t}) - (P^r_{g,t} - S^r_{g,t})]}_{\text{Partial Elig (c,c,c) - Partial Elig (c,c,r)}} \\
& = \underbrace{(B^r_{g,t} - B^c_{g,t})A^c_{g,t}E^c_{g,t}(P^r_{g,t} - S^r_{g,t})}_{\text{Partial Award (c,c,r)}} \\
& + \underbrace{B^c_{g,t}(A^r_{g,t} - A^c_{g,t})E^c_{g,t}(P^c_{g,t} - S^c_{g,t})}_{\text{Partial Apply (c,c,c)}} \\
& + \underbrace{B^c_{g,t}A^c_{g,t}(E^r_{g,t} - E^c_{g,t})(P^r_{g,t} - S^r_{g,t})}_{\text{Partial Elig (c,c,r)}} \\
& + \underbrace{((N^r_{g,t} - N^c_{g,t}) - (B^r_{g,t} - B^c_{g,t})A^c_{g,t}E^c_{g,t} - B^c_{g,t}(A^r_{g,t} - A^c_{g,t})E^c_{g,t} - B^c_{g,t}A^c_{g,t}(E^r_{g,t} - E^c_{g,t}))(P^c_{g,t} - S^c_{g,t})}_{\text{Interaction (c)}} \\
& \underbrace{-(X^r_{g,t} - X^c_{g,t})S^c_{g,t}}_{\text{Partial Exit (c,c,c,c)}} \\
& + \underbrace{[N^r_{g,t} - ((B^r_{g,t} - B^c_{g,t})A^c_{g,t}E^c_{g,t}) - (B^c_{g,t}A^c_{g,t}(E^r_{g,t} - E^c_{g,t}))](P^r_{g,t} - P^c_{g,t})}_{\text{Population Discrepancy}} \\
& + \underbrace{[(1 - N^r_{g,t} - X^r_{g,t}) + ((B^r_{g,t} - B^c_{g,t})A^c_{g,t}E^c_{g,t}) + (B^c_{g,t}A^c_{g,t}(E^r_{g,t} - E^c_{g,t}))]}_{k''}(S^r_{g,t} - S^c_{g,t})
\end{aligned}
$$

Example 5: When measuring impacts of components of entry, fixing some remaining components at counterfactual (c) values and others at actual (r) values. Using equation (37), this affects how we define the impact of interactions within the entry process.

$$
\begin{aligned}
S^r_{g,t+1} - S^c_{g,t+1} = & \underbrace{(N^r_{g,t} - N^c_{g,t})(P^c_{g,t} - S^c_{g,t})}_{\text{Partial Entry}} \underbrace{-(X^r_{g,t} - X^c_{g,t})S^c_{g,t}}_{\text{Partial Exit}} \\
& + \underbrace{N^r_{g,t}(P^r_{g,t} - P^c_{g,t})}_{\text{Population Discrepancy}} + \underbrace{(1 - N^r_{g,t} - X^r_{g,t})}_{k^r}(S^r_{g,t} - S^c_{g,t}) \\
& = \underbrace{(B^r_{g,t} - B^c_{g,t})A^c_{g,t}E^c_{g,t}(P^c_{g,t} - S^c_{g,t})}_{\text{Partial Award (c,c,c)}} \\
& + \underbrace{B^r_{g,t}(A^r_{g,t} - A^c_{g,t})E^r_{g,t}(P^c_{g,t} - S^c_{g,t})}_{\text{Partial Apply (r,r,c)}} \\
& + \underbrace{B^r_{g,t}A^c_{g,t}(E^r_{g,t} - E^c_{g,t})(P^c_{g,t} - S^c_{g,t})}_{\text{Partial Elig (r,c,c)}} \\
& + \underbrace{((N^r_{g,t} - N^c_{g,t}) - (B^r_{g,t} - B^c_{g,t})A^c_{g,t}E^c_{g,t} - B^r_{g,t}(A^r_{g,t} - A^c_{g,t})E^r_{g,t} - B^r_{g,t}A^c_{g,t}(E^r_{g,t} - E^c_{g,t}))(P^c_{g,t} - S^c_{g,t})}_{\text{Interaction (c)}} \\
& \underbrace{-(X^r_{g,t} - X^c_{g,t})S^c_{g,t}}_{\text{Partial Exit (c,c,c,c)}} \\
& + \underbrace{N^r_{g,t}(P^r_{g,t} - P^c_{g,t})}_{\text{Population Discrepancy}} + \underbrace{(1 - N^r_{g,t} - X^r_{g,t})}_{k^r}(S^r_{g,t} - S^c_{g,t})
\end{aligned}
$$

Example 6: Fixing non-beneficiary populations at actual (r) values for the impact of applications, interactions within entry, and exit but not for the impact of awards or eligibility (mixture of example 4 and 5). Using both equations (37) and (38), this affects how we define the impact of interactions within entry, which also has implications for the definition of k.

$$
\begin{aligned}
S^r_{g,t+1} - S^c_{g,t+1} = {} & \underbrace{(N^r_{g,t} - N^c_{g,t})(P^c_{g,t} - S^c_{g,t})}_{\text{Partial Entry}} \underbrace{-(X^r_{g,t} - X^c_{g,t})S^c_{g,t}}_{\text{Partial Exit}} \\
& + \underbrace{N^r_{g,t}(P^r_{g,t} - P^c_{g,t})}_{\text{Population Discrepancy}} + \underbrace{(1 - N^r_{g,t} - X^r_{g,t})}_{k^r}(S^r_{g,t} - S^c_{g,t}) \\
& = \underbrace{(B^r_{g,t} - B^c_{g,t})A^c_{g,t}E^c_{g,t}(P^r_{g,t} - S^r_{g,t})}_{\text{Partial Award (c,c,r)}} \\
& + \underbrace{B^r_{g,t}(A^r_{g,t} - A^c_{g,t})E^r_{g,t}(P^c_{g,t} - S^c_{g,t})}_{\text{Partial Apply (r,r,c)}} \\
& + \underbrace{B^r_{g,t}A^c_{g,t}(E^r_{g,t} - E^c_{g,t})(P^r_{g,t} - S^r_{g,t})}_{\text{Partial Elig (r,c,r)}} \\
& + \underbrace{((N^r_{g,t} - N^c_{g,t}) - (B^r_{g,t} - B^c_{g,t})A^c_{g,t}E^c_{g,t} - B^r_{g,t}(A^r_{g,t} - A^c_{g,t})E^r_{g,t} - B^r_{g,t}A^c_{g,t}(E^r_{g,t} - E^c_{g,t}))(P^c_{g,t} - S^c_{g,t})}_{\text{Interaction (c)}} \\
& \underbrace{-(X^r_{g,t} - X^c_{g,t})S^c_{g,t}}_{\text{Partial Exit (c,c,c,c)}} \\
& + \underbrace{N^r_{g,t}(P^r_{g,t} - P^c_{g,t})}_{\text{Population Discrepancy}} + \underbrace{(1 - N^r_{g,t} - X^r_{g,t})}_{k^r}(S^r_{g,t} - S^c_{g,t}) \\
& + (B^r_{g,t} - B^c_{g,t})A^c_{g,t}E^c_{g,t}[(P^c_{g,t} - S^c_{g,t}) - (P^r_{g,t} - S^r_{g,t})] \\
& + B^r_{g,t}A^c_{g,t}(E^r_{g,t} - E^c_{g,t})[(P^c_{g,t} - S^c_{g,t}) - (P^r_{g,t} - S^r_{g,t})] \\
& = \underbrace{(B^r_{g,t} - B^c_{g,t})A^c_{g,t}E^c_{g,t}(P^r_{g,t} - S^r_{g,t})}_{\text{Partial Award (c,c,r)}} \\
& + \underbrace{B^r_{g,t}(A^r_{g,t} - A^c_{g,t})E^r_{g,t}(P^c_{g,t} - S^c_{g,t})}_{\text{Partial Apply (r,r,c)}} \\
& + \underbrace{B^r_{g,t}A^c_{g,t}(E^r_{g,t} - E^c_{g,t})(P^r_{g,t} - S^r_{g,t})}_{\text{Partial Elig (r,c,r)}} \\
& + \underbrace{((N^r_{g,t} - N^c_{g,t}) - (B^r_{g,t} - B^c_{g,t})A^c_{g,t}E^c_{g,t} - B^r_{g,t}(A^r_{g,t} - A^c_{g,t})E^r_{g,t} - B^r_{g,t}A^c_{g,t}(E^r_{g,t} - E^c_{g,t}))(P^c_{g,t} - S^c_{g,t})}_{\text{Interaction (c)}} \\
& \underbrace{-(X^r_{g,t} - X^c_{g,t})S^c_{g,t}}_{\text{Partial Exit (c,c,c,c)}} \\
& + \underbrace{[N^r_{g,t} - ((B^r_{g,t} - B^c_{g,t})A^c_{g,t}E^c_{g,t}) - (B^r_{g,t}A^c_{g,t}(E^r_{g,t} - E^c_{g,t}))](P^r_{g,t} - P^c_{g,t})}_{\text{Population Discrepancy}} \\
& + \underbrace{[(1 - N^r_{g,t} - X^r_{g,t}) + ((B^r_{g,t} - B^c_{g,t})A^c_{g,t}E^c_{g,t}) + (B^r_{g,t}A^c_{g,t}(E^r_{g,t} - E^c_{g,t}))]}_{k'''}(S^r_{g,t} - S^c_{g,t})
\end{aligned}
$$

Example 7: In exit, only evaluate impact of death among beneficiaries by fixing SSDI stocks at actual (r) values.

$$
\begin{aligned}
S^r_{g,t+1} - S^c_{g,t+1} &= \underbrace{(N^r_{g,t} - N^c_{g,t})(P^c_{g,t} - S^c_{g,t})}_{\text{Partial Entry}} \underbrace{-(X^r_{g,t} - X^c_{g,t})S^c_{g,t}}_{\text{Partial Exit}} \\
&+ \underbrace{N^r_{g,t}(P^r_{g,t} - P^c_{g,t})}_{\text{Population Discrepancy}} + \underbrace{(1 - N^r_{g,t} - X^r_{g,t})}_{k^r}(S^r_{g,t} - S^c_{g,t}) \\
&= \underbrace{(B^r_{g,t} - B^c_{g,t})A^c_{g,t}E^c_{g,t}(P^c_{g,t} - S^c_{g,t})}_{\text{Partial Award (c,c,c)}} \\
&+ \underbrace{B^c_{g,t}(A^r_{g,t} - A^c_{g,t})E^c_{g,t}(P^c_{g,t} - S^c_{g,t})}_{\text{Partial Apply (c,c,c)}} \\
&+ \underbrace{B^c_{g,t}A^c_{g,t}(E^r_{g,t} - E^c_{g,t})(P^c_{g,t} - S^c_{g,t})}_{\text{Partial Elig (c,c,c)}} \\
&+ \underbrace{((N^r_{g,t} - N^c_{g,t}) - (B^r_{g,t} - B^c_{g,t})A^c_{g,t}E^c_{g,t} - B^c_{g,t}(A^r_{g,t} - A^c_{g,t})E^c_{g,t} - B^c_{g,t}A^c_{g,t}(E^r_{g,t} - E^c_{g,t}))(P^c_{g,t} - S^c_{g,t})}_{\text{Interaction (c)}} \\
&\underbrace{-(XRet^r_{g,t} - XRet^c_{g,t})S^c_{g,t} - (XMort^r_{g,t} - XMort^c_{g,t})S^r_{g,t} - (XRecov^r_{g,t} - XRecov^c_{g,t})S^c_{g,t} - (XOth^r_{g,t} - XOth^c_{g,t})S^c_{g,t}}_{\text{Partial Exit (c,r,c,c)}} \\
&+ \underbrace{N^r_{g,t}(P^r_{g,t} - P^c_{g,t})}_{\text{Population Discrepancy}} + \underbrace{(1 - N^r_{g,t} - X^r_{g,t})}_{k^r}(S^r_{g,t} - S^c_{g,t}) \\
&+ (XMort^r_{g,t} - XMort^c_{g,t})(S^r_{g,t} - S^c_{g,t}) \\
&= \underbrace{(B^r_{g,t} - B^c_{g,t})A^c_{g,t}E^c_{g,t}(P^c_{g,t} - S^c_{g,t})}_{\text{Partial Award (c,c,c)}} \\
&+ \underbrace{B^c_{g,t}(A^r_{g,t} - A^c_{g,t})E^c_{g,t}(P^c_{g,t} - S^c_{g,t})}_{\text{Partial Apply (c,c,c)}} \\
&+ \underbrace{B^c_{g,t}A^c_{g,t}(E^r_{g,t} - E^c_{g,t})(P^c_{g,t} - S^c_{g,t})}_{\text{Partial Elig (c,c,c)}} \\
&+ \underbrace{((N^r_{g,t} - N^c_{g,t}) - (B^r_{g,t} - B^c_{g,t})A^c_{g,t}E^c_{g,t} - B^c_{g,t}(A^r_{g,t} - A^c_{g,t})E^c_{g,t} - B^c_{g,t}A^c_{g,t}(E^r_{g,t} - E^c_{g,t}))(P^c_{g,t} - S^c_{g,t})}_{\text{Interaction (c)}} \\
&\underbrace{-(XRet^r_{g,t} - XRet^c_{g,t})S^c_{g,t} - (XMort^r_{g,t} - XMort^c_{g,t})S^r_{g,t} - (XRecov^r_{g,t} - XRecov^c_{g,t})S^c_{g,t} - (XOth^r_{g,t} - XOth^c_{g,t})S^c_{g,t}}_{\text{Partial Exit (c,r,c,c)}} \\
&+ \underbrace{N^r_{g,t}(P^r_{g,t} - P^c_{g,t})}_{\text{Population Discrepancy}} + \underbrace{(1 - N^r_{g,t} - XRet^r_{g,t} - XMort^r_{g,t} - XRecov^r_{g,t} - XOth^r_{g,t})}_{k''''}(S^r_{g,t} - S^c_{g,t})
\end{aligned}
$$

Where $X = XRet + XMort + XRecov + XOth$ comes from partitioning SSDI exit rates into the four cause-specific exit rates.

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

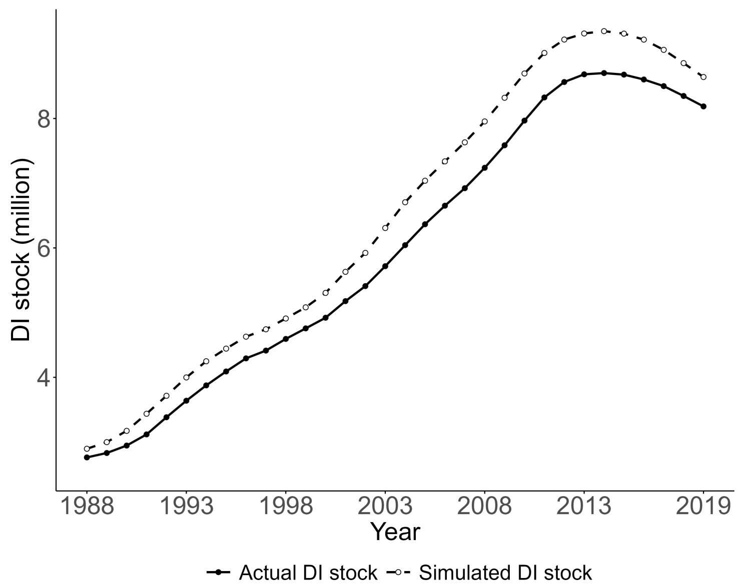
Following the concept of equation (11), with four covariates (sex, age, earnings bin and birthplace), there are $4! = 24$ arrangements that go into calculating the bounds.

G Population-level heterogeneity results

G.1 By sex, age, and skill

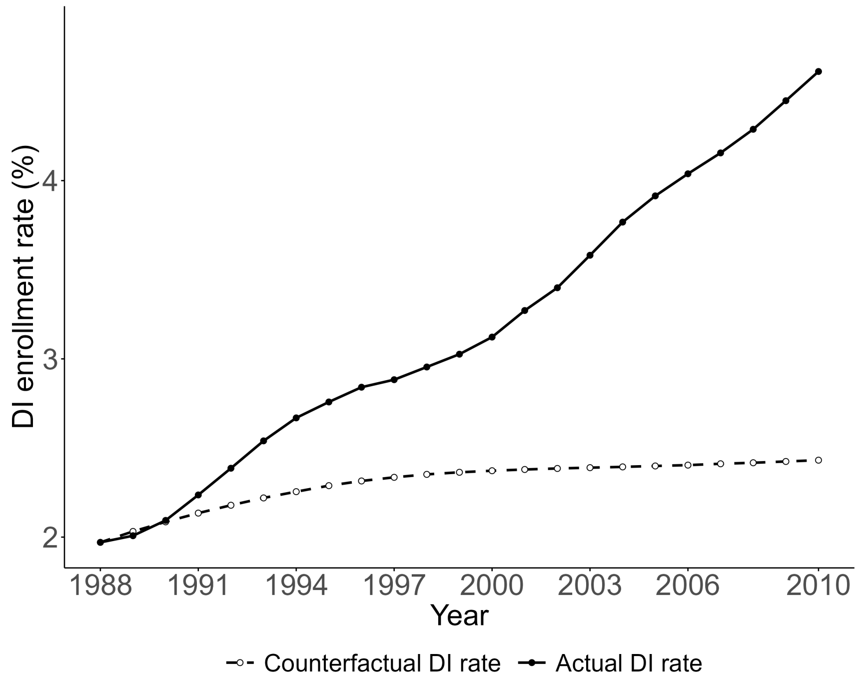
G.1.1 SSDI increase period (1988–2010)

Appendix Figure G.1: Counterfactual vs actual SSDI enrollment level, 1988–2010



Notes: Figure plots actual and counterfactual SSDI enrollment levels in each year from 1988 to 2010. Actual SSDI enrollment level uses the Continuous Work History Sample linked to the Payment History Update System and the Master Beneficiary Record. Counterfactual SSDI enrollment level uses equations (2), (3), and (4), using 1988 as the base year. Values for the enrollment rate are given in Appendix Table G.1.

Appendix Figure G.2: Counterfactual vs actual SSDI enrollment rate, 1988–2010



Notes: Figure plots actual and counterfactual SSDI enrollment rates in each year from 1988 to 2010. Actual SSDI enrollment rate uses the Continuous Work History Sample linked to the Payment History Update System and the Master Beneficiary Record. Counterfactual SSDI enrollment rate uses equations (2), (3), and (4), using 1988 as the base year. The exact annual values are given in Appendix Table G.1.

Appendix Table G.1: Counterfactual vs actual SSDI enrollment rate, 1988–2010

Year	Actual DI Rate (%)	Counterfactual DI Rate (%)	Total DI change (pp)
1988	1.97	1.97	0.00
1989	2.01	2.03	-0.02
1990	2.09	2.09	0.01
1991	2.24	2.13	0.10
1992	2.39	2.18	0.21
1993	2.54	2.22	0.32
1994	2.67	2.25	0.41
1995	2.76	2.29	0.47
1996	2.84	2.32	0.53
1997	2.88	2.34	0.55
1998	2.95	2.35	0.60
1999	3.03	2.36	0.66
2000	3.12	2.37	0.75
2001	3.27	2.38	0.89
2002	3.40	2.39	1.01
2003	3.58	2.39	1.19
2004	3.77	2.39	1.37
2005	3.91	2.40	1.52
2006	4.04	2.40	1.63
2007	4.16	2.41	1.74
2008	4.29	2.42	1.87
2009	4.45	2.42	2.02
2010	4.61	2.43	2.18

Notes: Table presents actual and counterfactual SSDI enrollment rates in each year from 1988 to 2010. Actual SSDI rate uses the Continuous Work History Sample linked to the Payment History Update System and the Master Beneficiary Record. Counterfactual SSDI rate uses equations (2), (3), and (4), using 1988 as the base year.

Appendix Table G.2: Demographic breakdown of entry share of SSDI enrollment rate, 1988–2010

Group	Absolute contribution (pp)	Contribution share (%)	Baseline population share (%)	Baseline entrants share (%)	Contribution/ baseline entrants
Men, Younger, \$10K+	0.00	0.06	22.15	12.15	0.01
Men, Younger, \$0-10K	0.03	2.10	8.43	9.94	0.21
Men, Older, \$10K+	0.21	17.90	13.01	33.67	0.53
Men, Older, \$0-10K	0.10	8.31	4.70	6.22	1.34
Women, Younger, \$10K+	0.04	3.52	13.34	4.38	0.80
Women, Younger, \$0-10K	0.28	23.18	15.96	7.22	3.21
Women, Older, \$10K+	0.07	6.22	3.62	5.90	1.05
Women, Older, \$0-10K	0.48	40.34	14.50	16.61	2.43
Missing	-0.02	-1.64	4.30	3.92	-0.42
Total	1.20	100.00	100.00	100.00	1.00

Notes: Table presents the "entry" share (from Table 1) of the difference between actual and counterfactual SSDI rates for the increase period (1988–2010), broken down into contribution from demographic subgroups using equation (35). "Contribution share" is "absolute contribution" as a percent of the total change. "Baseline population share" is the share of the US population that the group accounts for in 1988. "Baseline entrants share" is the share of SSDI entrants that the group accounts for in 1988. "Contribution/baseline entrants" presents the ratio of "contribution share" to "baseline entrants share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the change. The demographic groups are characterized by sex, average annual earnings between ages 25-34 (a measure of skill), and whether older or younger than 45 years old.

Appendix Table G.3: Demographic breakdown of application share of SSDI enrollment rate, 1988–2010

Group	Absolute contribution (pp)	Contribution share (%)	Baseline population share (%)	Baseline entrants share (%)	Contribution/ baseline entrants
Men, Younger, \$10K+	0.00	0.24	22.15	12.15	0.02
Men, Younger, \$0-10K	0.05	6.72	8.43	9.94	0.68
Men, Older, \$10K+	0.10	12.80	13.01	33.67	0.38
Men, Older, \$0-10K	0.02	2.74	4.70	6.22	0.44
Women, Younger, \$10K+	0.04	5.52	13.34	4.38	1.26
Women, Younger, \$0-10K	0.28	34.74	15.96	7.22	4.81
Women, Older, \$10K+	0.04	4.48	3.62	5.90	0.76
Women, Older, \$0-10K	0.30	37.18	14.50	16.61	2.24
Missing	-0.04	-4.42	4.30	3.92	-1.13
Total	0.80	100.00	100.00	100.00	1.00

Notes: Table presents the "application" share (from Table 1) of the difference between actual and counterfactual SSDI rates for the increase period (1988–2010), broken down into contribution from demographic subgroups using equation (10). "Contribution share" is "absolute contribution" as a percent of the total change. "Baseline population share" is the share of the US population that the group accounts for in 1988. "Baseline entrants share" is the share of SSDI entrants that the group accounts for in 1988. "Contribution/baseline entrants" presents the ratio of "contribution share" to "baseline entrants share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the change. The demographic groups are characterized by sex, average annual earnings between ages 25-34 (a measure of skill), and whether older or younger than 45 years old.

Appendix Table G.4: Demographic breakdown of award share of SSDI enrollment rate, 1988–2010

Group	Absolute contribution (pp)	Contribution share (%)	Baseline population share (%)	Baseline entrants share (%)	Contribution/ baseline entrants
Men, Younger, \$10K+	-0.00	-0.97	22.15	12.15	-0.08
Men, Younger, \$0-10K	-0.02	-12.78	8.43	9.94	-1.29
Men, Older, \$10K+	0.09	52.95	13.01	33.67	1.57
Men, Older, \$0-10K	0.03	17.65	4.70	6.22	2.84
Women, Younger, \$10K+	-0.00	-0.22	13.34	4.38	-0.05
Women, Younger, \$0-10K	-0.02	-11.71	15.96	7.22	-1.62
Women, Older, \$10K+	0.02	11.10	3.62	5.90	1.88
Women, Older, \$0-10K	0.08	45.76	14.50	16.61	2.76
Missing	-0.00	-1.78	4.30	3.92	-0.45
Total	0.17	100.00	100.00	100.00	1.00

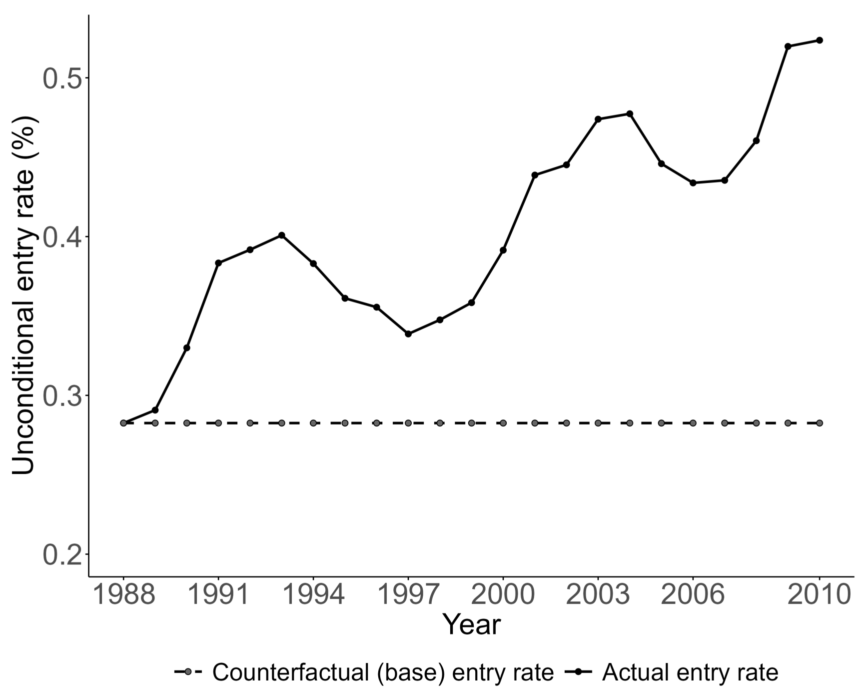
Notes: Table presents the "award" share (from Table 1) of the difference between actual and counterfactual SSDI rates for the increase period (1988–2010), broken down into contribution from demographic subgroups using equation (33). "Contribution share" is "absolute contribution" as a percent of the total change. "Baseline population share" is the share of the US population that the group accounts for in 1988. "Baseline entrants share" is the share of SSDI entrants that the group accounts for in 1988. "Contribution/baseline entrants" presents the ratio of "contribution share" to "baseline entrants share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the change. The demographic groups are characterized by sex, average annual earnings between ages 25-34 (a measure of skill), and whether older or younger than 45 years old.

Appendix Table G.5: Demographic breakdown of eligibility share of SSDI enrollment rate, 1988–2010

Group	Absolute contribution (pp)	Contribution share (%)	Baseline population share (%)	Baseline entrants share (%)	Contribution/ baseline entrants
Men, Younger, $10K+	0.00	1.30	22.15	12.15	0.11
Men, Younger, $0-10K	-0.00	-0.14	8.43	9.94	-0.01
Men, Older, $10K+	0.01	6.88	13.01	33.67	0.20
Men, Older, $0-10K	0.03	21.30	4.70	6.22	3.43
Women, Younger, $10K+	0.00	0.23	13.34	4.38	0.05
Women, Younger, $0-10K	0.03	17.94	15.96	7.22	2.48
Women, Older, $10K+	0.01	7.71	3.62	5.90	1.31
Women, Older, $0-10K	0.06	36.14	14.50	16.61	2.18
Missing	0.01	8.64	4.30	3.92	2.20
Total	0.15	100.00	100.00	100.00	1.00

Notes: Table presents the "eligibility" share (from Table 1) of the difference between actual and counterfactual SSDI rates for the increase period (1988–2010), broken down into contribution from demographic subgroups using equation (34). "Contribution share" is "absolute contribution" as a percent of the total change. "Baseline population share" is the share of the US population that the group accounts for in 1988. "Baseline entrants share" is the share of SSDI entrants that the group accounts for in 1988. "Contribution/baseline entrants" presents the ratio of "contribution share" to "baseline entrants share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the change. The demographic groups are characterized by sex, average annual earnings between ages 25-34 (a measure of skill), and whether older or younger than 45 years old.

Appendix Figure G.3: Counterfactual vs actual SSDI entry rate, 1988–2010



Notes: Figure plots actual and counterfactual SSDI entry rate in each year from 1988 to 2010. Actual entry rate uses the Continuous Work History Sample linked to the Payment History Update System and the Master Beneficiary Record. Counterfactual entry rate uses equations (2), (3), and (4), using 1988 as the base year. The exact annual values are given in Appendix Table G.6.

Appendix Table G.6: Counterfactual vs actual SSDI entry rate, 1988–2010

Year	Actual entry rate (%)	Counterfactual (base) entry rate (%)	Total difference (pp)
1988	0.28	0.28	0.00
1989	0.29	0.28	0.01
1990	0.33	0.28	0.05
1991	0.38	0.28	0.10
1992	0.39	0.28	0.11
1993	0.40	0.28	0.12
1994	0.38	0.28	0.10
1995	0.36	0.28	0.08
1996	0.36	0.28	0.07
1997	0.34	0.28	0.06
1998	0.35	0.28	0.07
1999	0.36	0.28	0.08
2000	0.39	0.28	0.11
2001	0.44	0.28	0.16
2002	0.45	0.28	0.16
2003	0.47	0.28	0.19
2004	0.48	0.28	0.19
2005	0.45	0.28	0.16
2006	0.43	0.28	0.15
2007	0.44	0.28	0.15
2008	0.46	0.28	0.18
2009	0.52	0.28	0.24
2010	0.52	0.28	0.24
Total			2.77

Notes: Table presents actual and counterfactual SSDI entry rate in each year from 1988 to 2010. Actual SSDI entry rate uses the Continuous Work History Sample linked to the Payment History Update System and the Master Beneficiary Record. Counterfactual SSDI entry rate uses equations (2), (3), and (4), using 1988 as the base year.

Appendix Table G.7: Decomposition of increase in SSDI entry rate, 1988–2010

		Absolute contribution (pp)	As a share of total (%)
Entry		2.10	80.4
	Award	0.46	23.5
	Application	1.36	48.7
	Eligibility	0.17	5.1
	Interaction within entry	0.10	3.1
Across group composition		0.68	21.0
Within-across interaction		-0.01	-1.5
Total		2.77	100.0

Notes: Table presents decomposition of SSDI entry rate increase from 1988 to 2010, using equation (9). The point estimates we report are the ones in which flows (e.g., B_t, A_t, E_t, X_t), when fixed, are held fixed at their counterfactual values.

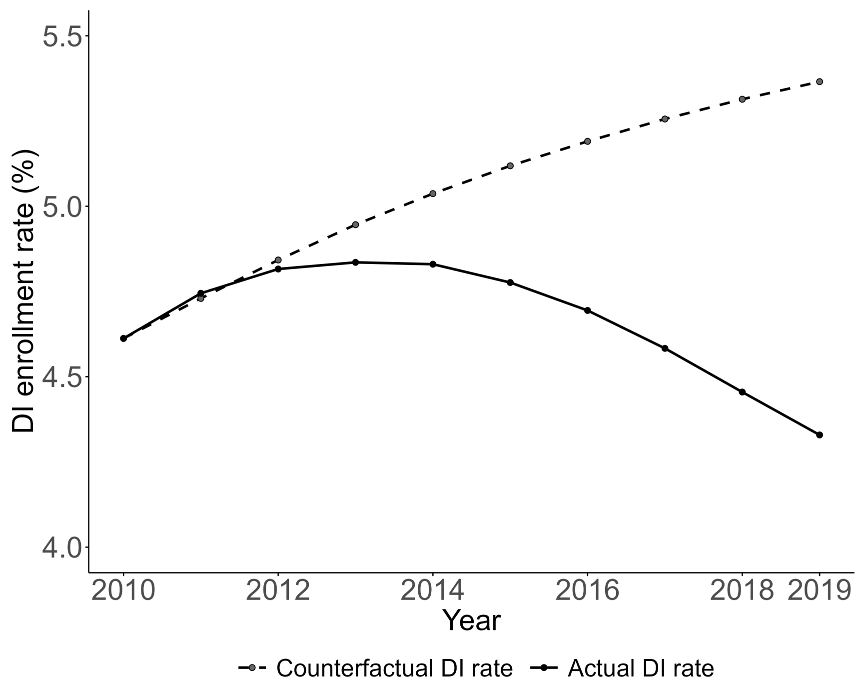
Appendix Table G.8: Demographic breakdown of entry share of SSDI entry rate, 1988–2010

Group	Absolute contribution (pp)	Contribution share (%)	Baseline entrants share (%)	Contribution/ baseline entrants
Men, Younger, $10K+	0.02	1.1	12.1	0.1
Men, Younger, $0-10K	0.10	4.9	9.9	0.5
Men, Older, $10K+	0.50	23.6	33.7	0.7
Men, Older, $0-10K	0.07	3.6	6.2	0.6
Women, Younger, $10K+	0.14	6.5	4.4	1.5
Women, Younger, $0-10K	0.51	24.5	7.2	3.4
Women, Older, $10K+	0.15	7.2	5.9	1.2
Women, Older, $0-10K	0.65	30.8	16.6	1.9
Missing	-0.05	-2.3	3.9	-0.6
Total	2.10	100.0	100.0	1.0

Notes: Table presents the "entry" share (from Appendix Table G.7) of the difference between actual and counterfactual SSDI entry rates for the increase period (1988–2010), broken down into contribution from demographic subgroups using equation (13). "Contribution share" is "absolute contribution" as a percent of the total change. "Baseline population share" is the share of the US population that the group accounts for in 1988. "Baseline entrants share" is the share of SSDI entrants that the group accounts for in 1988. "Contribution/baseline entrants" presents the ratio of "contribution share" to "baseline entrants share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the change. The demographic groups are characterized by sex, average annual earnings between ages 25-34 (a measure of skill), and whether older or younger than 45 years old.

G.1.2 SSDI decrease period (2010–2019)

Appendix Figure G.4: Counterfactual vs actual SSDI enrollment rate, 2010–2019



Notes: Figure plots actual and counterfactual SSDI enrollment rates in each year from 2010 to 2019. Actual SSDI rate uses the Continuous Work History Sample linked to the Payment History Update System and the Master Beneficiary Record. Counterfactual SSDI rate uses equations (2), (3), and (4), using 2010 as the base year. The exact annual values are given in Appendix Table G.9.

Appendix Table G.9: Counterfactual vs actual SSDI enrollment rate, 2010–2019

Year	Actual DI Rate (%)	Counterfactual DI Rate (%)	Total DI change (pp)
2010	4.61	4.61	0.00
2011	4.74	4.73	0.01
2012	4.82	4.84	-0.03
2013	4.84	4.95	-0.11
2014	4.83	5.04	-0.21
2015	4.78	5.12	-0.34
2016	4.69	5.19	-0.50
2017	4.58	5.26	-0.67
2018	4.45	5.31	-0.86
2019	4.33	5.37	-1.04

Notes: Table presents actual and counterfactual SSDI enrollment rates in each year from 2010 to 2019. Actual SSDI rate uses the Continuous Work History Sample linked to the Payment History Update System and the Master Beneficiary Record. Counterfactual SSDI rate uses equations (2), (3), and (4), using 2010 as the base year.

Appendix Table G.10: Demographic breakdown of entry share of SSDI enrollment rate, 2010–2019

Group	Absolute contribution (pp)	Contribution share (%)	Baseline population share (%)	Baseline entrants share (%)	Contribution/ baseline entrants
Older, Men, $10K+	0.31	31.80	17.77	31.30	1.02
Older, Men, $0-10K	0.12	12.19	6.85	9.60	1.27
Older, Women, $10K+	0.11	11.47	11.29	14.93	0.77
Older, Women, $0-10K	0.17	16.75	13.06	19.31	0.87
Younger, Men, $10K+	0.07	6.61	16.31	6.18	1.07
Younger, Men, $0-10K	0.07	6.74	7.70	5.64	1.19
Younger, Women, $10K+	0.04	4.17	12.92	4.40	0.95
Younger, Women, $0-10K	0.08	8.09	10.22	6.70	1.21
Missing	0.02	2.18	3.89	1.93	1.13
Total	0.99	100.00	100.00	100.00	1.00

Notes: Table presents the "entry" share (from Table 2) of the difference between actual and counterfactual SSDI rates for the decrease period (2010–2019), broken down into contribution from demographic subgroups using equation (35). "Contribution share" is "absolute contribution" as a percent of the total change. "Baseline population share" is the share of the US population that the group accounts for in 2010. "Baseline entrants share" is the share of SSDI entrants that the group accounts for in 2010. "Contribution/baseline entrants" presents the ratio of "contribution share" to "baseline entrants share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the change. The demographic groups are characterized by sex, average annual earnings between ages 25-34 (a measure of skill), and whether older or younger than 45 years old.

Appendix Table G.11: Demographic breakdown of application share of SSDI enrollment rate, 2010–2019

Group	Absolute contribution (pp)	Contribution share (%)	Baseline population share (%)	Baseline entrants share (%)	Contribution/ baseline entrants
Older, Men, $10K+	0.24	40.93	17.77	31.30	1.31
Older, Men, $0-10K	0.07	12.77	6.85	9.60	1.33
Older, Women, $10K+	0.05	8.89	11.29	14.93	0.60
Older, Women, $0-10K	0.03	4.82	13.06	19.31	0.25
Younger, Men, $10K+	0.05	8.29	16.31	6.18	1.34
Younger, Men, $0-10K	0.05	8.92	7.70	5.64	1.58
Younger, Women, $10K+	0.02	4.23	12.92	4.40	0.96
Younger, Women, $0-10K	0.04	7.75	10.22	6.70	1.16
Missing	0.02	3.40	3.89	1.93	1.76
Total	0.58	100.00	100.00	100.00	1.00

Notes: Table presents the "application" share (from Table 2) of the difference between actual and counterfactual SSDI rates for the decrease period (2010–2019), broken down into contribution from demographic subgroups using equation (10). "Contribution share" is "absolute contribution" as a percent of the total change. "Baseline population share" is the share of the US population that the group accounts for in 2010. "Baseline entrants share" is the share of SSDI entrants that the group accounts for in 2010. "Contribution/baseline entrants" presents the ratio of "contribution share" to "baseline entrants share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the change. The demographic groups are characterized by sex, average annual earnings between ages 25-34 (a measure of skill), and whether older or younger than 45 years old.

Appendix Table G.12: Demographic breakdown of award share of SSDI enrollment rate, 2010–2019

Group	Absolute contribution (pp)	Contribution share (%)	Baseline population share (%)	Baseline entrants share (%)	Contribution/ baseline entrants
Older, Men, $10K+	0.10	22.75	17.77	31.30	0.73
Older, Men, $0-10K	0.05	10.69	6.85	9.60	1.11
Older, Women, $10K+	0.07	15.71	11.29	14.93	1.05
Older, Women, $0-10K	0.11	25.89	13.06	19.31	1.34
Younger, Men, $10K+	0.03	6.01	16.31	6.18	0.97
Younger, Men, $0-10K	0.01	3.29	7.70	5.64	0.58
Younger, Women, $10K+	0.02	5.19	12.92	4.40	1.18
Younger, Women, $0-10K	0.04	9.77	10.22	6.70	1.46
Missing	0.00	0.70	3.89	1.93	0.36
Total	0.44	100.00	100.00	100.00	1.00

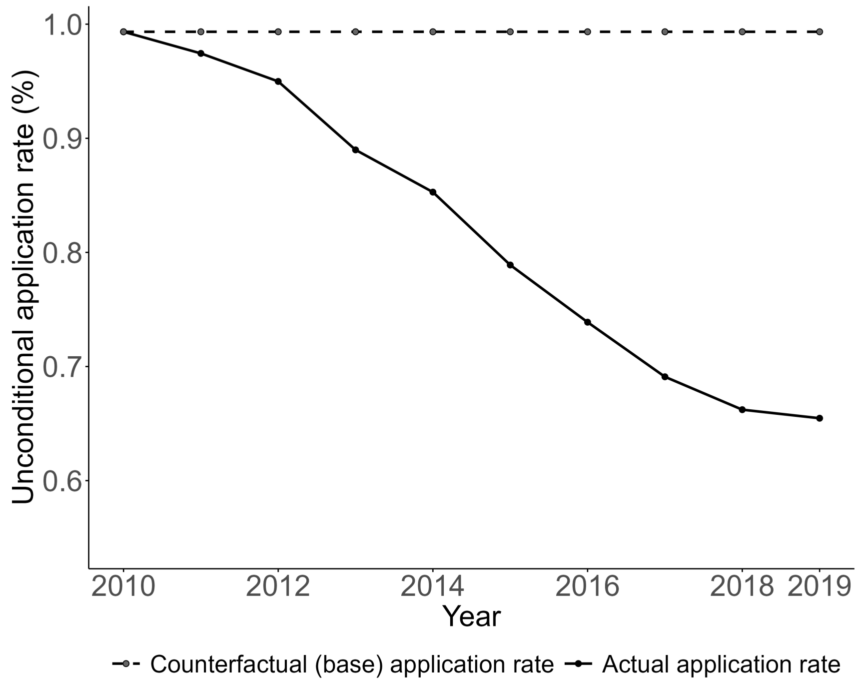
Notes: Table presents the "award" share (from Table 2) of the difference between actual and counterfactual SSDI rates for the decrease period (2010–2019), broken down into contribution from demographic subgroups using equation (33). "Contribution share" is "absolute contribution" as a percent of the total change. "Baseline population share" is the share of the US population that the group accounts for in 2010. "Baseline entrants share" is the share of SSDI entrants that the group accounts for in 2010. "Contribution/baseline entrants" presents the ratio of "contribution share" to "baseline entrants share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the change. The demographic groups are characterized by sex, average annual earnings between ages 25-34 (a measure of skill), and whether older or younger than 45 years old.

Appendix Table G.13: Demographic breakdown of eligibility share of SSDI enrollment rate, 2010–2019

Group	Absolute contribution (pp)	Contribution share (%)	Baseline population share (%)	Baseline entrants share (%)	Contribution/ baseline entrants
Older, Men, $10K+	0.01	7.23	17.77	31.30	0.23
Older, Men, $0-10K	0.02	23.39	6.85	9.60	2.44
Older, Women, $10K+	0.00	1.15	11.29	14.93	0.08
Older, Women, $0-10K	0.04	51.23	13.06	19.31	2.65
Younger, Men, $10K+	0.00	1.26	16.31	6.18	0.20
Younger, Men, $0-10K	0.01	9.11	7.70	5.64	1.61
Younger, Women, $10K+	-0.00	-0.36	12.92	4.40	-0.08
Younger, Women, $0-10K	0.01	6.43	10.22	6.70	0.96
Missing	0.00	0.56	3.89	1.93	0.29
Total	0.08	100.00	100.00	100.00	1.00

Notes: Table presents the "eligibility" share (from Table 2) of the difference between actual and counterfactual SSDI rates for the decrease period (2010–2019), broken down into contribution from demographic subgroups using equation (34). "Contribution share" is "absolute contribution" as a percent of the total change. "Baseline population share" is the share of the US population that the group accounts for in 2010. "Baseline entrants share" is the share of SSDI entrants that the group accounts for in 2010. "Contribution/baseline entrants" presents the ratio of "contribution share" to "baseline entrants share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the change. The demographic groups are characterized by sex, average annual earnings between ages 25-34 (a measure of skill), and whether older or younger than 45 years old.

Appendix Figure G.5: Counterfactual vs actual SSDI application rate, 2010–2019



Notes: Figure plots actual and counterfactual SSDI application rate in each year from 2010 to 2019. Actual application rate uses the Continuous Work History Sample linked to the Payment History Update System and the Master Beneficiary Record. Counterfactual application rate uses equations (2), (3), and (4), using 2010 as the base year. The exact annual values are given in Appendix Table G.14.

Appendix Table G.14: Counterfactual vs actual SSDI application rate, 2010–2019

Year	Actual application rate (%)	Counterfactual (base) application rate (%)	Total difference (pp)
2010	0.99	0.99	0.00
2011	0.97	0.99	-0.02
2012	0.95	0.99	-0.04
2013	0.89	0.99	-0.10
2014	0.85	0.99	-0.14
2015	0.79	0.99	-0.20
2016	0.74	0.99	-0.25
2017	0.69	0.99	-0.30
2018	0.66	0.99	-0.33
2019	0.65	0.99	-0.34
Total			-1.74

Table presents actual and counterfactual SSDI application rate in each year from 2010 to 2019. Actual SSDI application rate uses the Continuous Work History Sample linked to the Payment History Update System and the Master Beneficiary Record. Counterfactual SSDI application rate uses equations (2), (3), and (4), using 2010 as the base year.

Appendix Table G.15: Decomposition of decline in SSDI application rate, 2010–2019

	Absolute contribution (pp)	As a share of total (%)
Application	-1.51	80.8
Eligibility	-0.20	16.7
Interaction within apply	0.05	-2.3
Across group composition	-0.12	7.3
Within-across interaction	0.05	-2.5
Total	-1.74	100.0

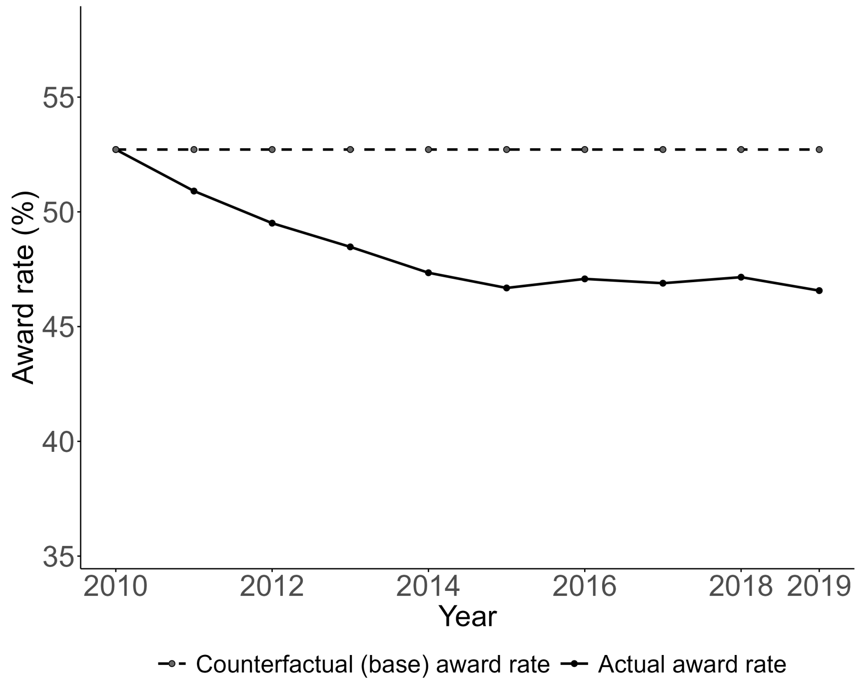
Notes: Table presents decomposition of SSDI application rate decline from 2010 to 2019, using equation (12). The point estimates we report are the ones in which flows (e.g., B_t, A_t, E_t, X_t), when fixed, are held fixed at their counterfactual values.

Appendix Table G.16: Demographic breakdown of application share of SSDI application rate, 2010–2019

Group	Absolute contribution (pp)	Contribution share (%)	Baseline applicants share (%)	Contribution/ baseline applicants
Men, Younger, \$10K+	-0.17	11.1	7.8	1.4
Men, Younger, \$0-10K	-0.22	14.8	9.2	1.6
Men, Older, \$10K+	-0.46	30.3	25.3	1.2
Men, Older, \$0-10K	-0.18	11.6	9.5	1.2
Women, Younger, \$10K+	-0.06	4.1	5.4	0.8
Women, Younger, \$0-10K	-0.19	12.6	11.3	1.1
Women, Older, \$10K+	-0.11	7.0	12.0	0.6
Women, Older, \$0-10K	-0.08	5.6	17.7	0.3
Missing	-0.04	2.9	1.8	1.6
Total	-1.51	100.0	100.0	1.0

Notes: Table presents the "application" share (from Appendix Table G.15) of the difference between actual and counterfactual SSDI application rates for the decline period (2010–2019), broken down into contribution from demographic subgroups using equation (12). "Contribution share" is "absolute contribution" as a percent of the total change. "Baseline population share" is the share of the US population that the group accounts for in 2010. "Baseline applicants share" is the share of SSDI applicants that the group accounts for in 2010. "Contribution/baseline applicants" presents the ratio of "contribution share" to "baseline applicants share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the change. The demographic groups are characterized by sex, average annual earnings between ages 25-34 (a measure of skill), and whether older or younger than 45 years old.

Appendix Figure G.6: Counterfactual vs actual SSDI award rate (conditional on application), 2010–2019



Notes: Figure plots actual and counterfactual SSDI award rate (conditional on application) in each year from 2010 to 2019. Actual award rate uses the Continuous Work History Sample linked to the Payment History Update System and the Master Beneficiary Record. Counterfactual award rate uses equations (2), (3), and (4), using 2010 as the base year. The exact annual values are given in Appendix Table G.17.

Appendix Table G.17: Counterfactual vs actual SSDI award rate (conditional on application), 2010–2019

Year	Actual award rate (%)	Counterfactual (base) award rate (%)	Total difference (pp)
2010	52.72	52.72	0.00
2011	50.91	52.72	-1.81
2012	49.51	52.72	-3.21
2013	48.47	52.72	-4.24
2014	47.35	52.72	-5.37
2015	46.68	52.72	-6.03
2016	47.08	52.72	-5.64
2017	46.89	52.72	-5.83
2018	47.15	52.72	-5.56
2019	46.57	52.72	-6.15
Total			-43.83

Notes: Table presents actual and counterfactual SSDI award rate (conditional on application) in each year from 2010 to 2019. Actual SSDI award rate uses the Continuous Work History Sample linked to the Payment History Update System and the Master Beneficiary Record. Counterfactual SSDI award rate uses equations (2), (3), and (4), using 2010 as the base year.

Appendix Table G.18: Decomposition of decline in SSDI award rate, 2010–2019

	Absolute contribution (pp)	As a share of total (%)
Award	-54.15	122.5
Across group applicant share	8.83	-19.2
Within-across interaction	1.49	-3.3
Total	-43.83	100.0

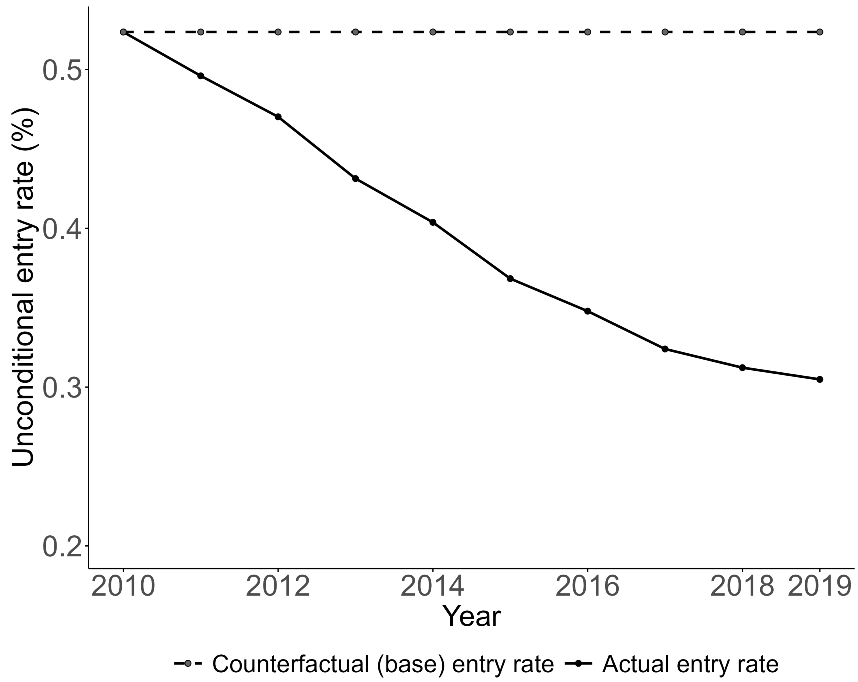
Notes: Table presents decomposition of SSDI award rate decline from 2010 to 2019, using equation (14). The point estimates we report are the ones in which flows (e.g., B_t, A_t, E_t, X_t), when fixed, are held fixed at their counterfactual values.

Appendix Table G.19: Demographic breakdown of award share of SSDI award rate, 2010–2019

Group	Absolute contribution (pp)	Contribution share (%)	Baseline entrants share (%)	Contribution/ baseline entrants
Younger, Men, \$10K+	-5.00	0.1	6.2	1.5
Younger, Men, \$0-10K	-2.73	0.1	5.6	0.9
Younger, Women, \$10K+	-4.07	0.1	4.4	1.7
Younger, Women, \$0-10K	-6.70	0.1	6.7	1.8
Older, Men, \$10K+	-10.52	0.2	31.3	0.6
Older, Men, \$0-10K	-5.28	0.1	9.6	1.0
Older, Women, \$10K+	-7.57	0.1	14.9	0.9
Older, Women, \$0-10K	-11.99	0.2	19.3	1.1
Missing	-0.30	0.0	1.9	0.3
Total	-54.15	1.0	100.0	1.0

Notes: Table presents the "award" share (from Appendix Table G.18) of the difference between actual and counterfactual SSDI award rates for the decline period (2010–2019), broken down into contribution from demographic subgroups using equation (14). "Contribution share" is "absolute contribution" as a percent of the total change. "Baseline population share" is the share of the US population that the group accounts for in 2010. "Baseline entrants share" is the share of SSDI entrants that the group accounts for in 2010. "Contribution/baseline entrants" presents the ratio of "contribution share" to "baseline entrants share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the change. The demographic groups are characterized by sex, average annual earnings between ages 25-34 (a measure of skill), and whether older or younger than 45 years old.

Appendix Figure G.7: Counterfactual vs actual SSDI entry rate, 2010–2019



Notes: Figure plots actual and counterfactual SSDI entry rate in each year from 2010 to 2019. Actual entry rate uses the Continuous Work History Sample linked to the Payment History Update System and the Master Beneficiary Record. Counterfactual entry rate uses equations (2), (3), and (4), using 2010 as the base year. The exact annual values are given in Appendix Table G.20.

Appendix Table G.20: Counterfactual vs actual SSDI entry rate, 2010–2019

Year	Actual entry rate (%)	Counterfactual (base) entry rate (%)	Total difference (pp)
2010	0.52	0.52	0.00
2011	0.50	0.52	-0.03
2012	0.47	0.52	-0.05
2013	0.43	0.52	-0.09
2014	0.40	0.52	-0.12
2015	0.37	0.52	-0.16
2016	0.35	0.52	-0.18
2017	0.32	0.52	-0.20
2018	0.31	0.52	-0.21
2019	0.30	0.52	-0.22
Total			-1.25

Notes: Table presents actual and counterfactual SSDI entry rate in each year from 2010 to 2019. Actual SSDI entry rate uses the Continuous Work History Sample linked to the Payment History Update System and the Master Beneficiary Record. Counterfactual SSDI entry rate uses equations (2), (3), and (4), using 2010 as the base year.

Appendix Table G.21: Decomposition of decrease in SSDI entry rate, 2010–2019

		Absolute contribution (pp)	As a share of total (%)
Entry		-1.25	100.1
	Award	-0.54	49.7
	Application	-0.75	51.6
	Eligibility	-0.09	7.9
	Interaction within entry	0.14	-9.1
Across group composition		-0.04	2.4
Within-across interaction		0.04	-2.5
Total		-1.25	100.0

Notes: Table presents decomposition of SSDI entry rate decline from 2010 to 2019, using equation (9). The point estimates we report are the ones in which flows (e.g., B_t, A_t, E_t, X_t), when fixed, are held fixed at their counterfactual values.

Appendix Table G.22: Demographic breakdown of entry share of SSDI entry rate, 2010–2019

Group	Absolute contribution (pp)	Contribution share (%)	Baseline entrants share (%)	Contribution/ baseline entrants
Younger, Men, $10K+	-0.11	8.7	6.2	1.4
Younger, Men, $0-10K	-0.10	8.1	5.6	1.4
Younger, Women, $10K+	-0.06	4.9	4.4	1.1
Younger, Women, $0-10K	-0.12	9.6	6.7	1.4
Older, Men, $10K+	-0.38	30.7	31.3	1.0
Older, Men, $0-10K	-0.14	10.9	9.6	1.1
Older, Women, $10K+	-0.14	10.8	14.9	0.7
Older, Women, $0-10K	-0.18	14.2	19.3	0.7
Missing	-0.03	2.1	1.9	1.1
Total	-1.25	100.0	100.0	1.0

Notes: Table presents the "entry" share (from Appendix Table G.21) of the difference between actual and counterfactual SSDI entry rates for the decline period (2010–2019), broken down into contribution from demographic subgroups using equation (13). "Contribution share" is "absolute contribution" as a percent of the total change. "Baseline population share" is the share of the US population that the group accounts for in 2010. "Baseline entrants share" is the share of SSDI entrants that the group accounts for in 2010. "Contribution/baseline entrants" presents the ratio of "contribution share" to "baseline entrants share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the change. The demographic groups are characterized by sex, average annual earnings between ages 25-34 (a measure of skill), and whether older or younger than 45 years old.

G.2 By veteran status

G.2.1 Enrollment decomposition in SSDI decrease period (2010–2019), including veteran status

Appendix Table G.23: Decomposition results for the decrease in SSDI enrollment from 2010 to 2019, including veteran status

	Absolute contribution (pp)			As a share of total (%)		
	Minimum	Maximum	Used in graph	Minimum	Maximum	Used in graph
Across-group composition	**0.01**	**-0.06**	**-0.06**	**-0.8**	**5.5**	**5.5**
Sex	0.00	-0.03	0.00	-0.3	2.5	-0.0
Age	0.20	0.02	0.07	-19.4	-1.7	-6.6
Earnings	0.03	-0.11	-0.04	-3.2	10.6	3.6
Immigrant status	-0.06	-0.17	-0.11	5.8	16.8	10.6
Veteran	0.04	-0.00	-0.00	-4.2	0.2	0.0
Within-group SSDI rates	**-0.97**	**-1.04**	**-1.04**	**94.5**	**100.8**	**100.8**
Entry	-0.93	-1.01	-0.99	90.2	98.0	96.2
Eligibility	*-0.05*	*-0.09*	*-0.08*	*4.7*	*8.4*	*8.1*
Application	*-0.48*	*-0.60*	*-0.58*	*46.1*	*57.8*	*56.6*
Award	*-0.31*	*-0.44*	*-0.43*	*29.7*	*43.0*	*42.0*
Exit	-0.02	-0.04	-0.04	1.5	4.2	3.8
Death	*0.04*	*0.03*	*0.04*	*-3.9*	*-3.4*	*-3.9*
Recovery	*-0.06*	*-0.08*	*-0.08*	*5.6*	*7.4*	*7.4*
Retirement	*0.01*	*0.01*	*0.01*	*-1.1*	*-0.7*	*-0.8*
Other	*-0.01*	*-0.01*	*-0.01*	*0.6*	*1.1*	*1.1*
Friction in population	-0.01	-0.01	-0.01	0.9	1.1	0.9
Population discrepancies	0.00	0.00	0.00	-0.2	-0.1	-0.1
Within-across interaction			**0.06**			**-6.3**
Total to be explained	-1.03	-1.03	-1.03	100.0	100.0	100.0

Notes: Table presents decomposition of the increase in SSDI enrollment rates from 2010 to 2019 into various components. The counterfactual SSDI enrollment rate in 2019 is 5.37 percent while the actual enrollment rate in 2019 is 4.33 percent, creating 1.04 pp of SSDI decline to be decomposed (see Appendix Table G.9). Across-group composition change, within-group change in SSDI enrollment rate, and the interaction between the two are calculated using equation (5). Across-group composition change is decomposed into specific characteristics using equation (11). Within-group SSDI rate is decomposed into entry, exit, friction in population, and population discrepancies using equation (6) and footnotes 13 and 15. Entry is decomposed 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) using equation (9). Exit is decomposed into death, retirement (defined as aging into the retirement program), recovery (defined as being found no longer eligible due to continuing disability review), and "other" (the residual) using equation (8). "Minimum" means the minimum bound, "Maximum" means the maximum bound, and "Used in graph" means the point estimate used in Figure 3. See Section 2.1 for details on the decomposition method, and Appendix Section F for details on the construction of bounds.

Appendix Table G.24: Demographic breakdown of entry share of SSDI enrollment rate including veteran status, 2010–2019

Veteran status	Absolute contribution (pp)	Contribution share (%)	Baseline population share (%)	Baseline entrants share (%)	Contribution/ baseline entrants
Veteran, younger male	-0.02	1.6	2.5	1.8	0.9
Veteran, younger female	-0.00	0.3	0.5	0.3	0.9
Veteran, older male	-0.05	4.7	2.5	5.0	1.0
Veteran, older female	-0.00	0.5	0.4	0.6	0.7
Non-Veteran	-0.92	92.9	94.1	92.3	1.0
Total	-0.99	100.0	100.0	100.0	1.0

Notes: Table presents the "entry" share (from Table 2) of the difference between actual and counterfactual SSDI rates for the decrease period (2010–2019), broken down into contribution from demographic subgroups using equation (35). "Contribution share" is "absolute contribution" as a percent of the total change. "Baseline population share" is the share of the US population that the group accounts for in 2010. "Baseline entrants share" is the share of SSDI entrants that the group accounts for in 2010. "Contribution/baseline entrants" presents the ratio of "contribution share" to "baseline entrants share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the change. We identify veteran status by linking EIN from the Detailed Earnings Files to publicly available military EINs. The other demographic groups are characterized by sex, average annual earnings between ages 25-34 (a measure of skill), and whether older or younger than 45 years old.

Appendix Table G.25: Demographic breakdown of application share of SSDI enrollment rate including veteran status, 2010–2019

Veteran status	Absolute contribution (pp)	Contribution share (%)	Baseline population share (%)	Baseline entrants share (%)	Contribution/ baseline entrants
Veteran, younger male	-0.00	0.5	2.5	1.8	0.3
Veteran, younger female	-0.00	0.0	0.5	0.3	0.1
Veteran, older male	-0.02	4.2	2.5	5.0	0.8
Veteran, older female	-0.00	0.1	0.4	0.6	0.2
Non-Veteran	-0.56	95.2	94.1	92.3	1.0
Total	-0.58	100.0	100.0	100.0	1.0

Notes: Table presents the "application" share (from Table 2) of the difference between actual and counterfactual SSDI rates for the decrease period (2010–2019), broken down into contribution from demographic subgroups using equation (10). "Contribution share" is "absolute contribution" as a percent of the total change. "Baseline population share" is the share of the US population that the group accounts for in 2010. "Baseline entrants share" is the share of SSDI entrants that the group accounts for in 2010. "Contribution/baseline entrants" presents the ratio of "contribution share" to "baseline entrants share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the change. We identify veteran status by linking EIN from the Detailed Earnings Files to publicly available military EINs. The other demographic groups are characterized by sex, average annual earnings between ages 25-34 (a measure of skill), and whether older or younger than 45 years old.

Appendix Table G.26: Demographic breakdown of award share of SSDI enrollment rate including veteran status, 2010–2019

Veteran status	Absolute contribution (pp)	Contribution share (%)	Baseline population share (%)	Baseline entrants share (%)	Contribution/ baseline entrants
Veteran, younger male	-0.01	3.2	2.5	1.8	1.8
Veteran, younger female	-0.00	0.7	0.5	0.3	2.1
Veteran, older male	-0.03	6.2	2.5	5.0	1.2
Veteran, older female	-0.00	1.0	0.4	0.6	1.6
Non-Veteran	-0.38	88.9	94.1	92.3	1.0
Total	-0.43	100.0	100.0	100.0	1.0

Notes: Table presents the "award" share (from Table 2) of the difference between actual and counterfactual SSDI rates for the decrease period (2010–2019), broken down into contribution from demographic subgroups using equation (33). "Contribution share" is "absolute contribution" as a percent of the total change. "Baseline population share" is the share of the US population that the group accounts for in 2010. "Baseline entrants share" is the share of SSDI entrants that the group accounts for in 2010. "Contribution/baseline entrants" presents the ratio of "contribution share" to "baseline entrants share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the change. We identify veteran status by linking EIN from the Detailed Earnings Files to publicly available military EINs. The other demographic groups are characterized by sex, average annual earnings between ages 25-34 (a measure of skill), and whether older or younger than 45 years old.

Appendix Table G.27: Demographic breakdown of eligibility share of SSDI enrollment rate including veteran status, 2010–2019

Veteran status	Absolute contribution (pp)	Contribution share (%)	Baseline population share (%)	Baseline entrants share (%)	Contribution/ baseline entrants
Veteran, younger male	-0.00	1.0	2.5	1.8	0.6
Veteran, younger female	-0.00	0.3	0.5	0.3	0.9
Veteran, older male	-0.00	4.5	2.5	5.0	0.9
Veteran, older female	-0.00	0.6	0.4	0.6	1.0
Non-Veteran	-0.08	93.5	94.1	92.3	1.0
Total	-0.08	100.0	100.0	100.0	1.0

Notes: Table presents the "eligibility" share (from Table 2) of the difference between actual and counterfactual SSDI rates for the decrease period (2010–2019), broken down into contribution from demographic subgroups using equation (34). "Contribution share" is "absolute contribution" as a percent of the total change. "Baseline population share" is the share of the US population that the group accounts for in 2010. "Baseline entrants share" is the share of SSDI entrants that the group accounts for in 2010. "Contribution/baseline entrants" presents the ratio of "contribution share" to "baseline entrants share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the change. We identify veteran status by linking EIN from the Detailed Earnings Files to publicly available military EINs. The other demographic groups are characterized by sex, average annual earnings between ages 25-34 (a measure of skill), and whether older or younger than 45 years old.

G.2.2 Unconditional application rate decomposition in SSDI decrease period (2010–2019), including veteran status

Appendix Table G.28: Counterfactual vs actual SSDI application rate including veteran status, 2010–2019

Year	Actual application rate (%)	Counterfactual (base) application rate (%)	Total difference (pp)
2010	0.99	0.99	0.00
2011	0.97	0.99	-0.02
2012	0.95	0.99	-0.04
2013	0.89	0.99	-0.10
2014	0.85	0.99	-0.14
2015	0.79	0.99	-0.20
2016	0.74	0.99	-0.25
2017	0.69	0.99	-0.30
2018	0.66	0.99	-0.33
2019	0.65	0.99	-0.34
Total			-1.74

Notes: Table presents actual and counterfactual SSDI application rate in each year from 2010 to 2019. Actual SSDI application rate uses the Continuous Work History Sample linked to the Payment History Update System and the Master Beneficiary Record. Counterfactual SSDI application rate uses equations (2), (3), and (4), using 2010 as the base year.

Appendix Table G.29: Decomposition of decline in SSDI application rate including veteran status, 2010–2019

	Absolute contribution (pp)	As a share of total (%)
Application	-1.52	81.4
Eligibility	-0.20	16.6
Interaction within apply	0.04	-2.2
Across group composition	-0.13	7.8
Within-across interaction	0.07	-3.6
Total	-1.74	100.0

Notes: Notes: Table presents decomposition of SSDI application rate decline from 2010 to 2019, using equation (12). The point estimates we report are the ones in which flows (e.g., B_t, A_t, E_t, X_t), when fixed, are held fixed at their counterfactual values.

Appendix Table G.30: Demographic breakdown of application share of SSDI application rate including veteran status, 2010–2019

Group	Absolute contribution (pp)	Contribution share (%)	Baseline applicants share (%)	Contribution/ baseline applicants
Veteran, younger male	-0.01	0.8	2.3	0.4
Veteran, younger female	0.00	-0.2	0.5	-0.3
Veteran, older male	-0.05	3.4	4.5	0.8
Veteran, older female	-0.00	0.1	0.6	0.2
Non-Veteran	-1.45	95.8	92.0	1.0
Total	-1.52	100.0	100.0	1.0

Notes: Table presents the "application" share (from Appendix Table G.15) of the difference between actual and counterfactual SSDI application rates for the decline period (2010–2019), broken down into contribution from demographic subgroups using equation (12). "Contribution share" is "absolute contribution" as a percent of the total change. "Baseline population share" is the share of the US population that the group accounts for in 2010. "Baseline applicants share" is the share of SSDI applicants that the group accounts for in 2010. "Contribution/baseline applicants" presents the ratio of "contribution share" to "baseline applicants share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the change. We identify veteran status by linking EIN from the Detailed Earnings Files to publicly available military EINs. The other demographic groups are characterized by sex, average annual earnings between ages 25-34 (a measure of skill), and whether older or younger than 45 years old.

G.2.3 Award rate decomposition in SSDI decrease period (2010–2019), including veteran status

Appendix Table G.31: Counterfactual vs actual SSDI award rate (conditional on application) including veteran status, 2010–2019

Year	Actual award rate (%)	Counterfactual (base) award rate (%)	Total difference (pp)
2010	52.71	52.71	0.00
2011	50.90	52.71	-1.81
2012	49.50	52.71	-3.21
2013	48.47	52.71	-4.24
2014	47.34	52.71	-5.37
2015	46.68	52.71	-6.03
2016	47.08	52.71	-5.64
2017	46.89	52.71	-5.83
2018	47.15	52.71	-5.56
2019	46.56	52.71	-6.15
Total			-43.84

Notes: Table presents actual and counterfactual SSDI award rate (conditional on application) in each year from 2010 to 2019. Actual SSDI award rate uses the Continuous Work History Sample linked to the Payment History Update System and the Master Beneficiary Record. Counterfactual SSDI award rate uses equations (2), (3), and (4), using 2010 as the base year.

Appendix Table G.32: Decomposition of decline in SSDI award rate including veteran status, 2010–2019

	Absolute contribution (pp)	As a share of total (%)
Award	-53.83	122.0
Across group applicant share	8.40	-18.3
Within-across interaction	1.59	-3.6
Total	-43.84	100.0

Notes: Table presents decomposition of SSDI award rate decline from 2010 to 2019, using equation (14). The point estimates we report are the ones in which flows (e.g., B_t, A_t, E_t, X_t), when fixed, are held fixed at their counterfactual values.

Appendix Table G.33: Demographic breakdown of award share of SSDI award rate including veteran status, 2010–2019

Group	Absolute contribution (pp)	Contribution share (%)	Baseline entrants share (%)	Contribution/ baseline entrants
Veteran, younger male	-2.20	4.1	1.8	2.2
Veteran, younger female	-0.44	0.8	0.3	2.5
Veteran, older male	-2.94	5.5	5.0	1.1
Veteran, older female	-0.50	0.9	0.6	1.5
Non-Veteran	-47.74	88.7	92.3	1.0
Total	-53.83	100.0	100.0	1.0

Notes: Table presents the "award" share (from Appendix Table G.18) of the difference between actual and counterfactual SSDI award rates for the decline period (2010–2019), broken down into contribution from demographic subgroups using equation (14). "Contribution share" is "absolute contribution" as a percent of the total change. "Baseline population share" is the share of the US population that the group accounts for in 2010. "Baseline entrants share" is the share of SSDI entrants that the group accounts for in 2010. "Contribution/baseline entrants" presents the ratio of "contribution share" to "baseline entrants share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the change. We identify veteran status by linking EIN from the Detailed Earnings Files to publicly available military EINs. The other demographic groups are characterized by sex, average annual earnings between ages 25-34 (a measure of skill), and whether older or younger than 45 years old.

G.2.4 Unconditional entry rate decomposition in SSDI decrease period (2010–2019), including veteran status

Appendix Table G.34: Counterfactual vs actual SSDI entry rate including veteran status, 2010–2019

Year	Actual entry rate (%)	Counterfactual (base) entry rate (%)	Total difference (pp)
2010	0.52	0.52	0.00
2011	0.50	0.52	-0.03
2012	0.47	0.52	-0.05
2013	0.43	0.52	-0.09
2014	0.40	0.52	-0.12
2015	0.37	0.52	-0.16
2016	0.35	0.52	-0.18
2017	0.32	0.52	-0.20
2018	0.31	0.52	-0.21
2019	0.30	0.52	-0.22
Total			-1.25

Notes: Table presents actual and counterfactual SSDI entry rate in each year from 2010 to 2019. Actual SSDI entry rate uses the Continuous Work History Sample linked to the Payment History Update System and the Master Beneficiary Record. Counterfactual SSDI entry rate uses equations (2), (3), and (4), using 2010 as the base year.

Appendix Table G.35: Decomposition of decline in SSDI entry rate including veteran status, 2010–2019

		Absolute contribution (pp)	As a share of total (%)
Entry		-1.26	100.7
	Award	-0.53	49.6
	Application	-0.76	52.3
	Eligibility	-0.09	7.9
	Interaction within entry	0.13	-9.0
Across group composition		-0.05	2.9
Within-across interaction		0.05	-3.6
Total		-1.25	100.0

Notes: Table presents decomposition of SSDI entry rate decline from 2010 to 2019, using equation (9). The point estimates we report are the ones in which flows (e.g., B_t, A_t, E_t, X_t), when fixed, are held fixed at their counterfactual values.

Appendix Table G.36: Demographic breakdown of entry share of SSDI entry rate including veteran status, 2010–2019

Group	Absolute contribution (pp)	Contribution share (%)	baseline entrants share (%)	Contribution/ baseline entrants
Veteran, younger male	-0.03	2.0	1.8	1.1
Veteran, younger female	-0.00	0.3	0.3	0.9
Veteran, older male	-0.05	4.3	5.0	0.9
Veteran, older female	-0.01	0.5	0.6	0.7
Non-Veteran	-1.17	92.9	92.3	1.0
Total	-1.26	100.0	100.0	1.0

Notes: Table presents the "entry" share (from Appendix Table G.21) of the difference between actual and counterfactual SSDI entry rates for the decline period (2010–2019), broken down into contribution from demographic subgroups using equation (13). "Contribution share" is "absolute contribution" as a percent of the total change. "Baseline population share" is the share of the US population that the group accounts for in 2010. "Baseline entrants share" is the share of SSDI entrants that the group accounts for in 2010. "Contribution/baseline entrants" presents the ratio of "contribution share" to "baseline entrants share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the change. We identify veteran status by linking EIN from the Detailed Earnings Files to publicly available military EINs. The other demographic groups are characterized by sex, average annual earnings between ages 25-34 (a measure of skill), and whether older or younger than 45 years old.

G.3 By pollution abatement

G.3.1 Enrollment decomposition in SSDI decrease period (2010–2019), including pollution abatement

Appendix Table G.37: Demographic breakdown of entry share of SSDI enrollment rate including pollution abatement, 2010–2019

Pollution abatement	Absolute contribution (pp)	Contribution share (%)	Baseline population share (%)	Baseline entrants share (%)	Contribution/ baseline entrants
More-abatement area	0.06	6.1	6.1	5.8	1.0
Less-abatement area	0.17	16.9	18.9	16.5	1.0
Unmatched	0.64	64.9	62.7	65.7	1.0
Matched area, no classification	0.12	12.2	12.3	11.9	1.0
Total	0.99	100.0	100.0	100.0	1.0

Notes: Table presents the "entry" share (from Table 2) of the difference between actual and counterfactual SSDI rates for the decrease period (2010–2019), broken down into contribution from subgroups based on pollution abatement status in one's place of birth, using equation (35). "Contribution share" is "absolute contribution" as a percent of the total change. "Baseline population share" is the share of the US population that the group accounts for in 2010. "Baseline entrants share" is the share of SSDI entrants that the group accounts for in 2010. "Contribution/baseline entrants" presents the ratio of "contribution share" to "baseline entrants share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the change. We identify abatement and non-abatement areas based on data provided by Isen et al. (2017) linked to place of birth in the Numident. "More-abatement" means that the area was flagged by the 1970 Clean Air Act Amendments to be in "non-attainment" and therefore legally required to reduce pollution levels. "Less-abatement" means that the area was not deemed "non-attainment" and therefore was not required to reduce pollution levels. "Matched area, no classification" means that the individual was matched to a place of birth in the Numident but that their place of birth was not classified as attainment or non-attainment. "Cannot match" means that the individual could not be matched to a place of birth.

Appendix Table G.38: Demographic breakdown of application share of SSDI enrollment rate including pollution abatement, 2010–2019

Pollution abatement	Absolute contribution (pp)	Contribution share (%)	Baseline population share (%)	Baseline entrants share (%)	Contribution/ baseline entrants
More-abatement area	0.04	6.3	6.1	5.8	1.1
Less-abatement area	0.10	18.1	18.9	16.5	1.1
Unmatched	0.35	62.4	62.7	65.7	0.9
Matched area, no classification	0.07	13.2	12.3	11.9	1.1
Total	0.56	100.0	100.0	100.0	1.0

Notes: Table presents the "application" share (from Table 2) of the difference between actual and counterfactual SSDI rates for the decrease period (2010–2019), broken down into contribution from subgroups based on pollution abatement status in one's place of birth, using equation (10). "Contribution share" is "absolute contribution" as a percent of the total change. "Baseline population share" is the share of the US population that the group accounts for in 2010. "Baseline entrants share" is the share of SSDI entrants that the group accounts for in 2010. "Contribution/baseline entrants" presents the ratio of "contribution share" to "baseline entrants share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the change. We identify abatement and non-abatement areas based on data provided by Isen et al. (2017) linked to place of birth in the Numident. "More-abatement" means that the area was flagged by the 1970 Clean Air Act Amendments to be in "non-attainment" and therefore legally required to reduce pollution levels. "Less-abatement" means that the area was not deemed "non-attainment" and therefore was not required to reduce pollution levels. "Matched area, no classification" means that the individual was matched to a place of birth in the Numident but that their place of birth was not classified as attainment or non-attainment. "Cannot match" means that the individual could not be matched to a place of birth.

Appendix Table G.39: Demographic breakdown of award share of SSDI enrollment rate including pollution abatement, 2010–2019

Pollution abatement	Absolute contribution (pp)	Contribution share (%)	Baseline population share (%)	Baseline entrants share (%)	Contribution/ baseline entrants
More-abatement area	0.03	6.2	6.1	5.8	1.1
Less-abatement area	0.07	16.1	18.9	16.5	1.0
Unmatched	0.29	66.0	62.7	65.7	1.0
Matched area, no classification	0.05	11.6	12.3	11.9	1.0
Total	0.44	100.0	100.0	100.0	1.0

Notes: Table presents the "award" share (from Table 2) of the difference between actual and counterfactual SSDI rates for the decrease period (2010–2019), broken down into contribution from subgroups based on pollution abatement status in one's place of birth, using equation (33). "Contribution share" is "absolute contribution" as a percent of the total change. "Baseline population share" is the share of the US population that the group accounts for in 2010. "Baseline entrants share" is the share of SSDI entrants that the group accounts for in 2010. "Contribution/baseline entrants" presents the ratio of "contribution share" to "baseline entrants share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the change. We identify abatement and non-abatement areas based on data provided by Isen et al. (2017) linked to place of birth in the Numident. "More-abatement" means that the area was flagged by the 1970 Clean Air Act Amendments to be in "non-attainment" and therefore legally required to reduce pollution levels. "Less-abatement" means that the area was not deemed "non-attainment" and therefore was not required to reduce pollution levels. "Matched area, no classification" means that the individual was matched to a place of birth in the Numident but that their place of birth was not classified as attainment or non-attainment. "Cannot match" means that the individual could not be matched to a place of birth.

Appendix Table G.40: Demographic breakdown of eligibility share of SSDI enrollment rate including pollution abatement, 2010–2019

Pollution abatement	Absolute contribution (pp)	Contribution share (%)	Baseline population share (%)	Baseline entrants share (%)	Contribution/ baseline entrants
More-abatement area	0.00	5.6	6.1	5.8	0.9
Less-abatement area	0.01	16.7	18.9	16.5	1.0
Unmatched	0.06	66.4	62.7	65.7	1.0
Matched area, no classification	0.01	11.3	12.3	11.9	0.9
Total	0.08	100.0	100.0	100.0	1.0

Notes: Table presents the "eligibility" share (from Table 2) of the difference between actual and counterfactual SSDI rates for the decrease period (2010–2019), broken down into contribution from subgroups based on pollution abatement status in one's place of birth, using equation (34). "Contribution share" is "absolute contribution" as a percent of the total change. "Baseline population share" is the share of the US population that the group accounts for in 2010. "Baseline entrants share" is the share of SSDI entrants that the group accounts for in 2010. "Contribution/baseline entrants" presents the ratio of "contribution share" to "baseline entrants share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the change. We identify abatement and non-abatement areas based on data provided by Isen et al. (2017) linked to place of birth in the Numident. "More-abatement" means that the area was flagged by the 1970 Clean Air Act Amendments to be in "non-attainment" and therefore legally required to reduce pollution levels. "Less-abatement" means that the area was not deemed "non-attainment" and therefore was not required to reduce pollution levels. "Matched area, no classification" means that the individual was matched to a place of birth in the Numident but that their place of birth was not classified as attainment or non-attainment. "Cannot match" means that the individual could not be matched to a place of birth.

G.3.2 Unconditional application rate decomposition in SSDI decrease period (2010–2019), including pollution abatement

Appendix Table G.41: Counterfactual vs actual SSDI application rate including pollution abatement, 2010–2019

Year	Actual application rate (%)	Counterfactual (base) application rate (%)	Total difference (pp)
2010	0.99	0.99	0.00
2011	0.97	0.99	-0.02
2012	0.95	0.99	-0.04
2013	0.89	0.99	-0.10
2014	0.85	0.99	-0.14
2015	0.79	0.99	-0.20
2016	0.74	0.99	-0.25
2017	0.69	0.99	-0.30
2018	0.66	0.99	-0.33
2019	0.65	0.99	-0.34
Total			-1.74

Notes: Table presents actual and counterfactual SSDI application rate in each year from 2010 to 2019. Actual SSDI application rate uses the Continuous Work History Sample linked to the Payment History Update System and the Master Beneficiary Record. Counterfactual SSDI application rate uses equations (2), (3), and (4), using 2010 as the base year.

Appendix Table G.42: Decomposition of decline in SSDI application rate including pollution abatement, 2010–2019

	Absolute contribution (pp)	As a share of total (%)
Application	-0.78	42.1
Eligibility	-0.10	7.8
Interaction within apply	0.02	-1.2
Across group composition	-0.02	-0.1
Within-across interaction	0.03	-1.8
Total	-0.84	46.9

Notes: Table presents decomposition of SSDI application rate decline from 2010 to 2019, using equation (12). The point estimates we report are the ones in which flows (e.g., B_t, A_t, E_t, X_t), when fixed, are held fixed at their counterfactual values.

Appendix Table G.43: Demographic breakdown of application share of SSDI application rate including pollution abatement, 2010–2019

Group	Absolute contribution (pp)	Contribution share (%)	Baseline applicants share (%)	Contribution/ baseline applicants
More-abatement area	-0.05	5.86	6.29	0.93
Less-abatement area	-0.13	16.42	18.36	0.89
Matched area, no classification	-0.10	12.26	13.18	0.93
Unmatched	-0.51	65.47	62.17	1.05
Total	-0.78	100.0	100.0	1.0

Notes: Table presents the "application" share (from Appendix Table G.42) of the difference between actual and counterfactual SSDI application rates for the decline period (2010–2019), broken down into contribution from subgroups based on pollution abatement status in one's place of birth, using equation (12). "Contribution share" is "absolute contribution" as a percent of the total change. "Baseline population share" is the share of the US population that the group accounts for in 2010. "Baseline applicants share" is the share of SSDI applicants that the group accounts for in 2010. "Contribution/baseline applicants" presents the ratio of "contribution share" to "baseline applicants share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the change. We identify abatement and non-abatement areas based on data provided by Isen et al. (2017) linked to place of birth in the Numident. "More-abatement" means that the area was flagged by the 1970 Clean Air Act Amendments to be in "non-attainment" and therefore legally required to reduce pollution levels. "Less-abatement" means that the area was not deemed "non-attainment" and therefore was not required to reduce pollution levels. "Matched area, no classification" means that the individual was matched to a place of birth in the Numident but that their place of birth was not classified as attainment or non-attainment. "Cannot match" means that the individual could not be matched to a place of birth.

G.3.3 Award rate decomposition in SSDI decrease period (2010–2019), including pollution abatement

Appendix Table G.44: Counterfactual vs actual SSDI award rate (conditional on application) including pollution abatement, 2010–2019

Year	Actual award rate (%)	Counterfactual (base) award rate (%)	Total difference (pp)
2010	52.71	52.71	0.00
2011	50.90	52.71	-1.81
2012	49.50	52.71	-3.21
2013	48.46	52.71	-4.25
2014	47.34	52.71	-5.37
2015	46.67	52.71	-6.04
2016	47.07	52.71	-5.64
2017	46.88	52.71	-5.83
2018	47.14	52.71	-5.57
2019	46.56	52.71	-6.15
Total			-43.86

Notes: Table presents actual and counterfactual SSDI award rate (conditional on application) in each year from 2010 to 2019. Actual SSDI award rate uses the Continuous Work History Sample linked to the Payment History Update System and the Master Beneficiary Record. Counterfactual SSDI award rate uses equations (2), (3), and (4), using 2010 as the base year.

Appendix Table G.45: Decomposition of decline in SSDI award rate including pollution abatement, 2010–2019

	Absolute contribution (pp)	As a share of total (%)
Award	-54.32	123.0
Across group applicant share	7.96	-17.2
Within-across interaction	2.49	-5.8
Total	-43.86	100.0

Notes: Table presents decomposition of SSDI award rate decline from 2010 to 2019, using equation (14). The point estimates we report are the ones in which flows (e.g., B_t, A_t, E_t, X_t), when fixed, are held fixed at their counterfactual values.

Appendix Table G.46: Demographic breakdown of award share of SSDI award rate including pollution abatement, 2010–2019

Group	Absolute contribution (pp)	Contribution share (%)	Baseline entrants share (%)	Contribution/ baseline entrants
More-abatement area	-3.80	6.99	5.84	1.20
Less-abatement area	-9.54	17.56	16.53	1.06
Matched area, no classification	-6.89	12.68	11.94	1.06
Unmatched	-34.09	62.77	65.69	0.96
Total	-54.32	100.0	100.0	1.0

Notes: Table presents the "award" share (from Appendix Table G.45) of the difference between actual and counterfactual SSDI award rates for the decline period (2010–2019), broken down into contribution from subgroups based on pollution abatement status in one's place of birth, using equation (14). "Contribution share" is "absolute contribution" as a percent of the total change. "Baseline population share" is the share of the US population that the group accounts for in 2010. "Baseline entrants share" is the share of SSDI entrants that the group accounts for in 2010. "Contribution/baseline entrants" presents the ratio of "contribution share" to "baseline entrants share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the change. We identify abatement and non-abatement areas based on data provided by Isen et al. (2017) linked to place of birth in the Numident. "More-abatement" means that the area was flagged by the 1970 Clean Air Act Amendments to be in "non-attainment" and therefore legally required to reduce pollution levels. "Less-abatement" means that the area was not deemed "non-attainment" and therefore was not required to reduce pollution levels. "Matched area, no classification" means that the individual was matched to a place of birth in the Numident but that their place of birth was not classified as attainment or non-attainment. "Cannot match" means that the individual could not be matched to a place of birth.

G.3.4 Unconditional entry rate decomposition in SSDI decrease period (2010–2019), including pollution abatement

Appendix Table G.47: Counterfactual vs actual SSDI entry rate including pollution abatement, 2010–2019

Year	Actual entry rate (%)	Counterfactual (base) entry rate (%)	Total difference (pp)
2010	0.52	0.52	0.00
2011	0.50	0.52	-0.03
2012	0.47	0.52	-0.05
2013	0.43	0.52	-0.09
2014	0.40	0.52	-0.12
2015	0.37	0.52	-0.16
2016	0.35	0.52	-0.18
2017	0.32	0.52	-0.20
2018	0.31	0.52	-0.21
2019	0.30	0.52	-0.22
Total			-1.25

Notes: Table presents actual and counterfactual SSDI entry rate in each year from 2010 to 2019. Actual SSDI entry rate uses the Continuous Work History Sample linked to the Payment History Update System and the Master Beneficiary Record. Counterfactual SSDI entry rate uses equations (2), (3), and (4), using 2010 as the base year.

Appendix Table G.48: Decomposition of decline in SSDI entry rate including pollution abatement, 2010–2019

		Absolute contribution (pp)	As a share of total (%)
Entry		-1.27	101.8
	Award	-0.54	50.0
	Application	-0.78	53.7
	Eligibility	-0.10	8.7
	Interaction within entry	0.15	-10.6
Across group composition		-0.02	0.4
Within-across interaction		0.03	-2.2
Total		-1.25	100.0

Notes: Table presents decomposition of SSDI entry rate decline from 2010 to 2019, using equation (9). The point estimates we report are the ones in which flows (e.g., B_t, A_t, E_t, X_t), when fixed, are held fixed at their counterfactual values.

Appendix Table G.49: Demographic breakdown of entry share of SSDI entry rate including pollution abatement, 2010–2019

Group	Absolute contribution (pp)	Contribution share (%)	baseline entrants share (%)	Contribution/ baseline entrants
More-abatement area	-0.08	6.3	5.8	1.1
Less-abatement area	-0.22	17.0	16.5	1.0
Matched area, no classification	-0.16	12.3	11.9	1.0
Unmatched	-0.82	64.4	65.7	1.0
Total	-1.27	100.0	100.0	1.0

Notes: Table presents the "entry" share (from Appendix Table G.48) of the difference between actual and counterfactual SSDI entry rates for the decline period (2010–2019), broken down into contribution from subgroups based on pollution abatement status in one's place of birth, using equation (13). "Contribution share" is "absolute contribution" as a percent of the total change. "Baseline population share" is the share of the US population that the group accounts for in 2010. "Baseline entrants share" is the share of SSDI entrants that the group accounts for in 2010. "Contribution/baseline entrants" presents the ratio of "contribution share" to "baseline entrants share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the change. We identify abatement and non-abatement areas based on data provided by Isen et al. (2017) linked to place of birth in the Numident. "More-abatement" means that the area was flagged by the 1970 Clean Air Act Amendments to be in "non-attainment" and therefore legally required to reduce pollution levels. "Less-abatement" means that the area was not deemed "non-attainment" and therefore was not required to reduce pollution levels. "Matched area, no classification" means that the individual was matched to a place of birth in the Numident but that their place of birth was not classified as attainment or non-attainment. "Cannot match" means that the individual could not be matched to a place of birth.

G.4 By early-career industry

G.4.1 Enrollment decomposition in SSDI decrease period (2010–2019), by early-career industry

Appendix Table G.50: Demographic breakdown of entry share of SSDI enrollment rate by early-career industry, 2010–2019

Industry	Absolute contribution (pp)	Contribution share (%)	Baseline population share (%)	Baseline entrants share (%)	Contribution/ baseline entrants
Military	0.01	1.4	2.0	2.4	0.6
Ag/mining/utilities/construction	0.13	13.0	8.4	11.9	1.1
Manufacturing	0.14	14.1	9.9	13.6	1.0
Wholesale/retail/transportation	0.10	10.2	9.0	9.9	1.0
White collar/management	0.13	12.4	14.0	13.0	1.0
Education/health care/govt	0.16	16.2	18.5	17.6	0.9
No Earning	0.02	2.4	9.4	2.0	1.2
Employed, likely small employer	0.28	28.1	24.9	27.6	1.0
Missing	0.02	2.1	3.8	1.9	1.1
Total	0.99	100.0	100.0	100.0	1.0

Notes: Table presents the "entry" share (from Table 2) of the difference between actual and counterfactual SSDI rates for the decrease period (2010–2019), broken down into contribution from subgroups based on primary industry of work between the ages of 25 and 34 years old, using equation (35). "Contribution share" is "absolute contribution" as a percent of the total change. "Baseline population share" is the share of the US population that the group accounts for in 2010. "Baseline entrants share" is the share of SSDI entrants that the group accounts for in 2010. "Contribution/baseline entrants" presents the ratio of "contribution share" to "baseline entrants share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the change. We identify a person's primary industry using EIN from the Detailed Earnings File linked to NAICS code from the Department of Labor Form 5500. We define primary industry as the industry in which the person worked the most years between 25 and 34 years old. "Employed, likely small employer" means that the applicant had an employer but the employer's EIN is not listed in Form 5500.

Appendix Table G.51: Demographic breakdown of application share of SSDI enrollment rate by early-career industry, 2010–2019

Industry	Absolute contribution (pp)	Contribution share (%)	Baseline population share (%)	Baseline entrants share (%)	Contribution/ baseline entrants
Military	-0.00	-0.2	2.0	2.4	-0.1
Ag/mining/utilities/construction	0.09	14.5	8.4	11.9	1.2
Manufacturing	0.10	16.1	9.9	13.6	1.2
Wholesale/retail/transportation	0.06	10.4	9.0	9.9	1.0
White collar/management	0.07	11.3	14.0	13.0	0.9
Education/health care/govt	0.09	14.6	18.5	17.6	0.8
No Earning	0.01	1.0	9.4	2.0	0.5
Employed, likely small employer	0.18	29.1	24.9	27.6	1.0
Missing	0.02	3.2	3.8	1.9	1.7
Total	0.62	100.0	100.0	100.0	1.0

Notes: Table presents the "application" share (from Table 2) of the difference between actual and counterfactual SSDI rates for the decrease period (2010–2019), broken down into contribution from subgroups based on primary industry of work between the ages of 25 and 34 years old, using equation (10). "Contribution share" is "absolute contribution" as a percent of the total change. "Baseline population share" is the share of the US population that the group accounts for in 2010. "Baseline entrants share" is the share of SSDI entrants that the group accounts for in 2010. "Contribution/baseline entrants" presents the ratio of "contribution share" to "baseline entrants share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the change. We identify a person's primary industry using EIN from the Detailed Earnings File linked to NAICS code from the Department of Labor Form 5500. We define primary industry as the industry in which the person worked the most years between 25 and 34 years old. "Employed, likely small employer" means that the applicant had an employer but the employer's EIN is not listed in Form 5500.

Appendix Table G.52: Demographic breakdown of award share of SSDI enrollment rate by early-career industry, 2010–2019

Industry	Absolute contribution (pp)	Contribution share (%)	Baseline population share (%)	Baseline entrants share (%)	Contribution/ baseline entrants
Military	0.02	3.8	2.0	2.4	1.6
Ag/mining/utilities/construction	0.05	11.5	8.4	11.9	1.0
Manufacturing	0.05	12.3	9.9	13.6	0.9
Wholesale/retail/transportation	0.05	11.3	9.0	9.9	1.1
White collar/management	0.06	13.6	14.0	13.0	1.0
Education/health care/govt	0.08	18.7	18.5	17.6	1.1
No Earning	0.01	2.6	9.4	2.0	1.3
Employed, likely small employer	0.11	25.7	24.9	27.6	0.9
Missing	0.00	0.7	3.8	1.9	0.4
Total	0.43	100.0	100.0	100.0	1.0

Notes: Table presents the "award" share (from Table 2) of the difference between actual and counterfactual SSDI rates for the decrease period (2010–2019), broken down into contribution from subgroups based on primary industry of work between the ages of 25 and 34 years old, using equation (33). "Contribution share" is "absolute contribution" as a percent of the total change. "Baseline population share" is the share of the US population that the group accounts for in 2010. "Baseline entrants share" is the share of SSDI entrants that the group accounts for in 2010. "Contribution/baseline entrants" presents the ratio of "contribution share" to "baseline entrants share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the change. We identify a person's primary industry using EIN from the Detailed Earnings File linked to NAICS code from the Department of Labor Form 5500. We define primary industry as the industry in which the person worked the most years between 25 and 34 years old. "Employed, likely small employer" means that the applicant had an employer but the employer's EIN is not listed in Form 5500.

Appendix Table G.53: Demographic breakdown of eligibility share of SSDI enrollment rate by early-career industry, 2010–2019

Industry	Absolute contribution (pp)	Contribution share (%)	Baseline population share (%)	Baseline entrants share (%)	Contribution/ baseline entrants
Military	0.00	0.7	2.0	2.4	0.3
Ag/mining/utilities/construction	0.01	12.9	8.4	11.9	1.1
Manufacturing	0.01	10.4	9.9	13.6	0.8
Wholesale/retail/transportation	0.01	5.6	9.0	9.9	0.6
White collar/management	0.01	13.3	14.0	13.0	1.0
Education/health care/govt	0.01	16.3	18.5	17.6	0.9
No Earning	0.01	13.0	9.4	2.0	6.4
Employed, likely small employer	0.02	27.4	24.9	27.6	1.0
Missing	0.00	0.3	3.8	1.9	0.1
Total	0.08	100.0	100.0	100.0	1.0

Notes: Table presents the "eligibility" share (from Table 2) of the difference between actual and counterfactual SSDI rates for the decrease period (2010–2019), broken down into contribution from subgroups based on primary industry of work between the ages of 25 and 34 years old, using equation (34). "Contribution share" is "absolute contribution" as a percent of the total change. "Baseline population share" is the share of the US population that the group accounts for in 2010. "Baseline entrants share" is the share of SSDI entrants that the group accounts for in 2010. "Contribution/baseline entrants" presents the ratio of "contribution share" to "baseline entrants share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the change. We identify a person's primary industry using EIN from the Detailed Earnings File linked to NAICS code from the Department of Labor Form 5500. We define primary industry as the industry in which the person worked the most years between 25 and 34 years old. "Employed, likely small employer" means that the applicant had an employer but the employer's EIN is not listed in Form 5500.

G.4.2 Unconditional application rate decomposition in SSDI decrease period (2010–2019), by early-career industry

Appendix Table G.54: Counterfactual vs actual SSDI application rate by early-career industry, 2010–2019

Year	Actual application rate (%)	Counterfactual (base) application rate (%)	Total difference (pp)
2010	0.99	0.99	0.00
2011	0.97	0.99	-0.02
2012	0.95	0.99	-0.04
2013	0.89	0.99	-0.10
2014	0.85	0.99	-0.14
2015	0.79	0.99	-0.20
2016	0.74	0.99	-0.25
2017	0.69	0.99	-0.30
2018	0.66	0.99	-0.33
2019	0.65	0.99	-0.34
Total			-1.74

Notes: Table presents actual and counterfactual SSDI application rate in each year from 2010 to 2019. Actual SSDI application rate uses the Continuous Work History Sample linked to the Payment History Update System and the Master Beneficiary Record. Counterfactual SSDI application rate uses equations (2), (3), and (4), using 2010 as the base year.

Appendix Table G.55: Decomposition of decline in SSDI application rate by early-career industry, 2010–2019

	Absolute contribution (pp)	As a share of total (%)
Application	-1.58	86.2
Eligibility	-0.22	18.1
Interaction within apply	0.05	-2.3
Across group composition	-0.05	1.0
Within-across interaction	0.06	-3.0
Total	-1.74	100.0

Notes: Table presents decomposition of SSDI application rate decline from 2010 to 2019, using equation (12). The point estimates we report are the ones in which flows (e.g., B_t, A_t, E_t, X_t), when fixed, are held fixed at their counterfactual values.

Appendix Table G.56: Demographic breakdown of application share of SSDI application rate by early-career industry, 2010–2019

Group	Absolute contribution (pp)	Contribution share (%)	Baseline applicants share (%)	Contribution/ baseline applicants
Ag/mining/utilities/construction	-0.25	15.94	12.63	1.26
Manufacturing	-0.25	15.61	13.22	1.18
Wholesale/retail/transportation	-0.18	11.15	10.71	1.04
White collar/management	-0.19	11.96	13.53	0.88
Education/health care/govt	-0.26	16.69	19.10	0.87
Military	0.01	-0.71	2.24	-0.32
No Earning	-0.02	1.33	1.82	0.73
Employed, likely small employer	-0.40	25.29	24.99	1.01
Missing	-0.04	2.74	1.75	1.57
Total	-1.58	100.0	100.0	1.0

Notes: Table presents the "application" share (from Appendix Table G.55) of the difference between actual and counterfactual SSDI application rates for the decline period (2010–2019), broken down into contribution from subgroups based on primary industry of work between the ages of 25 and 34 years old, using equation (12). "Contribution share" is "absolute contribution" as a percent of the total change. "Baseline population share" is the share of the US population that the group accounts for in 2010. "Baseline applicants share" is the share of SSDI applicants that the group accounts for in 2010. "Contribution/baseline applicants" presents the ratio of "contribution share" to "baseline applicants share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the change. We identify a person's primary industry using EIN from the Detailed Earnings File linked to NAICS code from the Department of Labor Form 5500. We define primary industry as the industry in which the person worked the most years between 25 and 34 years old. "Employed, likely small employer" means that the applicant had an employer but the employer's EIN is not listed in Form 5500.

G.4.3 Award rate decomposition in SSDI decrease period (2010–2019), by early-career industry

Appendix Table G.57: Counterfactual vs actual SSDI award rate (conditional on application) by early-career industry, 2010–2019

Year	Actual award rate (%)	Counterfactual (base) award rate (%)	Total difference (pp)
2010	52.70	52.70	0.00
2011	50.89	52.70	-1.81
2012	49.49	52.70	-3.21
2013	48.46	52.70	-4.24
2014	47.33	52.70	-5.37
2015	46.67	52.70	-6.03
2016	47.06	52.70	-5.64
2017	46.88	52.70	-5.82
2018	47.13	52.70	-5.57
2019	46.55	52.70	-6.15
Total			-43.84

Notes: Table presents actual and counterfactual SSDI award rate (conditional on application) in each year from 2010 to 2019. Actual SSDI award rate uses the Continuous Work History Sample linked to the Payment History Update System and the Master Beneficiary Record. Counterfactual SSDI award rate uses equations (2), (3), and (4), using 2010 as the base year.

Appendix Table G.58: Decomposition of decline in SSDI award rate by early-career industry, 2010–2019

	Absolute contribution (pp)	As a share of total (%)
Award	-54.23	123.0
Across group applicant share	7.70	-16.6
Within-across interaction	2.69	-6.4
Total	-43.84	100.0

Notes: Table presents decomposition of SSDI award rate decline from 2010 to 2019, using equation (14). The point estimates we report are the ones in which flows (e.g., B_t, A_t, E_t, X_t), when fixed, are held fixed at their counterfactual values.

Appendix Table G.59: Demographic breakdown of award share of SSDI award rate by early-career industry, 2010–2019

Group	Absolute contribution (pp)	Contribution share (%)	Baseline entrants share (%)	Contribution/ baseline entrants
Ag/mining/utilities/construction	-6.57	12.11	11.95	1.01
Manufacturing	-6.44	11.88	13.63	0.87
Wholesale/retail/transportation	-6.36	11.74	9.92	1.18
White collar/management	-8.00	14.75	12.97	1.14
Education/health care/govt	-10.74	19.81	17.62	1.12
Military	-2.01	3.71	2.40	1.54
No Earning	-1.32	2.43	2.03	1.19
Employed, likely small employer	-12.50	23.06	27.61	0.84
Missing	-0.28	0.52	1.87	0.28
Total	-54.23	100.0	100.0	1.0

Notes: Table presents the “award” share (from Appendix Table G.58) of the difference between actual and counterfactual SSDI award rates for the decline period (2010–2019), broken down into contribution from subgroups based on primary industry of work between the ages of 25 and 34 years old, using equation (14). “Contribution share” is “absolute contribution” as a percent of the total change. “Baseline population share” is the share of the US population that the group accounts for in 2010. “Baseline entrants share” is the share of SSDI entrants that the group accounts for in 2010. “Contribution/baseline entrants” presents the ratio of “contribution share” to “baseline entrants share,” indicating whether that subgroup is under- (<1) or over- (>1) represented in the change. We identify a person’s primary industry using EIN from the Detailed Earnings File linked to NAICS code from the Department of Labor Form 5500. We define primary industry as the industry in which the person worked the most years between 25 and 34 years old. “Employed, likely small employer” means that the applicant had an employer but the employer’s EIN is not listed in Form 5500.

G.4.4 Unconditional entry rate decomposition in SSDI decrease period (2010–2019), by early-career industry

Appendix Table G.60: Counterfactual vs actual SSDI entry rate by early-career industry, 2010–2019

Year	Actual entry rate (%)	Counterfactual (base) entry rate (%)	Total difference (pp)
2010	0.52	0.52	0.00
2011	0.50	0.52	-0.03
2012	0.47	0.52	-0.05
2013	0.43	0.52	-0.09
2014	0.40	0.52	-0.12
2015	0.37	0.52	-0.16
2016	0.35	0.52	-0.18
2017	0.32	0.52	-0.20
2018	0.31	0.52	-0.21
2019	0.30	0.52	-0.22
Total			-1.25

Notes: Table presents actual and counterfactual SSDI entry rate in each year from 2010 to 2019. Actual SSDI entry rate uses the Continuous Work History Sample linked to the Payment History Update System and the Master Beneficiary Record. Counterfactual SSDI entry rate uses equations (2), (3), and (4), using 2010 as the base year.

Appendix Table G.61: Decomposition of decline in SSDI entry rate by early-career industry, 2010–2019

		Absolute contribution (pp)	As a share of total (%)
Entry		-1.29	103.9
	Award	-0.54	50.1
	Application	-0.80	55.8
	Eligibility	-0.10	8.7
	Interaction within entry	0.15	-10.7
Across group composition		0.01	-1.8
Within-across interaction		0.03	-2.1
Total		-1.25	100.0

Notes: Table presents decomposition of SSDI entry rate decline from 2010 to 2019, using equation (9). The point estimates we report are the ones in which flows (e.g., B_t, A_t, E_t, X_t), when fixed, are held fixed at their counterfactual values.

Appendix Table G.62: Demographic breakdown of entry share of SSDI entry rate by early-career industry, 2010–2019

Group	Absolute contribution (pp)	Contribution share (%)	baseline entrants share (%)	Contribution/ baseline entrants
Ag/mining/utilities/construction	-0.18	13.8	11.9	1.2
Manufacturing	-0.18	14.2	13.6	1.0
Wholesale/retail/transportation	-0.14	10.5	9.9	1.1
White collar/management	-0.17	13.1	13.0	1.0
Education/health care/govt	-0.21	16.6	17.6	0.9
Military	-0.02	1.4	2.4	0.6
No Earning	-0.03	2.3	2.0	1.2
Employed, likely small employer	-0.34	26.0	27.6	0.9
Missing	-0.03	2.0	1.9	1.1
Total	-1.29	100.0	100.0	1.0

Notes: Table presents the "entry" share (from Appendix Table G.61) of the difference between actual and counterfactual SSDI entry rates for the decline period (2010–2019), broken down into contribution from subgroups based on primary industry of work between the ages of 25 and 34 years old, using equation (13). "Contribution share" is "absolute contribution" as a percent of the total change. "Baseline population share" is the share of the US population that the group accounts for in 2010. "Baseline entrants share" is the share of SSDI entrants that the group accounts for in 2010. "Contribution/baseline entrants" presents the ratio of "contribution share" to "baseline entrants share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the change. We identify a person's primary industry using EIN from the Detailed Earnings File linked to NAICS code from the Department of Labor Form 5500. We define primary industry as the industry in which the person worked the most years between 25 and 34 years old. "Employed, likely small employer" means that the applicant had an employer but the employer's EIN is not listed in Form 5500.

H Applicant-level heterogeneity results

H.1 SSDI increase period (1988–2010)

Appendix Table H.1: SSDI entry increase by diagnosis

		Absolute contribution (pp)	Contribution share (%)
Apply and award in Entry		1.84	87.5
	Award	0.38	17.9
	Application	1.36	64.8
	Applicant share	-0.19	-9.1
	Interaction within award and apply	0.29	13.8
Eligibility		0.17	8.3
Interaction with eligibility		0.09	4.2
Total		2.10	100.0

Notes: Table presents results from decomposing the Entry row in Appendix Table G.21 using equation (18), by diagnosis. "Award," "Applicant share," "Interaction within award and apply," "Application," and "Eligibility" present the corresponding terms from equation (18).

Appendix Table H.2: Heterogeneity in SSDI entry increase by diagnosis

Diagnosis	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Musculoskeletal	0.81	44.0	22.7	1.9
Mental	0.52	28.4	17.2	1.7
Cardiovascular	0.02	0.9	11.6	0.1
Endocrine	0.16	8.6	2.0	4.3
Other	0.41	22.5	36.1	0.6
Missing	-0.08	-4.5	10.4	-0.4
Total	1.84	100.0	100.0	1.0

Table presents results from decomposing the difference between actual and counterfactual SSDI entry rates in 2010 using 1988 as the base year by diagnosis. "Absolute contribution" uses the first terms of equation (16) with diagnoses as the d groups; "contribution share" presents the same number as a percent of the total decline. "Baseline share" presents entrant shares in 1988. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the entry decline. Diagnosis is recorded by the disability examiner assigned to the case.

H.2 SSDI decrease period (2010–2019)

H.2.1 Heterogeneity by applicant severity

Appendix Table H.3: Heterogeneity in SSDI application decline by severity

Severity	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Least severe	-0.72	47.5	62.4	0.8
Moderately severe	-0.26	17.0	12.6	1.3
Most severe	-0.48	31.9	20.5	1.6
Unknown	-0.05	3.6	4.5	0.8
Total	-1.51	100.0	100.0	1.0

Notes: Table presents results from decomposing the Application row in Appendix Table G.15 using equation (15), by severity. "Absolute contribution" reports results from equation (15) with severity levels as the d groups; "contribution share" presents the same number as a percent of the total decline. "Baseline share" presents applicant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the applicant decline. "Least severe" means that the applicant was rejected at the disability examiner level (but could have been allowed on appeal). "Moderately severe" means that the disability examiner assigned a diary reason of "medical improvement expected" or "medical improvement possible." "Most severe" means that the disability examiner assigned a diary reason of "medical improvement not expected."

Appendix Table H.4: SSDI award decline by severity

	Absolute contribution (pp)	Contribution share (%)
Award	-36.59	67.6
Applicant share	-18.83	34.8
Interaction	1.28	-2.4
Total	-54.15	100.0

Notes: Table presents results from decomposing the Award row in Appendix Table G.18 using equation (16), by severity. "Award" corresponds to the first term in equation (16), "Applicant share" refers to the second term, and "Interaction" refers to the interaction term.

Appendix Table H.5: Heterogeneity in SSDI award decline by severity

Severity	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Least severe	-35.71	97.6	37.8	2.6
Moderately severe	1.66	-4.5	21.3	-0.2
Most severe	-2.06	5.6	32.5	0.2
Unknown	-0.48	1.3	8.4	0.2
Total	-36.59	100.0	100.0	1.0

Notes: Table presents results from decomposing the Award row from Appendix Table H.4 into d (severity) groups from the first term in equation (16) in 2019 using 2010 as the base year. "Absolute contribution" reports results from the first term of equation (16)) with severity levels as the d groups; "contribution share" presents the same number as a percent of the total decline. "Baseline share" presents entrant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the award decline. "Least severe" means that the applicant was rejected at the disability examiner level (but could have been allowed on appeal). "Moderately severe" means that the disability examiner assigned a diary reason of "medical improvement expected" or "medical improvement possible." "Most severe" means that the disability examiner assigned a diary reason of "medical improvement not expected."

Appendix Table H.6: SSDI entry decline by severity

		Absolute contribution (pp)	Contribution share
Apply and award in Entry		-1.19	95.2
	Award	-0.36	29.1
	Application	-0.75	60.3
	Applicant share	-0.19	15.0
	Interaction within award and apply	0.12	-9.2
Eligibility		-0.09	7.5
Interaction with eligibility		0.03	-2.6
Total		-1.25	100.0

Notes: Table presents results from decomposing the Entry row in Appendix Table G.21 using equation (18), by severity. "Award," "Applicant share," "Interaction within award and apply," "Application," and "Eligibility" present the corresponding terms from equation (18).

Appendix Table H.7: Heterogeneity in SSDI entry decline by severity

Severity	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Least severe	-0.48	40.4	37.8	1.1
Moderately severe	-0.22	18.7	21.3	0.9
Most severe	-0.43	36.3	32.5	1.1
Unknown	-0.05	4.6	8.4	0.5
Total	-1.19	100.0	100.0	1.0

Notes: Table presents results from decomposing the "Apply and award in Entry" row in Appendix Table H.6 into d (severity) groups from the corresponding terms in equation (18) in 2019 using 2010 as the base year. "Absolute contribution" reports results from equation (18) with severity levels as the d groups; "contribution share" presents the same number as a percent of the total decline. "Baseline share" presents entrant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the entry decline. "Least severe" means that the applicant was rejected at the disability examiner level (but could have been allowed on appeal). "Moderately severe" means that the disability examiner assigned a diary reason of "medical improvement expected" or "medical improvement possible." "Most severe" means that the disability examiner assigned a diary reason of "medical improvement not expected."

H.2.2 Heterogeneity by applicant diagnosis

Appendix Table H.8: Heterogeneity in SSDI application decline by diagnosis

Diagnosis	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Musculoskeletal	-0.34	22.6	32.0	0.7
Mental	-0.36	23.9	18.7	1.3
Cardiovascular	-0.15	10.0	7.6	1.3
Endocrine	-0.15	10.1	3.7	2.7
Other	-0.45	29.9	33.6	0.9
Missing	-0.05	3.6	4.5	0.8
Total	-1.51	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI application rates in 2019 using 2010 as the base year by diagnosis. "Absolute contribution" uses equation (15) with diagnoses as the d groups; "contribution share" presents the same number as a percent of the total change. "Baseline share" presents applicant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the application decline. Diagnosis is recorded by the disability examiner assigned to the case.

Appendix Table H.9: SSDI award decline by diagnosis

	Absolute contribution (pp)	Contribution share (%)
Award	-64.51	119.1
Applicant share	4.76	-8.8
Interaction	5.60	-10.3
Total	-54.15	100.0

Notes: Table presents results from decomposing the Award row in Appendix Table G.18 using equation (16), by diagnosis. "Award" corresponds to the first term in equation (16), "Applicant share" refers to the second term, and "Interaction" refers to the interaction term.

Appendix Table H.10: Heterogeneity in SSDI award decline by diagnosis

Diagnosis	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Musculoskeletal	-23.46	36.4	29.9	1.2
Mental	-19.40	30.1	18.1	1.7
Cardiovascular	-3.21	5.0	7.6	0.7
Endocrine	-3.72	5.8	3.1	1.9
Other	-14.24	22.1	32.9	0.7
Missing	-0.48	0.7	8.4	0.1
Total	-64.51	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI award rates in 2019 using 2010 as the base year by diagnosis. "Absolute contribution" uses the first terms of equation (16) with diagnoses as the d groups; "contribution share" presents the same number as a percent of the total decline. "Baseline share" presents entrant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the award decline. Diagnosis is recorded by the disability examiner assigned to the case.

Appendix Table H.11: SSDI entry decline by diagnosis

		Absolute contribution (pp)	Contribution share
Apply and award in Entry		-1.19	95.2
	Award	-0.64	51.3
	Application	-0.75	60.3
	Applicant share	0.05	-3.8
	Interaction within award and apply	0.16	-12.6
Eligibility		-0.09	7.5
Interaction with eligibility		0.03	-2.6
Total		-1.25	100.0

Notes: Table presents results from decomposing the Entry row in Appendix Table G.21 using equation (18), by diagnosis. "Award," "Applicant share," "Interaction within award and apply," "Application," and "Eligibility" present the corresponding terms from equation (18).

Appendix Table H.12: Heterogeneity in SSDI entry decline by diagnosis

Diagnosis	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Musculoskeletal	-0.33	28.0	29.9	0.9
Mental	-0.31	26.4	18.1	1.5
Cardiovascular	-0.10	8.8	7.6	1.2
Endocrine	-0.09	7.2	3.1	2.4
Other	-0.30	25.0	32.9	0.8
Missing	-0.05	4.6	8.4	0.5
Total	-1.19	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI entry rates in 2019 using 2010 as the base year by diagnosis. "Absolute contribution" uses the first terms of equation (16) with diagnoses as the d groups; "contribution share" presents the same number as a percent of the total decline. "Baseline share" presents entrant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the entry decline. Diagnosis is recorded by the disability examiner assigned to the case.

H.2.3 Heterogeneity by applicant decision "step"

Appendix Table H.13: Heterogeneity in SSDI application decline by decision "step"

Decision step	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Step 1-2, deny (not severe)	-0.12	7.8	14.8	0.5
Step 3, allow (listings)	-0.28	18.6	16.4	1.1
Step 4, deny (past work)	-0.82	54.6	19.0	2.9
Step 5, allow (any work)	-0.46	30.3	16.7	1.8
Step 5, deny (any work)	0.26	-16.9	21.0	-0.8
Other	-0.03	2.1	7.7	0.3
Missing	-0.05	3.6	4.5	0.8
Total	-1.51	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI application rates in 2019 using 2010 as the base year by SSA decision "step." "Absolute contribution" uses equation (15) with decision steps as the d groups; "contribution share" presents the same number as a percent of the total change. "Baseline share" presents the applicant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the application decline. "Step 1-2 deny" means that the applicant was rejected Steps 1 or 2 of the SSA decision process (working or not severe). "Step 3 allow" means that applicant was allowed at Step 3 (meets medical listings). "Step 4 deny" means that applicant was denied at Step 4 (capacity for past work). "Step 5 allow/deny" means that the applicant was allowed/denied at Step 5 (any work).

Appendix Table H.14: SSDI award decline by decision "step"

	Absolute contribution (pp)	Contribution share (%)
Award	-33.54	61.9
Applicant share	-18.02	33.3
Interaction	-2.60	4.8
Total	-54.15	100.0

Notes: Table presents results from decomposing the Award row in Appendix Table G.18 using equation (16), by decision "step." "Award" corresponds to the first term in equation (16), "Applicant share" refers to the second term, and "Interaction" refers to the interaction term.

Appendix Table H.15: Heterogeneity in SSDI award decline by decision "step"

Decision step	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Step 1-2, deny (not severe)	-6.81	20.3	6.3	3.2
Step 3, allow (listings)	0.50	-1.5	26.0	-0.1
Step 4, deny (past work)	-8.00	23.9	13.9	1.7
Step 5, allow (any work)	0.21	-0.6	27.7	-0.0
Step 5, deny (any work)	-17.21	51.3	15.8	3.2
Other	-1.75	5.2	2.0	2.7
Missing	-0.48	1.4	8.4	0.2
Total	-33.54	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI award rates in 2019 using 2010 as the base year by SSA decision "step." "Absolute contribution" uses equation (15) with decision steps as the d groups; "contribution share" presents the same number as a percent of the total change. "Baseline share" presents the entrant decision steps shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the award decline. "Step 1-2 deny" means that the applicant was rejected Steps 1 or 2 of the SSA decision process (working or not severe). "Step 3 allow" means that applicant was allowed at Step 3 (meets medical listings). "Step 4 deny" means that applicant was denied at Step 4 (capacity for past work). "Step 5 allow/deny" means that the applicant was allowed/denied at Step 5 (any work).

Appendix Table H.16: SSDI entry decline by decision "step"

		Absolute contribution (pp)	Contribution share
Apply and award in Entry		-1.19	95.2
	Award	-0.33	26.6
	Application	-0.75	60.3
	Applicant share	-0.18	14.3
	Interaction within award and apply	0.08	-6.1
Eligibility		-0.09	7.5
Interaction with eligibility		0.03	-2.6
Total		-1.25	100.0

Notes: Table presents results from decomposing the Entry row in Appendix Table G.21 using equation (18), by decision "step." "Award," "Applicant share," "Interaction within award and apply," "Application," and "Eligibility" present the corresponding terms from equation (18).

Appendix Table H.17: Heterogeneity in SSDI entry decline by decision "step"

Decision step	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Step 1-2, deny (not severe)	-0.08	6.7	6.3	1.1
Step 3, allow (listings)	-0.24	19.9	26.0	0.8
Step 4, deny (past work)	-0.30	25.4	13.9	1.8
Step 5, allow (any work)	-0.42	35.0	27.7	1.3
Step 5, deny (any work)	-0.08	7.1	15.8	0.4
Other	-0.02	1.4	2.0	0.7
Missing	-0.05	4.6	8.4	0.5
Total	-1.19	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI entry rates in 2019 using 2010 as the base year by SSA decision "step." "Absolute contribution" uses equation (15) with decision steps as the d groups; "contribution share" presents the same number as a percent of the total change. "Baseline share" presents the entrant decision steps shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the entry decline. "Step 1-2 deny" means that the applicant was rejected Steps 1 or 2 of the SSA decision process (working or not severe). "Step 3 allow" means that applicant was allowed at Step 3 (meets medical listings). "Step 4 deny" means that applicant was denied at Step 4 (capacity for past work). "Step 5 allow/deny" means that the applicant was allowed/denied at Step 5 (any work).

H.2.4 Heterogeneity by state

Appendix Table H.18: Heterogeneity in SSDI application decline by state

State	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Alabama	-0.04	2.4	2.2	1.1
Florida	-0.09	6.0	5.5	1.1
Georgia	-0.04	2.6	3.1	0.8
Hawaii	-0.00	0.2	0.3	0.7
Idaho	-0.00	0.3	0.5	0.5
Illinois	-0.07	4.9	3.6	1.4
Indiana	-0.04	2.4	2.4	1.0
Iowa	-0.01	0.7	0.9	0.8
Kansas	-0.01	1.0	0.8	1.1
Kentucky	-0.04	2.5	2.1	1.2
Louisiana	-0.03	1.8	1.7	1.0
Alaska	-0.00	0.1	0.2	0.7
Maine	-0.01	0.7	0.5	1.3
Maryland	-0.02	1.2	1.6	0.7
Massachusetts	-0.03	1.8	2.0	0.9
Michigan	-0.07	4.6	4.0	1.2
Minnesota	-0.02	1.2	1.4	0.9
Mississippi	-0.02	1.6	1.5	1.1
Missouri	-0.04	2.9	2.4	1.2
Montana	-0.01	0.5	0.3	1.7
Nebraska	-0.00	0.3	0.5	0.6
Nevada	-0.01	0.7	0.7	1.0
Arizona	-0.02	1.3	1.5	0.9
New Hampshire	-0.01	0.6	0.4	1.3
New Jersey	-0.02	1.2	2.1	0.6
New Mexico	-0.01	0.6	0.7	0.9
New York	-0.05	3.1	5.0	0.6
North Carolina	-0.06	3.7	3.6	1.0
North Dakota	-0.00	0.0	0.2	0.1
Ohio	-0.08	5.0	4.1	1.2
Oklahoma	-0.02	1.0	1.4	0.7
Oregon	-0.02	1.2	1.1	1.2
Pennsylvania	-0.05	3.6	4.5	0.8
Arkansas	-0.02	1.5	1.5	1.0
Puerto Rico	-0.05	3.6	1.0	3.5
Rhode Island	-0.01	0.3	0.4	0.9
South Carolina	-0.03	1.8	1.8	1.0
South Dakota	-0.00	0.2	0.2	1.0
Tennessee	-0.06	3.8	2.7	1.4
Texas	-0.08	5.3	6.5	0.8
Utah	-0.01	0.4	0.4	1.1
Vermont	-0.00	0.2	0.2	1.2
Virgin Islands	-0.02	1.3	2.2	0.6
California	-0.14	9.4	8.6	1.1
Washington	-0.02	1.3	1.8	0.7
West Virginia	-0.01	0.5	1.0	0.5
Wisconsin	-0.04	2.3	1.7	1.4
Wyoming	-0.00	0.1	0.1	0.6
Colorado	-0.02	1.5	1.1	1.4
Connecticut	-0.01	0.7	1.0	0.7
Delaware	-0.01	0.4	0.3	1.4
District of Columbia	-0.00	0.1	0.2	0.4
Unknown	-0.00	0.0	0.1	0.3
Missing	-0.05	3.6	4.5	0.8
Total	-1.51	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI application rates in 2019 using 2010 as the base year by state. "Absolute contribution" uses equation (15) with states as the d groups; "contribution share" presents the same number as a percent of the total change. "Baseline share" presents applicant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the application decline. State is observed in the F831 or MEDIB file.

Appendix Table H.19: SSDI award decline by state

	Absolute contribution (pp)	Contribution share (%)
Award	-62.37	115.2
Applicant share	-7.38	13.6
Interaction	15.60	-28.8
Total	-54.15	100.0

Notes: Table presents results from decomposing the Award row in Appendix Table G.18 using equation (16), by state. "Award" corresponds to the first term in equation (16), "Applicant share" refers to the second term, and "Interaction" refers to the interaction term.

Appendix Table H.20: Heterogeneity in SSDI award decline by state

State	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Alabama	-1.89	3.0	2.4	1.3
Florida	-2.78	4.5	4.9	0.9
Georgia	-1.57	2.5	2.7	0.9
Hawaii	-0.38	0.6	0.3	2.3
Idaho	-0.34	0.5	0.4	1.2
Illinois	-1.54	2.5	3.3	0.7
Indiana	-1.42	2.3	2.2	1.0
Iowa	-0.15	0.2	0.8	0.3
Kansas	-0.46	0.7	0.7	1.0
Kentucky	-1.69	2.7	2.0	1.4
Louisiana	-0.86	1.4	1.7	0.8
Alaska	-0.26	0.4	0.2	2.8
Maine	-0.52	0.8	0.5	1.5
Maryland	-0.89	1.4	1.5	1.0
Massachusetts	-0.88	1.4	2.1	0.7
Michigan	-2.11	3.4	3.8	0.9
Minnesota	-0.76	1.2	1.3	0.9
Mississippi	-0.90	1.4	1.1	1.3
Missouri	-1.48	2.4	2.3	1.0
Montana	-0.35	0.6	0.3	2.1
Nebraska	-0.21	0.3	0.5	0.7
Nevada	-0.71	1.1	0.7	1.7
Arizona	-1.45	2.3	1.4	1.7
New Hampshire	-0.42	0.7	0.5	1.3
New Jersey	-2.20	3.5	2.3	1.5
New Mexico	-0.52	0.8	0.7	1.3
New York	-3.83	6.1	5.7	1.1
North Carolina	-1.60	2.6	3.2	0.8
North Dakota	-0.25	0.4	0.1	2.9
Ohio	-1.66	2.7	3.6	0.7
Oklahoma	-0.86	1.4	1.3	1.0
Oregon	-0.78	1.3	1.0	1.3
Pennsylvania	-2.20	3.5	4.5	0.8
Arkansas	-0.96	1.5	1.5	1.0
Puerto Rico	-2.48	4.0	1.4	2.8
Rhode Island	-0.21	0.3	0.4	0.9
South Carolina	-1.16	1.9	1.7	1.1
South Dakota	-0.25	0.4	0.1	3.1
Tennessee	-1.52	2.4	2.6	0.9
Texas	-4.79	7.7	6.4	1.2
Utah	-0.61	1.0	0.4	2.3
Vermont	-0.28	0.5	0.2	2.0
Virgin Islands	-1.27	2.0	2.2	0.9
California	-5.13	8.2	7.9	1.0
Washington	-1.40	2.2	1.9	1.2
West Virginia	-0.66	1.1	1.0	1.1
Wisconsin	-0.48	0.8	1.5	0.5
Wyoming	-0.30	0.5	0.1	3.5
Colorado	-1.08	1.7	1.0	1.7
Connecticut	-0.54	0.9	0.9	1.0
Delaware	-0.25	0.4	0.3	1.4
District of Columbia	-0.30	0.5	0.2	2.4
Unknown	-0.30	0.5	0.1	4.2
Missing	-0.49	0.8	8.4	0.1
Total	-62.37	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI award rates in 2019 using 2010 as the base year by state. "Absolute contribution" uses the first terms of equation (16) with states as the d groups; "contribution share" presents the same number as a percent of the total decline. "Baseline share" presents entrant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the award decline. State is observed in the F831 or MEDIB file.

Appendix Table H.21: SSDI entry decline by state

		Absolute contribution (pp)	Contribution share
Apply and award in Entry		-1.19	95.2
	Award	-0.62	49.6
	Application	-0.75	60.3
	Applicant share	-0.07	5.9
	Interaction within award and apply	0.26	-20.6
Eligibility		-0.09	7.5
Interaction with eligibility		0.03	-2.6
Total		-1.25	100.0

Notes: Table presents results from decomposing the Entry row in Appendix Table G.21 using equation (18), by state. "Award," "Applicant share," "Interaction within award and apply," "Application," and "Eligibility" present the corresponding terms from equation (18).

Appendix Table H.22: Heterogeneity in SSDI entry decline by state

State	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Alabama	-0.03	2.7	2.4	1.1
Florida	-0.06	5.2	4.9	1.1
Georgia	-0.03	2.7	2.7	1.0
Hawaii	-0.00	0.3	0.3	1.0
Idaho	-0.00	0.3	0.4	0.7
Illinois	-0.05	4.0	3.3	1.2
Indiana	-0.03	2.2	2.2	1.0
Iowa	-0.00	0.3	0.8	0.4
Kansas	-0.01	0.8	0.7	1.1
Kentucky	-0.03	2.3	2.0	1.2
Louisiana	-0.02	1.6	1.7	0.9
Alaska	-0.00	0.2	0.2	1.1
Maine	-0.01	0.7	0.5	1.2
Maryland	-0.01	1.2	1.5	0.8
Massachusetts	-0.02	1.6	2.1	0.7
Michigan	-0.05	4.2	3.8	1.1
Minnesota	-0.01	1.2	1.3	0.9
Mississippi	-0.02	1.4	1.1	1.2
Missouri	-0.03	2.5	2.3	1.1
Montana	-0.01	0.4	0.3	1.6
Nebraska	-0.00	0.2	0.5	0.4
Nevada	-0.01	0.8	0.7	1.2
Arizona	-0.02	1.7	1.4	1.3
New Hampshire	-0.01	0.5	0.5	1.0
New Jersey	-0.03	2.3	2.3	1.0
New Mexico	-0.01	0.6	0.7	0.9
New York	-0.06	4.9	5.7	0.9
North Carolina	-0.04	3.0	3.2	0.9
North Dakota	-0.00	0.1	0.1	0.7
Ohio	-0.04	3.7	3.6	1.0
Oklahoma	-0.01	1.1	1.3	0.8
Oregon	-0.02	1.3	1.0	1.3
Pennsylvania	-0.04	3.3	4.5	0.7
Arkansas	-0.02	1.5	1.5	1.0
Puerto Rico	-0.05	4.4	1.4	3.1
Rhode Island	-0.00	0.2	0.4	0.6
South Carolina	-0.02	1.9	1.7	1.1
South Dakota	-0.00	0.2	0.1	1.3
Tennessee	-0.04	3.2	2.6	1.2
Texas	-0.08	6.6	6.4	1.0
Utah	-0.01	0.6	0.4	1.5
Vermont	-0.00	0.2	0.2	0.8
Virgin Islands	-0.02	1.6	2.2	0.8
California	-0.10	8.7	7.9	1.1
Washington	-0.02	1.7	1.9	0.9
West Virginia	-0.01	0.7	1.0	0.7
Wisconsin	-0.02	1.7	1.5	1.1
Wyoming	-0.00	0.1	0.1	1.0
Colorado	-0.02	1.5	1.0	1.5
Connecticut	-0.01	0.7	0.9	0.8
Delaware	-0.00	0.2	0.3	0.8
District of Columbia	-0.00	0.2	0.2	0.8
Unknown	-0.00	0.1	0.1	0.9
Missing	-0.05	4.5	8.4	0.5
Total	-1.19	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI entry rates in 2019 using 2010 as the base year by state. “Absolute contribution” uses the first terms of equation (16) with states as the d groups; “contribution share” presents the same number as a percent of the total decline. “Baseline share” presents entrant shares in 2007. “Contribution/baseline” presents the ratio of “contribution share” to “baseline share,” indicating whether that subgroup is under- (<1) or over- (>1) represented in the entry decline. State is observed in the F831 or MEDIB file.

H.2.5 Heterogeneity by Medicaid expansion

Appendix Table H.23: Heterogeneity in SSDI application decline by Medicaid expansion

Medicaid expansion	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
After 2019 or never	-0.62	41.2	38.7	1.1
Expansion in 2015-2016	-0.13	8.4	9.0	0.9
Expansion in 2014	-0.70	46.7	47.7	1.0
Unknown	-0.00	0.0	0.1	0.3
Missing	-0.05	3.6	4.5	0.8
Total	-1.51	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI application rates in 2019 using 2010 as the base year, by state Medicaid expansion date. "Absolute contribution" uses equation (15) with states as the d groups; "contribution share" presents the same number as a percent of the total change. "Baseline share" presents applicant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the application decline. State is observed in the F831 or MEDIB file.

Appendix Table H.24: SSDI award decline by Medicaid expansion

	Absolute contribution (pp)	Contribution share (%)
Award	-62.37	115.2
Applicant share	-7.38	13.6
Interaction	15.60	-28.8
Total	-54.15	100.0

Notes: Table presents results from decomposing the Award row in Appendix Table G.18 using equation (16), by state Medicaid expansion date. "Award" corresponds to the first term in equation (16), "Applicant share" refers to the second term, and "Interaction" refers to the interaction term.

Appendix Table H.25: Heterogeneity in SSDI award decline by Medicaid expansion

Medicaid expansion	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
After 2019 or never	-25.45	40.8	36.5	1.1
Expansion in 2015-2016	-5.08	8.1	8.8	0.9
Expansion in 2014	-31.05	49.8	46.2	1.1
Unknown	-0.30	0.5	0.1	4.2
Missing	-0.49	0.8	8.4	0.1
Total	-62.37	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI award rates in 2019 using 2010 as the base year, by state Medicaid expansion date. "Absolute contribution" uses the first terms of equation (16) with states as the d groups; "contribution share" presents the same number as a percent of the total decline. "Baseline share" presents entrant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the award decline. State is observed in the F831 or MEDIB file.

Appendix Table H.26: SSDI entry decline by Medicaid expansion

		Absolute contribution (pp)	Contribution share
Apply and award in Entry		-1.19	95.2
	Award	-0.62	49.6
	Application	-0.75	60.3
	Applicant share	-0.07	5.9
	Interaction within award and apply	0.26	-20.6
Eligibility		-0.09	7.5
Interaction with eligibility		0.03	-2.6
Total		-1.25	100.0

Notes: Table presents results from decomposing the Entry row in Appendix Table G.21 using equation (18), by state Medicaid expansion date. "Award," "Applicant share," "Interaction within award and apply," "Application," and "Eligibility" present the corresponding terms from equation (18).

Appendix Table H.27: Heterogeneity in SSDI entry decline by Medicaid expansion

Medicaid expansion	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
After 2019 or never	-0.49	41.1	36.5	1.1
Expansion in 2015-2016	-0.09	7.7	8.8	0.9
Expansion in 2014	-0.55	46.5	46.2	1.0
Unknown	-0.00	0.1	0.1	0.9
Missing	-0.05	4.5	8.4	0.5
Total	-1.19	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI entry rates in 2019 using 2010 as the base year, by state Medicaid expansion date. "Absolute contribution" uses the first terms of equation (16) with states as the d groups; "contribution share" presents the same number as a percent of the total decline. "Baseline share" presents entrant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the entry decline. State is observed in the F831 or MEDIB file.

H.2.6 Heterogeneity by applicant urban/rural status

Appendix Table H.28: Heterogeneity in SSDI application decline by population density

Urban status	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Big City	-0.99	65.8	64.4	1.0
Big City CZ	-0.13	8.9	9.8	0.9
Small City	-0.19	12.3	11.4	1.1
Rural Area	-0.15	9.9	9.5	1.0
Missing	-0.05	3.1	4.8	0.7
Total	-1.51	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI application rates in 2019 using 2010 as the base year by population density. "Absolute contribution" uses equation (15) with urban status as the d groups; "contribution share" presents the same number as a percent of the total change. "Baseline share" presents applicant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the application decline. ZIP code is observed in the F831 or MEDIB file, and linked to the USDA Rural-Urban Commuting Area (RUCA) Codes.

Appendix Table H.29: SSDI award decline by population density

	Absolute contribution (pp)	Contribution share (%)
Award	-55.79	103.0
Applicant share	-0.32	0.6
Interaction	1.96	-3.6
Total	-54.15	100.0

Notes: Table presents results from decomposing the Award row in Appendix Table G.18 using equation (16), by population density. "Award" corresponds to the first term in equation (16), "Applicant share" refers to the second term, and "Interaction" refers to the interaction term.

Appendix Table H.30: Heterogeneity in SSDI award decline by population density

Urban status	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Big City	-37.16	66.6	61.5	1.1
Big City CZ	-5.91	10.6	9.9	1.1
Small City	-6.38	11.4	10.7	1.1
Rural Area	-5.71	10.2	9.2	1.1
Missing	-0.64	1.2	8.7	0.1
Total	-55.79	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI award rates in 2019 using 2010 as the base year by population density. "Absolute contribution" uses the first terms of equation (16) with urban status as the d groups; "contribution share" presents the same number as a percent of the total decline. "Baseline share" presents entrant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the award decline. ZIP code is observed in the F831 or MEDIB file. We link ZIP code to the USDA Rural-Urban Commuting Area (RUCA) Codes.

Appendix Table H.31: SSDI entry decline by population density

		Absolute contribution (pp)	Contribution share
Apply and award in Entry		-1.19	95.2
	Award	-0.55	44.3
	Application	-0.75	60.3
	Applicant share	-0.00	0.3
	Interaction within award and apply	0.12	-9.8
Eligibility		-0.09	7.5
Interaction with eligibility		0.03	-2.6
Total		-1.25	100.0

Notes: Table presents results from decomposing the Entry row in Appendix Table G.21 using equation (18), by population density. "Award," "Applicant share," "Interaction within award and apply," "Application," and "Eligibility" present the corresponding terms from equation (18).

Appendix Table H.32: Heterogeneity in SSDI entry decline by population density

Urban status	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Big City	-0.78	65.7	61.5	1.1
Big City CZ	-0.11	9.2	9.9	0.9
Small City	-0.13	11.2	10.7	1.0
Rural Area	-0.11	9.5	9.2	1.0
Missing	-0.05	4.3	8.7	0.5
Total	-1.19	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI entry rates in 2019 using 2010 as the base year by population density. "Absolute contribution" uses the first terms of equation (16) with urban status as the d groups; "contribution share" presents the same number as a percent of the total decline. "Baseline share" presents entrant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the entry decline. ZIP code is observed in the F831 or MEDIB file. We link ZIP code to the USDA Rural-Urban Commuting Area (RUCA) Codes.

H.2.7 Heterogeneity by ALJ award change

Appendix Table H.33: Heterogeneity in SSDI application decline by ALJ award change

ALJ change	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Less affected	-1.15	76.3	79.3	1.0
More affected	-0.20	13.4	12.7	1.1
Other	-0.10	6.8	3.5	1.9
Missing	-0.05	3.6	4.5	0.8
Total	-1.51	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI application rates in 2019 using 2010 as the base year by 2008 award rates at the appeals level. "Absolute contribution" uses equation (15) with award rate group as the d groups; "contribution share" presents the same number as a percent of the total change. "Baseline share" presents applicant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the application decline. ZIP code is observed in the F831 or MEDIB file. We link ZIP code to appeals award rates calculated using SSA administrative data. "Less affected" means a 2008 appeals award rate of less than 0.4 (and therefore experiences a smaller decline in award rates as a result of the ALJ reform). "More affected" means a 2008 median appeals award rate above 0.4 (and therefore experiences a larger decline in award rates as a result of the ALJ reform).

Appendix Table H.34: SSDI award decline by ALJ award change

	Absolute contribution (pp)	Contribution share (%)
Award	-55.24	102.0
Applicant share	-0.57	1.1
Interaction	1.66	-3.1
Total	-54.15	100.0

Notes: Table presents results from decomposing the Award row in Appendix Table G.18 using equation (16), by ALJ award change. "Award" corresponds to the first term in equation (16), "Applicant share" refers to the second term, and "Interaction" refers to the interaction term.

Appendix Table H.35: Heterogeneity in SSDI award decline by ALJ award change

ALJ change	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Less affected	-41.74	75.6	74.2	1.0
More affected	-9.09	16.5	13.7	1.2
Other	-3.93	7.1	3.7	1.9
Missing	-0.48	0.9	8.4	0.1
Total	-55.24	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI award rates in 2019 using 2010 as the base year by 2008 award rates at the appeals level. "Absolute contribution" uses the first terms of equation (16) with award rate group as the d groups; "contribution share" presents the same number as a percent of the total decline. "Baseline share" presents entrant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the award decline. ZIP code is observed in the F831 or MEDIB file. We link ZIP code to appeals award rates calculated using SSA administrative data. "Less affected" means a 2008 appeals award rate of less than 0.4 (and therefore experiences a smaller decline in award rates as a result of the ALJ reform). "More affected" means a 2008 median appeals award rate above 0.4 (and therefore experiences a larger decline in award rates as a result of the ALJ reform).

Appendix Table H.36: SSDI entry decline by ALJ award change

		Absolute contribution (pp)	Contribution share
Apply and award in Entry		-1.19	95.2
	Award	-0.55	43.9
	Application	-0.75	60.3
	Applicant share	-0.01	0.5
	Interaction within award and apply	0.12	-9.5
Eligibility		-0.09	7.5
Interaction with eligibility		0.03	-2.6
Total		-1.25	100.0

Notes: Table presents results from decomposing the Entry row in Appendix Table G.21 using equation (18), by ALJ award change. "Award," "Applicant share," "Interaction within award and apply," "Application," and "Eligibility" present the corresponding terms from equation (18).

Appendix Table H.37: Heterogeneity in SSDI entry decline by ALJ award change

ALJ change	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Less affected	-0.88	73.8	74.2	1.0
More affected	-0.18	14.8	13.7	1.1
Other	-0.08	6.9	3.7	1.9
Missing	-0.05	4.6	8.4	0.5
Total	-1.19	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI entry rates in 2019 using 2010 as the base year by 2008 award rates at the appeals level. "Absolute contribution" uses the first terms of equation (16) with award rate group as the d groups; "contribution share" presents the same number as a percent of the total decline. "Baseline share" presents entrant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the entry decline. ZIP code is observed in the F831 or MEDIB file. We link ZIP code to appeals award rates calculated using SSA administrative data. "Less affected" means a 2008 appeals award rate of less than 0.4 (and therefore experiences a smaller decline in award rates as a result of the ALJ reform). "More affected" means a 2008 median appeals award rate above 0.4 (and therefore experiences a larger decline in award rates as a result of the ALJ reform).

H.2.8 Heterogeneity by unemployment rate change

Appendix Table H.38: Heterogeneity in SSDI application decline by unemployment rate change

Unemp rate change	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Most improving labor market	-0.67	44.1	40.6	1.1
Moderately improving	-0.50	33.4	33.7	1.0
Least improving labor market	-0.18	12.0	17.2	0.7
Unknown	-0.16	10.5	8.5	1.2
Total	-1.51	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI application rates in 2019 using 2010 as the base year by the change in the unemployment rate between 2010 and 2019. "Absolute contribution" uses equation (15) with unemployment rate change group as the d groups; "contribution share" presents the same number as a percent of the total change. "Baseline share" presents applicant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the application decline. ZIP code is observed in the F831 or MEDIB file. We link ZIP code to Bureau of Labor Statistics Local Area Unemployment Statistics. "Most improving labor market" means that the change in the unemployment rate from 2010 to 2019 is in the top tercile. "Moderately improving" means in the middle tercile. "Least improving" means the bottom tercile.

Appendix Table H.39: SSDI award decline by unemployment rate change

	Absolute contribution (pp)	Contribution share (%)
Award	-55.63	102.7
Applicant share	-0.18	0.3
Interaction	1.66	-3.1
Total	-54.15	100.0

Notes: Table presents results from decomposing the Award row in Appendix Table G.18 using equation (16), by unemployment rate change. "Award" corresponds to the first term in equation (16), "Applicant share" refers to the second term, and "Interaction" refers to the interaction term.

Appendix Table H.40: Heterogeneity in SSDI award decline by unemployment rate change

Unemp rate change	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Most improving labor market	-22.87	41.1	37.7	1.1
Moderately improving	-18.84	33.9	32.8	1.0
Least improving labor market	-9.38	16.9	16.9	1.0
Unknown	-4.54	8.2	12.6	0.6
Total	-55.63	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI award rates in 2019 using 2010 as the base year by the change in the unemployment rate between 2010 and 2019. "Absolute contribution" uses the first terms of equation (16) with unemployment rate change group as the d groups; "contribution share" presents the same number as a percent of the total decline. "Baseline share" presents entrant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the award decline. ZIP code is observed in the F831 or MEDIB file. We link ZIP code to Bureau of Labor Statistics Local Area Unemployment Statistics. "Most improving labor market" means that the change in the unemployment rate from 2010 to 2019 is in the top tercile. "Moderately improving" means in the middle tercile. "Least improving" means the bottom tercile.

Appendix Table H.41: SSDI entry decline by unemployment rate change

		Absolute contribution (pp)	Contribution share
Apply and award in Entry		-1.19	95.2
	Award	-0.55	44.2
	Application	-0.75	60.3
	Applicant share	-0.00	0.1
	Interaction within award and apply	0.12	-9.5
Eligibility		-0.09	7.5
Interaction with eligibility		0.03	-2.6
Total		-1.25	100.0

Notes: Table presents results from decomposing the Entry row in Appendix Table G.21 using equation (18), by unemployment rate change. "Award," "Applicant share," "Interaction within award and apply," "Application," and "Eligibility" present the corresponding terms from equation (18).

Appendix Table H.42: Heterogeneity in SSDI entry decline by unemployment rate change

Unemp rate change	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Most improving labor market	-0.50	41.7	37.7	1.1
Moderately improving	-0.39	33.0	32.8	1.0
Least improving labor market	-0.16	13.8	16.9	0.8
Unknown	-0.14	11.6	12.6	0.9
Total	-1.19	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI entry rates in 2019 using 2010 as the base year by the change in the unemployment rate between 2010 and 2019. "Absolute contribution" uses the first terms of equation (16) with unemployment rate change group as the d groups; "contribution share" presents the same number as a percent of the total decline. "Baseline share" presents entrant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the entry decline. ZIP code is observed in the F831 or MEDIB file. We link ZIP code to Bureau of Labor Statistics Local Area Unemployment Statistics. "Most improving labor market" means that the change in the unemployment rate from 2010 to 2019 is in the top tercile. "Moderately improving" means in the middle tercile. "Least improving" means the bottom tercile.

H.2.9 Heterogeneity by local minimum wage

Appendix Table H.43: Heterogeneity in SSDI application decline by minimum wage change

Minimum wage change	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
No increase	-0.50	33.1	34.4	1.0
Small increase	-0.28	18.7	16.3	1.1
Some increase	-0.29	19.4	22.7	0.9
Large increase	-0.07	4.6	4.1	1.1
Unknown	-0.31	20.6	18.0	1.1
Missing	-0.05	3.6	4.5	0.8
Total	-1.51	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI application rates in 2019 using 2010 as the base year by the change in the minimum wage between 2010 and 2016. "Absolute contribution" uses equation (15) with minimum wage change group as the d groups; "contribution share" presents the same number as a percent of the total change. "Baseline share" presents applicant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the application decline. ZIP code is observed in the F831 or MEDIB file. We link ZIP code to minimum wage changes using data from Vaghul and Zipperer (2022). "No increase" means no change in minimum wage from 2010 to 2016. "Low increase" means an increase of \$1 or less between 2010 and 2016. "Some increase" means an increase of between \$1 and \$2 between 2010 and 2016. "Large increase" means an increase above \$2 between 2010 and 2016.

Appendix Table H.44: SSDI award decline by minimum wage change

	Absolute contribution (pp)	Contribution share (%)
Award	-55.70	102.9
Applicant share	0.07	-0.1
Interaction	1.48	-2.7
Total	-54.15	100.0

Notes: Table presents results from decomposing the Award row in Appendix Table G.18 using equation (16), by minimum wage change. "Award" corresponds to the first term in equation (16), "Applicant share" refers to the second term, and "Interaction" refers to the interaction term.

Appendix Table H.45: Heterogeneity in SSDI award decline by minimum wage change

Minimum wage change	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
No increase	-18.69	33.5	32.8	1.0
Small increase	-8.81	15.8	15.0	1.1
Some increase	-13.72	24.6	22.8	1.1
Large increase	-1.76	3.2	3.7	0.8
Unknown	-12.25	22.0	17.2	1.3
Missing	-0.48	0.9	8.4	0.1
Total	-55.70	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI award rates in 2019 using 2010 as the base year by the change in the minimum wage between 2010 and 2016. "Absolute contribution" uses the first terms of equation (16) with minimum wage change group as the d groups; "contribution share" presents the same number as a percent of the total decline. "Baseline share" presents entrant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the award decline. ZIP code is observed in the F831 or MEDIB file. We link ZIP code to minimum wage changes using data from Vaghul and Zipperer (2022). "No increase" means no change in minimum wage from 2010 to 2016. "Low increase" means an increase of $1 or less between 2010 and 2016. "Some increase" means an increase of between $1 and $2 between 2010 and 2016. "Large increase" means an increase above $2 between 2010 and 2016.

Appendix Table H.46: SSDI entry decline by minimum wage change

		Absolute contribution (pp)	Contribution share
Apply and award in Entry		-1.19	95.2
	Award	-0.55	44.3
	Application	-0.75	60.3
	Applicant share	0.00	-0.1
	Interaction within award and apply	0.12	-9.4
Eligibility		-0.09	7.5
Interaction with eligibility		0.03	-2.6
Total		-1.25	100.0

Notes: Table presents results from decomposing the Entry row in Appendix Table G.21 using equation (18), by minimum wage change. "Award," "Applicant share," "Interaction within award and apply," "Application," and "Eligibility" present the corresponding terms from equation (18).

Appendix Table H.47: Heterogeneity in SSDI entry decline by minimum wage change

Minimum wage change	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
No increase	-0.39	32.5	32.8	1.0
Small increase	-0.20	16.8	15.0	1.1
Some increase	-0.26	21.5	22.8	0.9
Large increase	-0.05	3.9	3.7	1.0
Unknown	-0.25	20.7	17.2	1.2
Missing	-0.05	4.6	8.4	0.5
Total	-1.19	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI entry rates in 2019 using 2010 as the base year by the change in the minimum wage between 2010 and 2016. "Absolute contribution" uses the first terms of equation (16) with minimum wage change group as the d groups; "contribution share" presents the same number as a percent of the total decline. "Baseline share" presents entrant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the entry decline. ZIP code is observed in the F831 or MEDIB file. We link ZIP code to minimum wage changes using data from Vaghul and Zipperer (2022). "No increase" means no change in minimum wage from 2010 to 2016. "Low increase" means an increase of $1 or less between 2010 and 2016. "Some increase" means an increase of between $1 and $2 between 2010 and 2016. "Large increase" means an increase above $2 between 2010 and 2016.

H.2.10 Heterogeneity by local economic mobility

Appendix Table H.48: Heterogeneity in SSDI application decline by economic mobility

Economic mobility	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
High mobility	-0.76	50.3	56.1	0.9
Low mobility	-0.59	39.1	35.8	1.1
Other	-0.11	7.0	3.6	1.9
Missing	-0.05	3.6	4.5	0.8
Total	-1.51	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI application rates in 2019 using 2010 as the base year by the Chetty et al. (2014a) county economic mobility classification. "Absolute contribution" uses equation (15) with mobility classification as the d groups; "contribution share" presents the same number as a percent of the total change. "Baseline share" presents applicant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the application decline. ZIP code is observed in the F831 or MEDIB file. We link ZIP code to counties and then to the Chetty et al. (2014a) county economic mobility classification. "High mobility" means the county is in the top three quartiles of the Chetty et al. (2014a) classification. "Low mobility" means the county is the bottom quartile of the Chetty et al. (2014a) classification.

Appendix Table H.49: SSDI award decline by economic mobility

	Absolute contribution (pp)	Contribution share (%)
Award	-55.19	101.9
Applicant share	-0.35	0.7
Interaction	1.39	-2.6
Total	-54.15	100.0

Notes: Table presents results from decomposing the Award row in Appendix Table G.18 using equation (16), by economic mobility. "Award" corresponds to the first term in equation (16), "Applicant share" refers to the second term, and "Interaction" refers to the interaction term.

Appendix Table H.50: Heterogeneity in SSDI award decline by economic mobility

Economic mobility	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
High mobility	-33.69	61.1	55.0	1.1
Low mobility	-17.25	31.2	32.8	1.0
Other	-3.77	6.8	3.8	1.8
Missing	-0.48	0.9	8.4	0.1
Total	-55.19	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI award rates in 2019 using 2010 as the base year by the Chetty et al. (2014a) county economic mobility classification. "Absolute contribution" uses the first terms of equation (16) with mobility classification as the d groups; "contribution share" presents the same number as a percent of the total decline. "Baseline share" presents entrant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the award decline. ZIP code is observed in the F831 or MEDIB file. We link ZIP code to counties and then to the Chetty et al. (2014a) county economic mobility classification. "High mobility" means the county is in the top three quartiles of the Chetty et al. (2014a) classification. "Low mobility" means the county is the bottom quartile of the Chetty et al. (2014a) classification.

Appendix Table H.51: SSDI entry decline by economic mobility

		Absolute contribution (pp)	Contribution share
Apply and award in Entry		-1.19	95.2
	Award	-0.55	43.8
	Application	-0.75	60.3
	Applicant share	-0.00	0.3
	Interaction within award and apply	0.12	-9.3
Eligibility		-0.09	7.5
Interaction with eligibility		0.03	-2.6
Total		-1.25	100.0

Notes: Table presents results from decomposing the Entry row in Appendix Table G.21 using equation (18), by economic mobility. "Award," "Applicant share," "Interaction within award and apply," "Application," and "Eligibility" present the corresponding terms from equation (18).

Appendix Table H.52: Heterogeneity in SSDI entry decline by economic mobility

Economic mobility	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
High mobility	-0.64	53.7	55.0	1.0
Low mobility	-0.41	34.8	32.8	1.1
Other	-0.08	6.9	3.8	1.8
Missing	-0.05	4.6	8.4	0.5
Total	-1.19	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI entry rates in 2019 using 2010 as the base year by the Chetty et al. (2014a) county economic mobility classification. "Absolute contribution" uses the first terms of equation (16) with mobility classification as the d groups; "contribution share" presents the same number as a percent of the total decline. "Baseline share" presents entrant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the entry decline. ZIP code is observed in the F831 or MEDIB file. We link ZIP code to counties and then to the Chetty et al. (2014a) county economic mobility classification. "High mobility" means the county is in the top three quartiles of the Chetty et al. (2014a) classification. "Low mobility" means the county is the bottom quartile of the Chetty et al. (2014a) classification.

H.2.11 Heterogeneity by local opioid crisis severity

Appendix Table H.53: Heterogeneity in SSDI application decline by opioid crisis severity

Opioid severity	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Less affected	-0.98	65.1	67.4	1.0
More affected	-0.14	9.4	8.4	1.1
Other	-0.33	21.9	19.7	1.1
Missing	-0.05	3.6	4.5	0.8
Total	-1.51	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI application rates in 2019 using 2010 as the base year by the severity of the opioid crisis. "Absolute contribution" uses equation (15) with opioid crisis severity as the d groups; "contribution share" presents the same number as a percent of the total change. "Baseline share" presents applicant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the application decline. ZIP code is observed in the F831 or MEDIB file. We link ZIP code to counties and then to the county opioid death rate between 1999 and 2010 from the Centers for Disease Control and Prevention, National Center for Health Statistics (2021). "Less affected" means that the county is in the bottom three quartiles of opioid death rate from 1999 to 2010. "More affected" means that the county is in the top quartile of the opioid death rate from 1999 to 2010.

Appendix Table H.54: SSDI award decline by opioid crisis severity

	Absolute contribution (pp)	Contribution share (%)
Award	-55.37	102.3
Applicant share	-0.15	0.3
Interaction	1.37	-2.5
Total	-54.15	100.0

Notes: Table presents results from decomposing the Award row in Appendix Table G.18 using equation (16), by opioid crisis severity. "Award" corresponds to the first term in equation (16), "Applicant share" refers to the second term, and "Interaction" refers to the interaction term.

Appendix Table H.55: Heterogeneity in SSDI award decline by opioid crisis severity

Opioid severity	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Less affected	-36.63	66.2	64.5	1.0
More affected	-5.27	9.5	8.0	1.2
Other	-13.00	23.5	19.0	1.2
Missing	-0.48	0.9	8.4	0.1
Total	-55.37	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI award rates in 2019 using 2010 as the base year by the severity of the opioid crisis. "Absolute contribution" uses the first terms of equation (16) with opioid crisis severity as the d groups; "contribution share" presents the same number as a percent of the total decline. "Baseline share" presents entrant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the award decline. ZIP code is observed in the F831 or MEDIB file. We link ZIP code to counties and then to the county opioid death rate between 1999 and 2010 from the Centers for Disease Control and Prevention, National Center for Health Statistics (2021). "Less affected" means that the county is in the bottom three quartiles of opioid death rate from 1999 to 2010. "More affected" means that the county is in the top quartile of the opioid death rate from 1999 to 2010.

Appendix Table H.56: SSDI entry decline by opioid crisis severity

		Absolute contribution (pp)	Contribution share
Apply and award in Entry		-1.19	95.2
	Award	-0.55	44.0
	Application	-0.75	60.3
	Applicant share	-0.00	0.1
	Interaction within award and apply	0.12	-9.3
Eligibility		-0.09	7.5
Interaction with eligibility		0.03	-2.6
Total		-1.25	100.0

Notes: Table presents results from decomposing the Entry row in Appendix Table G.21 using equation (18), by opioid crisis severity. "Award," "Applicant share," "Interaction within award and apply," "Application," and "Eligibility" present the corresponding terms from equation (18).

Appendix Table H.57: Heterogeneity in SSDI entry decline by opioid crisis severity

Opioid severity	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Less affected	-0.77	64.6	64.5	1.0
More affected	-0.11	9.0	8.0	1.1
Other	-0.26	21.9	19.0	1.2
Missing	-0.05	4.6	8.4	0.5
Total	-1.19	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI entry rates in 2019 using 2010 as the base year by the severity of the opioid crisis. "Absolute contribution" uses the first terms of equation (16) with opioid crisis severity as the d groups; "contribution share" presents the same number as a percent of the total decline. "Baseline share" presents entrant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the entry decline. ZIP code is observed in the F831 or MEDIB file. We link ZIP code to counties and then to the county opioid death rate between 1999 and 2010 from the Centers for Disease Control and Prevention, National Center for Health Statistics (2021). "Less affected" means that the county is in the bottom three quartiles of opioid death rate from 1999 to 2010. "More affected" means that the county is in the top quartile of the opioid death rate from 1999 to 2010.

H.2.12 Heterogeneity by local smoking rates

Appendix Table H.58: Heterogeneity in SSDI application decline by smoking rates

Smoke	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Lowest quartile	-0.37	24.6	25.9	0.9
Second quartile	-0.36	24.1	26.1	0.9
Third quartile	-0.34	22.4	21.5	1.0
Highest quartile	-0.22	14.8	15.2	1.0
Unknown	-0.16	10.5	6.8	1.5
Missing	-0.05	3.6	4.5	0.8
Total	-1.51	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI application rates in 2019 using 2010 as the base year by county smoking rate from 2010–16. "Absolute contribution" uses equation (15) with county smoking rate as the d groups; "contribution share" presents the same number as a percent of the total change. "Baseline share" presents applicant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the application decline. ZIP code is observed in the F831 or MEDIB file. We link ZIP code to counties and then to the county smoking rate between 2010 and 2016 from the County Health Rankings & Roadmaps (2025). We group counties by quartile of smoking rate.

Appendix Table H.59: SSDI award decline by smoking rates

	Absolute contribution (pp)	Contribution share (%)
Award	-55.38	102.3
Applicant share	-0.57	1.1
Interaction	1.80	-3.3
Total	-54.15	100.0

Notes: Table presents results from decomposing the Award row in Appendix Table G.18 using equation (16), by smoking rates. "Award" corresponds to the first term in equation (16), "Applicant share" refers to the second term, and "Interaction" refers to the interaction term.

Appendix Table H.60: Heterogeneity in SSDI award decline by smoking rates

Smoke	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Lowest quartile	-14.51	26.2	24.7	1.1
Second quartile	-14.37	25.9	25.3	1.0
Third quartile	-11.65	21.0	20.5	1.0
Highest quartile	-8.65	15.6	14.3	1.1
Unknown	-5.71	10.3	6.9	1.5
Missing	-0.48	0.9	8.4	0.1
Total	-55.38	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI award rates in 2019 using 2010 as the base year by county smoking rate from 2010–16. "Absolute contribution" uses the first terms of equation (16) with county smoking rate as the d groups; "contribution share" presents the same number as a percent of the total decline. "Baseline share" presents entrant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the award decline. ZIP code is observed in the F831 or MEDIB file. We link ZIP code to counties and then to the county smoking rate between 2010 and 2016 from the County Health Rankings & Roadmaps (2025). We group counties by quartile of smoking rate.

Appendix Table H.61: SSDI entry decline by smoking rates

		Absolute contribution (pp)	Contribution share
Apply and award in Entry		-1.19	95.2
	Award	-0.55	44.0
	Application	-0.75	60.3
	Applicant share	-0.01	0.5
	Interaction within award and apply	0.12	-9.6
Eligibility		-0.09	7.5
Interaction with eligibility		0.03	-2.6
Total		-1.25	100.0

Notes: Table presents results from decomposing the Entry row in Appendix Table G.21 using equation (18), by smoking rates. "Award," "Applicant share," "Interaction within award and apply," "Application," and "Eligibility" present the corresponding terms from equation (18).

Appendix Table H.62: Heterogeneity in SSDI entry decline by smoking rates

Smoke	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Lowest quartile	-0.30	25.1	24.7	1.0
Second quartile	-0.29	24.7	25.3	1.0
Third quartile	-0.26	21.4	20.5	1.0
Highest quartile	-0.17	14.0	14.3	1.0
Unknown	-0.12	10.2	6.9	1.5
Missing	-0.05	4.5	8.4	0.5
Total	-1.19	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI entry rates in 2019 using 2010 as the base year by county smoking rate from 2010–16. "Absolute contribution" uses the first terms of equation (16) with county smoking rate as the d groups; "contribution share" presents the same number as a percent of the total decline. "Baseline share" presents entrant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the entry decline. ZIP code is observed in the F831 or MEDIB file. We link ZIP code to counties and then to the county smoking rate between 2010 and 2016 from the County Health Rankings & Roadmaps (2025). We group counties by quartile of smoking rate.

H.2.13 Heterogeneity by applicant pre-application industry

Appendix Table H.63: Heterogeneity in SSDI application decline by pre-application industry

Recent industry	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Military	0.01	-0.7	0.6	-1.2
Ag/mining/utilities/construction	-0.18	12.2	8.0	1.5
Manufacturing	-0.20	13.3	8.6	1.5
Wholesale/retail/transportation	-0.17	11.2	10.2	1.1
White collar/management	-0.15	9.8	11.0	0.9
Education/health care/govt	-0.25	16.3	18.1	0.9
No Earning	0.03	-1.7	3.7	-0.5
Employed, likely small employer	-0.54	36.0	35.2	1.0
Missing	-0.05	3.6	4.5	0.8
Total	-1.51	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI application rates in 2019 using 2010 as the base year by industry in which the applicant worked in the three years before application. "Absolute contribution" uses equation (15) with pre-application industry as the d groups; "contribution share" presents the same number as a percent of the total change. "Baseline share" presents applicant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the application decline. The EIN of the applicant's employer is observed in the Detailed Earnings File. We link EIN to the Department of Labor Form 5500 to determine NAICS classification. "Employed, likely small employer" means that the applicant had an employer but the employer's EIN is not listed in Form 5500.

Appendix Table H.64: SSDI award decline by pre-application industry

	Absolute contribution (pp)	Contribution share (%)
Award	-52.32	96.6
Applicant share	-4.36	8.1
Interaction	2.53	-4.7
Total	-54.15	100.0

Notes: Table presents results from decomposing the Award row in Appendix Table G.18 using equation (16), by pre-application industry. "Award" corresponds to the first term in equation (16), "Applicant share" refers to the second term, and "Interaction" refers to the interaction term.

Appendix Table H.65: Heterogeneity in SSDI award decline by pre-application industry

Recent industry	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Military	-1.01	1.9	0.7	2.9
Ag/mining/utilities/construction	-3.65	7.0	7.6	0.9
Manufacturing	-3.91	7.5	9.0	0.8
Wholesale/retail/transportation	-5.43	10.4	9.7	1.1
White collar/management	-6.83	13.1	10.5	1.2
Education/health care/govt	-9.09	17.4	17.3	1.0
No Earning	-1.89	3.6	1.5	2.5
Employed, likely small employer	-20.03	38.3	35.3	1.1
Missing	-0.48	0.9	8.4	0.1
Total	-52.32	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI award rates in 2019 using 2010 as the base year by industry in which the applicant worked in the three years before application. "Absolute contribution" uses the first terms of equation (16) with pre-application industry as the d groups; "contribution share" presents the same number as a percent of the total decline. "Baseline share" presents entrant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the award decline. The EIN of the applicant's employer is observed in the Detailed Earnings File. We link EIN to the Department of Labor Form 5500 to determine NAICS classification. "Employed, likely small employer" means that the applicant had an employer but the employer's EIN is not listed in Form 5500.

Appendix Table H.66: SSDI entry decline by pre-application industry

		Absolute contribution (pp)	Contribution share
Apply and award in Entry		-1.19	95.2
	Award	-0.52	41.6
	Application	-0.75	60.3
	Applicant share	-0.04	3.5
	Interaction within award and apply	0.13	-10.2
Eligibility		-0.09	7.5
Interaction with eligibility		0.03	-2.6
Total		-1.25	100.0

Notes: Table presents results from decomposing the Entry row in Appendix Table G.21 using equation (18), by pre-application industry. "Award," "Applicant share," "Interaction within award and apply," "Application," and "Eligibility" present the corresponding terms from equation (18).

Appendix Table H.67: Heterogeneity in SSDI entry decline by pre-application industry

Recent industry	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Military	-0.00	0.3	0.7	0.4
Ag/mining/utilities/construction	-0.11	9.3	7.6	1.2
Manufacturing	-0.14	11.5	9.0	1.3
Wholesale/retail/transportation	-0.12	10.4	9.7	1.1
White collar/management	-0.12	10.5	10.5	1.0
Education/health care/govt	-0.19	15.6	17.3	0.9
No Earning	-0.02	1.3	1.5	0.9
Employed, likely small employer	-0.43	36.4	35.3	1.0
Missing	-0.05	4.6	8.4	0.5
Total	-1.19	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI entry rates in 2019 using 2010 as the base year by industry in which the applicant worked in the three years before application. "Absolute contribution" uses the first terms of equation (16) with pre-application industry as the d groups; "contribution share" presents the same number as a percent of the total decline. "Baseline share" presents entrant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the entry decline. The EIN of the applicant's employer is observed in the Detailed Earnings File. We link EIN to the Department of Labor Form 5500 to determine NAICS classification. "Employed, likely small employer" means that the applicant had an employer but the employer's EIN is not listed in Form 5500.

H.2.14 Heterogeneity by applicant pre-application industry remote work

Appendix Table H.68: Heterogeneity in SSDI application decline by pre-application remote work

Work-from-home rates	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Low WFH	-0.06	3.8	3.3	1.2
Moderate WFH	-0.34	22.6	16.1	1.4
Substantial WFH	-0.21	14.2	13.4	1.1
High WFH	-0.32	21.4	22.6	0.9
Employed, unknown WFH	-0.54	36.0	36.3	1.0
Unemployed	0.03	-1.7	3.7	-0.5
Missing	-0.05	3.6	4.5	0.8
Total	-1.51	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI application rates in 2019 using 2010 as the base year by what share of jobs can be done remotely as classified by Dingel and Neiman (2020). "Absolute contribution" uses equation (15) with pre-application remote work share as the d groups; "contribution share" presents the same number as a percent of the total change. "Baseline share" presents applicant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the application decline. The EIN of the applicant's employer is observed in the Detailed Earnings File. We link EIN to the Department of Labor Form 5500 to determine NAICS classification, then to the Dingel and Neiman (2020) classification of share of jobs that can be done remotely. "Low WFH" means that fewer than 10% of jobs can be done remotely. "Moderate WFH" means that between 10% and 25% of jobs in the industry can be done remotely. "Substantial WFH" means that between 25% and 50% of jobs in the industry can be done remotely. "High WFH" means that more than 50% of jobs in the industry can be done remotely.

Appendix Table H.69: SSDI award decline by pre-application remote work

	Absolute contribution (pp)	Contribution share (%)
Award	-51.96	96.0
Applicant share	-3.99	7.4
Interaction	1.80	-3.3
Total	-54.15	100.0

Notes: Table presents results from decomposing the Award row in Appendix Table G.18 using equation (16), by pre-application remote work. "Award" corresponds to the first term in equation (16), "Applicant share" refers to the second term, and "Interaction" refers to the interaction term.

Appendix Table H.70: Heterogeneity in SSDI award decline by pre-application remote work

Work-from-home rates	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Low WFH	-1.86	3.6	2.9	1.2
Moderate WFH	-7.24	13.9	16.2	0.9
Substantial WFH	-7.41	14.3	12.7	1.1
High WFH	-11.95	23.0	21.9	1.1
Employed, unknown WFH	-21.13	40.7	36.5	1.1
Unemployed	-1.89	3.6	1.5	2.5
Missing	-0.48	0.9	8.4	0.1
Total	-51.96	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI award rates in 2019 using 2010 as the base year by what share of jobs can be done remotely as classified by Dingel and Neiman (2020). "Absolute contribution" uses the first terms of equation (16) with pre-application remote work share as the d groups; "contribution share" presents the same number as a percent of the total decline. "Baseline share" presents entrant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the award decline. The EIN of the applicant's employer is observed in the Detailed Earnings File. We link EIN to the Department of Labor Form 5500 to determine NAICS classification, then to the Dingel and Neiman (2020) classification of share of jobs that can be done remotely. "Low WFH" means that fewer than 10% of jobs can be done remotely. "Moderate WFH" means that between 10% and 25% of jobs in the industry can be done remotely. "Substantial WFH" means that between 25% and 50% of jobs in the industry can be done remotely. "High WFH" means that more than 50% of jobs in the industry can be done remotely.

Appendix Table H.71: SSDI entry decline by pre-application remote work

		Absolute contribution (pp)	Contribution share
Apply and award in Entry		-1.19	95.2
	Award	-0.52	41.3
	Application	-0.75	60.3
	Applicant share	-0.04	3.2
	Interaction within award and apply	0.12	-9.6
Eligibility		-0.09	7.5
Interaction with eligibility		0.03	-2.6
Total		-1.25	100.0

Notes: Table presents results from decomposing the Entry row in Appendix Table G.21 using equation (18), by pre-application remote work. "Award," "Applicant share," "Interaction within award and apply," "Application," and "Eligibility" present the corresponding terms from equation (18).

Appendix Table H.72: Heterogeneity in SSDI entry decline by pre-application remote work

Work-from-home rates	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Low WFH	-0.04	3.0	2.9	1.1
Moderate WFH	-0.23	19.4	16.2	1.2
Substantial WFH	-0.16	13.5	12.7	1.1
High WFH	-0.25	20.9	21.9	1.0
Employed, unknown WFH	-0.44	37.4	36.5	1.0
Unemployed	-0.02	1.3	1.5	0.9
Missing	-0.05	4.6	8.4	0.5
Total	-1.19	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI entry rates in 2019 using 2010 as the base year by what share of jobs can be done remotely as classified by Dingel and Neiman (2020). "Absolute contribution" uses the first terms of equation (16) with pre-application remote work share as the d groups; "contribution share" presents the same number as a percent of the total decline. "Baseline share" presents entrant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the entry decline. The EIN of the applicant's employer is observed in the Detailed Earnings File. We link EIN to the Department of Labor Form 5500 to determine NAICS classification, then to the Dingel and Neiman (2020) classification of share of jobs that can be done remotely. "Low WFH" means that fewer than 10% of jobs can be done remotely. "Moderate WFH" means that between 10% and 25% of jobs in the industry can be done remotely. "Substantial WFH" means that between 25% and 50% of jobs in the industry can be done remotely. "High WFH" means that more than 50% of jobs in the industry can be done remotely.

H.2.15 Heterogeneity by applicant pre-application employment

Appendix Table H.73: Heterogeneity in SSDI application decline by pre-application years of work

Pre-app employment	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
No earning	0.03	-1.9	3.8	-0.5
Earnings in some years	-0.12	8.0	17.1	0.5
Earnings in all years	-1.36	90.3	74.6	1.2
Missing	-0.05	3.6	4.5	0.8
Total	-1.51	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI application rates in 2019 using 2010 as the base year by how many years of the 5 years before application the applicant worked. "Absolute contribution" uses equation (15) with pre-application work years as the d groups; "contribution share" presents the same number as a percent of the total change. "Baseline share" presents applicant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the application decline. "No earnings" means the applicant did not work in any of the 5 years before application. "Earnings in some years" means the applicant worked for 1-3 years of the 5 years before application. "Earnings in all years" means the applicant worked for 4-5 years of the 5 years before application.

Appendix Table H.74: SSDI award decline by pre-application years of work

	Absolute contribution (pp)	Contribution share (%)
Award	-49.14	90.7
Applicant share	-6.48	12.0
Interaction	1.47	-2.7
Total	-54.15	100.0

Notes: Table presents results from decomposing the Award row in Appendix Table G.18 using equation (16), by pre-application years of work. "Award" corresponds to the first term in equation (16), "Applicant share" refers to the second term, and "Interaction" refers to the interaction term.

Appendix Table H.75: Heterogeneity in SSDI award decline by pre-application years of work

Pre-app employment	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
No earning	-1.93	3.9	1.5	2.6
Earnings in some years	-9.57	19.5	13.5	1.4
Earnings in all years	-37.15	75.6	76.6	1.0
Missing	-0.48	1.0	8.4	0.1
Total	-49.14	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI award rates in 2019 using 2010 as the base year by how many years of the 5 years before application the applicant worked. "Absolute contribution" uses the first terms of equation (16) with pre-application work years as the d groups; "contribution share" presents the same number as a percent of the total decline. "Baseline share" presents entrant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the award decline. "No earnings" means the applicant did not work in any of the 5 years before application. "Earnings in some years" means the applicant worked for 1-3 years of the 5 years before application. "Earnings in all years" means the applicant worked for 4-5 years of the 5 years before application.

Appendix Table H.76: SSDI entry decline by pre-application years of work

		Absolute contribution (pp)	Contribution share
Apply and award in Entry		-1.19	95.2
	Award	-0.49	39.0
	Application	-0.75	60.3
	Applicant share	-0.06	5.1
	Interaction within award and apply	0.12	-9.4
Eligibility		-0.09	7.5
Interaction with eligibility		0.03	-2.6
Total		-1.25	100.0

Notes: Table presents results from decomposing the Entry row in Appendix Table G.21 using equation (18), by pre-application years of work. "Award," "Applicant share," "Interaction within award and apply," "Application," and "Eligibility" present the corresponding terms from equation (18).

Appendix Table H.77: Heterogeneity in SSDI entry decline by pre-application years of work

Pre-app employment	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
No earning	-0.02	1.3	1.5	0.9
Earnings in some years	-0.12	10.4	13.5	0.8
Earnings in all years	-1.00	83.7	76.6	1.1
Missing	-0.05	4.6	8.4	0.5
Total	-1.19	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI entry rates in 2019 using 2010 as the base year by how many years of the 5 years before application the applicant worked. “Absolute contribution” uses the first terms of equation (16) with pre-application work years as the d groups; “contribution share” presents the same number as a percent of the total decline. “Baseline share” presents entrant shares in 2007. “Contribution/baseline” presents the ratio of “contribution share” to “baseline share,” indicating whether that subgroup is under- (<1) or over- (>1) represented in the entry decline. “No earnings” means the applicant did not work in any of the 5 years before application. “Earnings in some years” means the applicant worked for 1-3 years of the 5 years before application. “Earnings in all years” means the applicant worked for 4-5 years of the 5 years before application.

H.2.16 Heterogeneity by applicant pre-application employment (FTFY)

Appendix Table H.78: Heterogeneity in SSDI application decline by pre-application employment

Pre-app FTFY employment	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
No FTFY earning	-0.32	21.4	22.1	1.0
FTFY earnings in some years	-0.51	33.6	31.5	1.1
FTFY earnings in all years	-0.62	41.4	42.0	1.0
Missing	-0.05	3.6	4.5	0.8
Total	-1.51	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI application rates in 2019 using 2010 as the base year by how many years of the 5 years before application the applicant earned more than $15,000. “Absolute contribution” uses equation (15) with pre-application work years as the d groups; “contribution share” presents the same number as a percent of the total change. “Baseline share” presents applicant shares in 2007. “Contribution/baseline” presents the ratio of “contribution share” to “baseline share,” indicating whether that subgroup is under- (<1) or over- (>1) represented in the application decline. “No earnings” means the applicant did not work in any of the 5 years before application. “Earnings in some years” means the applicant earned more than $15,000 for 1-3 years of the 5 years before application. “Earnings in all years” means the applicant earned more than $15,000 for 4-5 years of the 5 years before application.

Appendix Table H.79: SSDI award decline by pre-application employment

	Absolute contribution (pp)	Contribution share (%)
Award	-55.71	102.9
Applicant share	0.52	-1.0
Interaction	1.05	-1.9
Total	-54.15	100.0

Notes: Table presents results from decomposing the Award row in Appendix Table G.18 using equation (16), by pre-application employment. “Award” corresponds to the first term in equation (16), “Applicant share” refers to the second term, and “Interaction” refers to the interaction term.

Appendix Table H.80: Heterogeneity in SSDI award decline by pre-application employment

Pre-app FTFY employment	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
No FTFY earning	-12.45	22.3	13.8	1.6
FTFY earnings in some years	-20.61	37.0	28.1	1.3
FTFY earnings in all years	-22.18	39.8	49.6	0.8
Missing	-0.48	0.9	8.4	0.1
Total	-55.71	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI award rates in 2019 using 2010 as the base year by how many years of the 5 years before application the applicant earned more than \$15,000. "Absolute contribution" uses the first terms of equation (16) with pre-application work years as the d groups; "contribution share" presents the same number as a percent of the total decline. "Baseline share" presents entrant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the award decline. "No earnings" means the applicant did not work in any of the 5 years before application. "Earnings in some years" means the applicant earned more than \$15,000 for 1-3 years of the 5 years before application. "Earnings in all years" means the applicant earned more than \$15,000 for 4-5 years of the 5 years before application.

Appendix Table H.81: SSDI entry decline by pre-application employment

		Absolute contribution (pp)	Contribution share
Apply and award in Entry		-1.19	95.2
	Award	-0.55	44.3
	Application	-0.75	60.3
	Applicant share	0.01	-0.4
	Interaction within award and apply	0.11	-9.0
Eligibility		-0.09	7.5
Interaction with eligibility		0.03	-2.6
Total		-1.25	100.0

Notes: Table presents results from decomposing the Entry row in Appendix Table G.21 using equation (18), by pre-application employment. "Award," "Applicant share," "Interaction within award and apply," "Application," and "Eligibility" present the corresponding terms from equation (18).

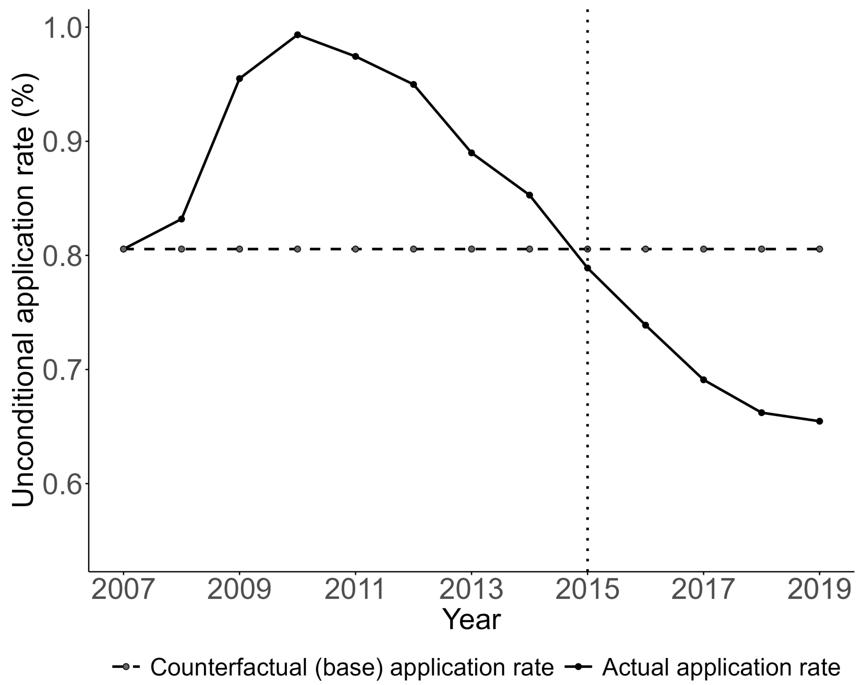
Appendix Table H.82: Heterogeneity in SSDI entry decline by pre-application employment

Pre-app FTFY employment	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
No FTFY earning	-0.18	15.2	13.8	1.1
FTFY earnings in some years	-0.39	32.4	28.1	1.2
FTFY earnings in all years	-0.57	47.8	49.6	1.0
Missing	-0.05	4.6	8.4	0.5
Total	-1.19	100.0	100.0	1.0

Notes: Table presents results from decomposing the difference between actual and counterfactual SSDI entry rates in 2019 using 2010 as the base year by how many years of the 5 years before application the applicant earned more than \$15,000. "Absolute contribution" uses the first terms of equation (16) with pre-application work years as the d groups; "contribution share" presents the same number as a percent of the total decline. "Baseline share" presents entrant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the entry decline. "No earnings" means the applicant did not work in any of the 5 years before application. "Earnings in some years" means the applicant earned more than \$15,000 for 1-3 years of the 5 years before application. "Earnings in all years" means the applicant earned more than \$15,000 for 4-5 years of the 5 years before application.

H.3 SSDI in Great Recession (2007–2014) and post-Great Recession period (2015–2019)

Appendix Figure H.1: Counterfactual vs actual SSDI application rate, 2007–2014 and 2015–2019



Notes: Figure plots actual and counterfactual SSDI application rate in each year from 2007 to 2019. Actual application rate uses the Continuous Work History Sample linked to the Payment History Update System and the Master Beneficiary Record. Counterfactual application rate uses equations (2), (3), and (4), using 2007 as the base year. The exact annual values are given in Appendix Table H.83.

Appendix Table H.83: Counterfactual vs actual SSDI application rate, 2007–2014 and 2015–2019

Period	Year	Actual application rate (%)	Counterfactual (base) application rate (%)	Total difference (pp)
Great Recession				
	2007	0.81	0.81	0.00
	2008	0.83	0.81	0.03
	2009	0.95	0.81	0.15
	2010	0.99	0.81	0.19
	2011	0.97	0.81	0.17
	2012	0.95	0.81	0.14
	2013	0.89	0.81	0.08
	2014	0.85	0.81	0.05
	Total			0.81
Post Great Recession				
	2015	0.79	0.81	-0.02
	2016	0.74	0.81	-0.07
	2017	0.69	0.81	-0.11
	2018	0.66	0.81	-0.14
	2019	0.65	0.81	-0.15
	Total			-0.49

Table presents actual and counterfactual SSDI application rate in each year from 2007 to 2019. Actual SSDI application rate uses the Continuous Work History Sample linked to the Payment History Update System and the Master Beneficiary Record. Counterfactual SSDI application rate uses equations (2), (3), and (4), using 2010 as the base year.

Appendix Table H.84: Decomposition of decline in SSDI application rate, 2007–2014 and 2015–2019

Period	Variable	Absolute contribution (pp)	As a share of total (%)
Great Recession			
	Application	0.89	66.1
	Eligibility	-0.09	-9.0
	Interaction within apply	-0.02	-1.8
	Across group composition	0.04	3.8
	Within-across interaction	-0.01	-0.7
	Total	0.81	58.3
Post Great Recession			
	Application	-0.34	17.3
	Eligibility	-0.15	24.3
	Interaction within apply	0.01	-0.3
	Across group composition	-0.02	0.6
	Within-across interaction	0.01	-0.2
	Total	-0.49	41.7

Notes: Table presents decomposition of SSDI application rate decline from 2007 to 2014 (Great Recession) and 2015 to 2019 (post-Great Recession), using equation (12). The point estimates we report are the ones in which flows (e.g., B_t, A_t, E_t, X_t), when fixed, are held fixed at their counterfactual values.

Appendix Table H.85: Heterogeneity in SSDI application change by severity during Great Recession (2007–2014) and post-GR (2015–2019)

Period	Diagnosis	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Great Recession					
	Musculoskeletal	0.43	48.2	32.0	1.5
	Mental	0.23	25.7	18.7	1.4
	Cardiovascular	0.03	3.1	7.6	0.4
	Endocrine	0.00	0.5	3.7	0.1
	Other	0.23	25.7	33.6	0.8
	Missing	-0.03	-3.2	4.5	-0.7
	Total	0.89	100.0	100.0	1.0
Post Great Recession					
	Musculoskeletal	0.02	-5.7	32.0	-0.2
	Mental	-0.07	19.9	18.7	1.1
	Cardiovascular	-0.08	22.0	7.6	2.9
	Endocrine	-0.07	20.3	3.7	5.4
	Other	-0.11	31.3	33.6	0.9
	Missing	-0.04	12.2	4.5	2.7
	Total	-0.34	100.0	100.0	1.0

Notes: Table presents results from decomposing the Application row in Appendix Table G.15 using equation (15), by diagnosis. "Absolute contribution" reports results from equation (15) with diagnosis as the *d* groups; "contribution share" presents the same number as a percent of the total decline. "Baseline share" presents entrant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the entry decline.

Appendix Table H.86: Heterogeneity in SSDI application change by severity during Great Recession (2007–2014) and post-GR (2015–2019)

Period	Severity	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/baseline
Great Recession					
	Least severe	0.71	80.4	62.4	1.3
	Moderately severe	0.05	5.7	12.6	0.4
	Most severe	0.15	17.1	20.5	0.8
	Unknown	-0.03	-3.2	4.5	-0.7
	Total	0.89	100.0	100.0	1.0
Post Great Recession					
	Least severe	-0.04	12.5	62.4	0.2
	Moderately severe	-0.12	34.0	12.6	2.7
	Most severe	-0.14	41.3	20.5	2.0
	Unknown	-0.04	12.2	4.5	2.7
	Total	-0.34	100.0	100.0	1.0

Notes: Table presents results from decomposing the Application row in Appendix Table G.15 using equation (15), by severity. "Absolute contribution" reports results from equation (15) with severity levels as the *d* groups; "contribution share" presents the same number as a percent of the total decline. "Baseline share" presents entrant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the entry decline. "Least severe" means that the applicant was rejected at the disability examiner level (but could have been allowed on appeal). "Moderately severe" means that the disability examiner assigned a diary reason of "medical improvement expected" or "medical improvement possible." "Most severe" means that the disability examiner assigned a diary reason of "medical improvement not expected."

Appendix Table H.87: Heterogeneity in SSDI application change by local unemployment rate change during Great Recession (2007–2014) and post-GR (2015–2019)

Period	Unemp rate change (07-14)	Absolute contribution (pp)	Contribution share (%)	Baseline share (%)	Contribution/ baseline
Great Recession					
	Most improving labor market	0.13	14.4	18.3	0.8
	Moderately improving	0.34	38.0	35.7	1.1
	Least improving labor market	0.42	47.0	37.4	1.3
	Unknown	0.01	0.6	8.5	0.1
	Total	0.89	100.0	100.0	1.0
Post Great Recession					
	Most improving labor market	-0.08	24.0	18.3	1.3
	Moderately improving	-0.11	33.4	35.7	0.9
	Least improving labor market	-0.07	19.0	37.4	0.5
	Unknown	-0.08	23.5	8.5	2.8
	Total	-0.34	100.0	100.0	1.0

Notes: Table presents results from decomposing the Application row in Appendix Table G.15 using equation (15), by local unemployment rate change. "Absolute contribution" reports results from equation (15) with unemployment rate categories as the d groups; "contribution share" presents the same number as a percent of the total decline. "Baseline share" presents entrant shares in 2007. "Contribution/baseline" presents the ratio of "contribution share" to "baseline share," indicating whether that subgroup is under- (<1) or over- (>1) represented in the entry decline. ZIP code is observed in the F831 or MEDIB file. We link ZIP code to Bureau of Labor Statistics Local Area Unemployment Statistics. "Most improving labor market" means that the change in the unemployment rate from 2010 to 2019 is in the top tercile. "Moderately improving" means in the middle tercile. "Least improving" means the bottom tercile.