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WHY DOES DISABILITY INCREASE DURING RECESSIONS? EVIDENCE FROM MEDICARE

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ABSTRACT

Social Security Disability Insurance (DI) awards rise in recessions, especially for workers over age 50. We use Medicare data to investigate how health, entry costs, and age-based DI eligibility rules shape this pattern. Recession-induced entrants have lower medical spending and mortality than typical recipients. The entry response to unemployment jumps 2–4 fold at ages 50 and 55, when eligibility rules relax. Using these age-based discontinuities as instruments, we find no difference in marginal entrants' health across unemployment levels. These findings demonstrate that DI's age-based eligibility rules play a major role in driving cyclical entry, while health shocks do not.

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1 Introduction

During recessions, awards of Social Security Disability Insurance (DI)—the federal safety net program for workers with work-limiting impairments—increase substantially, particularly among workers over age 50 (Black, Daniel and Sanders, 2002; Autor and Duggan, 2003; Liebman, 2015; Maestas, Mullen and Strand, 2021; Charles, Li and Stephens Jr, 2018). While this pattern is well established, much less is known about what drives these countercyclical inflows. This paper examines whether recession-induced DI entry reflects worsening health or reduced opportunity costs of program participation, and how age-based DI eligibility rules shape these dynamics.

We consider two broad channels through which recessions may increase DI enrollment, following Cutler, Meara and Richards-Shubik (2012). The first is a "health shock" channel: recessions may worsen health through job loss, income uncertainty, and stress, pushing more workers past DI's medical threshold (Sullivan and von Wachter, 2009; Schaller and Stevens, 2015; Schwandt, 2018; Coile, Levine and McKnight, 2014). Reduced work intensity, healthier behaviors, or a healthier environment could alternatively improve health and reduce DI qualifications (Ruhm, 2000; Finkelstein et al., 2025). The second is an "entry-cost" channel: weak labor markets reduce the opportunity cost of DI's strict earnings limits. This channel may be particularly strong for older workers, as DI applies more lenient eligibility standards to those approaching retirement age. If recessions primarily activate the health-shock channel and increase the number of workers with disabling conditions, DI serves its primary purpose by admitting those newly impaired. Conversely, while entry through the entry-cost channel could provide insurance against recession-induced earnings losses (Deshpande and Lockwood, 2022), DI was not intended for this purpose, and its de facto permanence and strict earnings restrictions make it a costly and incomplete form of insurance against temporary downturns.

Distinguishing between these channels requires addressing two main challenges. The first is measurement: linking the health of DI entrants to economic conditions at application requires more detailed health data than is currently available through the Social Security Administration (SSA), which administers the DI program. The second is identification: recessions could activate both channels simultaneously, and thus cyclicality in enrollment and entrant health alone is insufficient to determine their respective roles. For example, finding that high unemployment is associated with more and healthier DI entrants would be consistent with reduced entry costs alone attracting healthier applicants (von Wachter, Song and Manchester, 2011), adverse health shocks that harm marginal entrants but leave them healthier than typical DI recipients, or even improved health during recessions offset by sufficiently large reductions in entry costs. Without separating these mechanisms, analyses that ignore health shocks could either overstate or understate the role of labor market opportunities and other entry costs in driving DI entry during recessions.

We overcome these challenges through a novel combination of data on the health of DI recipients, local unemployment rates at the time of DI application, and age-based discontinuities in DI eligibility rules. To measure health, we leverage administrative data from Medicare, which provides health insurance to DI recipients beginning two years after they become eligible for cash benefits. For identification, we exploit a feature of the DI determination process called the Medical-Vocational Guidelines ("grid rules") that discontinuously relaxes eligibility criteria at ages 50 and 55. These age thresholds reduce entry costs for older workers with limited work capacity without directly affecting their health, and we use them to identify the spending of marginal DI entrants joining under varying levels of unemployment.

We begin by establishing new descriptive evidence on the health of DI recipients who applied under different economic conditions. Using data on recipients entering the program between 1991 and 2015—a period spanning multiple business cycles—we find that those who applied during high unemployment had lower subsequent Medicare spending and mortality than those who applied during low unemployment. Specifically, cohorts applying when county unemployment is one percentage point higher have 0.3% lower average Medicare spending. Absent unemployment-associated changes in health for the inframarginal recipients, such a reduction in spending would imply that the marginal DI entrants induced by higher unemployment have 9% lower spending than those entering at mean unemployment. We document a similar pattern for mortality, suggesting that these differences reflect health rather than prices or other supply-side determinants of medical spending.

Next, we examine how DI entry and entrant health vary by age. Higher unemployment increases DI entry at all ages, but this effect jumps 2–4 fold at ages 50 and 55, precisely when the eligibility criteria relax. While workers age 50 and above account for roughly half of all DI awards, they generate two-thirds of recession-induced entry. This finding is consistent with the hypothesis that there are individuals around the age cutoffs whose health satisfies the relaxed entry requirements and are induced into DI by the lower entry costs above the age cutoffs. Moreover, workers who enter just above these age thresholds have 3% lower average Medicare spending and mortality than those entering at slightly younger ages, implying that the marginal entrants induced by relaxed eligibility are about 8% healthier. The finding that spending falls sharply across the age discontinuity in eligibility is new to the literature, while the mortality result corroborates Strand and Messel (2019), who report lower mortality for those entering at higher ages.

To determine the relative roles of entry costs and health shocks in driving cyclical DI entry, we model DI entry under varying economic conditions. We use an approach from the treatment effects literature to derive a marginal treated outcome function for individuals based on their likelihood of taking up a treatment—in our case, joining DI (Heckman and Vytlacil, 2005; Brinch, Mogstad and Wiswall, 2017; Kowalski, 2021). Specifically, we separately derive the medical spending function for marginal DI entrants at mean and high unemployment, using the age discontinuities in eligibility as instruments for DI entry. If an increase in unemployment only impacts entry costs, then these two functions should coincide. However, if recessions activate the health shock channel, the marginal health spending function will shift á la Grossman (1972). In this case, the difference between the functions measures the importance of the health-shock channel. This forms the basis of our empirical test for the presence and importance of health shocks.

Specifically, since the age discontinuities admit individuals to DI without directly impacting health, entry via the age discontinuity provides an estimate of what a marginal group of individuals would have spent on health care in the absence of any recessionary health shocks. Comparing this estimate to the group's true healthcare cost allows us to identify whether, and to what extent, an increase in unemployment directly affects beneficiaries' health.

Bringing this test to the data, we find that the medical spending of marginal DI entrants is nearly the same whether their entry into DI is associated with aging into more relaxed entry criteria or an increase in unemployment. Repeating the exercise using mortality as an alternative measure of health, we also find that mortality for marginal entrants is very similar whether their entry into DI accompanies an increase in unemployment or aging across the discontinuity in the eligibility rules. Based on these observations, we conclude that there is no evidence of worsened health for individuals entering under high unemployment.

Next, we consider a full model of DI entry motivated by program rules and institutions. In the full model, individuals are characterized by their work capacity (degree of disability) and enter DI if the benefits exceed the costs. Benefits include the value of Medicare coverage as captured by the marginal medical spending function and decrease with work capacity. Costs, on the other hand, increase with work capacity since to receive DI, individuals must forego earnings and prove the severity of their impairment (Autor et al., 2015; Deshpande and Li, 2019; Kearney, Price and Wilson, 2021; Maestas, Mullen and Strand, 2013). The full model aligns with our empirical results and illustrates how changes in entry costs can generate the observed cyclicality in DI entry and medical spending over the business cycle.

We first use the full model to estimate counterfactual unemployment-induced DI entry in the absence of any health shocks for a range of assumptions. For our central assumption, our point estimates imply that entry costs alone would generate 98.5 percent of observed countercyclical DI entry.[1] Finally, we use our full model to explore how the sharp age discontinuity in DI affects the welfare impact of the program for 49- and 50-year-olds. If there are no recession-associated health shocks and poor economic conditions affect 49- and 50-year-olds similarly, then the welfare impact of cyclical DI entry is proportional to the recession-associated entry increase of each group. Since the DI rules generate twice as much recession sensitivity for individuals in their 50s as compared to individuals in their 40s, we conclude that the insurance benefit of DI is allocated to individuals in their 50s vs. those in their 40s at a two to one ratio.

Our paper provides new evidence on how economic conditions relate to disability program participation. Prior work has shown that DI applications and awards rise when labor market opportunities diminish (Black, Daniel and Sanders, 2002; Autor and Duggan, 2003; Charles, Li and Stephens Jr, 2018). Recession-induced applicants also tend to have less severe impairments and higher work capacity than the average applicant, and they are correspondingly more likely to be denied benefits (Lindner, Burdick and Meseguer, 2017; Maestas, Mullen and Strand, 2021). Our study is the first to use Medicare data to characterize DI entrant health status with respect to economic conditions. This allows us to measure health status based on post-award health outcomes (medical spending and mortality) that are directly relevant to the cost of Social Security programs and to complement prior work that could only observe the qualifying diagnoses at application. Second, we propose and implement a novel research design for disentangling the channels through which cyclical DI entry arises. Our method is derived from the treatment effects literature on identifying a marginal treated outcome function using a binary instrument (Heckman and Vytlacil, 2005; Brinch, Mogstad and Wiswall, 2017; Kowalski, 2021).

We also shed new light on the role DI's age-based guidelines play in the program's countercyclical dynamics. While prior studies have used the age cutoffs in regression-discontinuity designs to estimate the causal effect of DI receipt on labor supply and financial outcomes (Chen and Van der Klaauw, 2008; Deshpande, Gross and Su, 2021), our approach reveals how these age-based guidelines fundamentally shape the composition of entrants and the entry response to recessions. We show that the age-based guidelines not only admit healthier claimants but also generate most of DI's cyclical entry—a finding with important implications given recent policy scrutiny of these provisions (Davidson, 2020). This finding helps

[1] We describe countercyclical DI entry as attributable to either health shocks or entry costs. However, a third potential mechanism involves SSA examiners becoming more lenient in their screening judgments when economic conditions are poor. We do not focus on this channel because federal regulations state that DI award decisions should be based on a claimant's functional capacity to work and not an inability to obtain work, specifically including the case where no jobs are available because of cyclical economic conditions (20 C.F.R. §404.1566). In Section 5.4.2, we argue that if "screening effects" are present, they do not change our conclusion that unemployment-associated health shocks do not play a role in countercyclical DI entry.

explain prior findings that recession-driven entrants are disproportionately older, less impaired, and lower-skilled (Cutler, Meara and Richards-Shubik, 2012; Maestas, Mullen and Strand, 2021; Lindner, 2016; Autor and Duggan, 2003; Duggan, Singleton and Song, 2007).

In addition, the paper generates new evidence on the relationship between recessions and health for individuals with disabilities. Substantial individual-level evidence shows that job loss worsens health both in the United States (Sullivan and von Wachter, 2009; Schaller and Stevens, 2015) and in Europe (Browning and Heinesen, 2012; Eliason and Storrie, 2009).[2] However, those individual effects do not necessarily imply that recessions worsen health on average, particularly if there are countervailing health improvements among workers who do not experience job loss or individuals not in the labor force (Ruhm, 2000, 2003, 2005; Stevens et al., 2015). Recent attempts to characterize the relationship have generally found that health worsens on average during poor economic times (McInerney and Mellor, 2012; Ruhm, 2015), especially among the working-age population (Crost and Friedson, 2017; Schwandt and von Wachter, 2020; Coile, Levine and McKnight, 2014). The health impacts documented in these papers may not represent the type of permanent work-limiting impairment required for DI entry. This would reconcile our finding that recessions neither worsen nor improve long-run health among DI entrants.

Our finding that entry costs can fully account for cyclical DI entry suggests that existing elements of the safety net may not adequately support individuals with functional limitations during economic downturns. While many individuals receive support from unemployment insurance during recessions, Mueller, Rothstein and von Wachter (2016) find that DI entrants rarely receive unemployment benefits in the previous year, perhaps because of unstable work histories. DI does not currently provide temporary or partial disability benefits, but these could help those with disabilities experiencing frictional unemployment or underemployment. Policy could also encourage employers to better accommodate individuals with work-limiting disabilities, either via subsidies or experience ratings in disability insurance premiums (Aizawa, Kim and Rhee, 2020; Hawkins and Simola, 2021; Prinz and Ravesteijn, 2021).

[2]These studies find that job loss worsens mental health (often leading to increased suicide) and heart disease. These health conditions are common reasons for entry into the DI program; mental disorders are the primary diagnosis for about one-fifth of DI entrants over the sample period, with depression alone representing about 5%, while heart disease represents more than 10% (Social Security Administration, 2022). In addition, these diagnoses are among the most cyclically-sensitive (Maestas, Mullen and Strand, 2021).

2 Social Security Disability Insurance and Medicare

2.1 Disability Determination Process

DI is a federal program that pays cash benefits to individuals with a work-limiting disability who have sufficient work history. The SSA uses a five-step sequential evaluation process to determine whether qualifying applicants are disabled. At each step, an applicant is either awarded or denied benefits or continues to the next step. Each step can be expressed in the form of a question, as follows.

Step 1: Is the individual working? Applicants are denied benefits if their average monthly earnings exceed the Substantial Gainful Activity (SGA) threshold of $1,350 for non-blind individuals and $2,260 for blind individuals (in 2022).[3]

Step 2: Is the individual's condition severe? Applicants are denied benefits if their conditions do not significantly limit their ability to do basic work activities or are not expected to last longer than a year or result in death (20 C.F.R. §404.1520; 20 C.F.R. §404.1509).

Step 3: Is the individual's impairment "listed?" Applicants are awarded benefits if they have a listed medical condition (see the "Listing of Impairments," 20 C.F.R. §404 Subpart P, Appendix 1). For example, listed impairments include conditions of the musculoskeletal system that result in being unable to ambulate effectively and certain respiratory or cardiovascular diseases. Each listed impairment is defined by particular elements of the medical evaluation (e.g., medical lab values).

Step 4: Can the individual do the work they did previously? At the start of this step, SSA conducts a Residual Functional Capacity (RFC) assessment to determine the type of work the applicant can do on a sustained basis given their limitations. If the assessment finds that they can still perform the work associated with their previous occupation, they are denied benefits, even if they cannot obtain an employment offer in their former occupation. Federal regulations specifically include the case where no jobs are available because of cyclical economic conditions (20 C.F.R. §404.1566).

Step 5: Can the individual do any other type of work? Most applicants—70% over the years 2000–2014—are neither awarded nor denied benefits by the previous steps and are evaluated under step 5 (Deshpande, Gross and Su, 2021). In this final step, each applicant's RFC assessment is used to determine a categorical "maximum sustained work capacity" (MSWC): sedentary, light, medium, heavy, or very heavy. For applicants assigned

[3]See Gelber, Moore and Strand (2017) for an in-depth description of the role of the SGA threshold. Kostøl and Mogstad (2014) study the role of financial incentives in disability insurance enrollment in Norway.

a “sedentary” MSWC, the SSA further determines the set of occupations this person could actually perform out of roughly 200 unskilled sedentary occupations (each of which consists of multiple, specific jobs). If the SSA determines the individual could not actually perform a significant fraction of these jobs, the applicant is considered to have an RFC of “less than the full range of sedentary occupations” and is more likely to be awarded benefits (Social Security Administration, n.d.*b*). Together with the applicant’s age, level of formal education, and the skills acquired in previous work experience, the SSA determines whether the applicant can transition to other work within their MSWC. The table that determines whether they can do other work is known as the Medical-Vocational Guidelines, or “grid rules” (see 20 C.F.R. §404 Subpart P, Appendix 2). During our sample period, around 40% of denials were due to a finding that the applicant could transition to other work (Social Security Administration, 2017).

2.2 Age Discontinuities in the Medical-Vocational Grid Rules

The grid rules recommend the award or denial of DI benefits based on work capacity, education, acquired skills, and age. Applicants aged less than 50 who have a work capacity of “sedentary” or greater are usually denied benefits, but those with the same sedentary work capacity who are aged 50–54 may be awarded benefits. A similar age discontinuity in eligibility occurs at age 55 for individuals with a work capacity of “light.”

For an example of such a discontinuity, consider the grid rule recommendation for an applicant with a work capacity of “sedentary” who does not have a high school degree and whose work history consists of only unskilled labor. When considering whether this applicant can do any other type of work, the SSA does not expect them to transition to another industry after age 50. Thus, the grid rules recommend that such an individual be found disabled at age 50, but not at 49, even if the degree of impairment is equivalent. (Appendix Table A.1 summarizes the grid rule discontinuities.)

2.3 Medicare Eligibility for DI Recipients

Because individuals with disabilities have high medical needs and may not have access to employer-sponsored insurance, DI recipients are entitled to Medicare benefits.[4] All disabled DI recipients receive Medicare hospital insurance (Part A) at no charge. Medicare Part B, which covers physician services, is available for an additional monthly premium. DI recipients

[4]In addition to disabled workers, DI also pays cash benefits to nondisabled dependents of a disabled worker as well as to disabled individuals who were previously supported by a qualifying worker who has retired, become disabled, or died. Medicare entitlement is limited to DI recipients with disabilities.

whose incomes are low enough to qualify for Medicaid obtain state assistance with Part B premiums; most Medicare-Medicaid "dual eligibles" are not subject to Medicare cost-sharing requirements (coinsurance and co-pays). "Medigap" supplementary insurance for Medicare cost-sharing is rare among DI recipients, perhaps because of unfavorable underwriting regulation (Cubanski, Neuman and Damico, 2016; Armour and O'Hanlon, 2019). All Medicare recipients can choose to access benefits via a private Medicare Advantage plan.

Entitlement to Medicare begins 24 months after the month in which the individual begins receiving DI cash benefits. The month of DI entry depends on the month they applied as well as the dates in their medical history and is subject to various program rules. In what follows are three common scenarios.

As a first scenario, suppose that an individual who was recently working above the SGA level separates from her employer and immediately applies for DI. Regardless of the timeline of impairment in her medical record, Social Security would recognize her disability as beginning after she stopped working above the SGA level. There is a five-month statutory waiting period after the onset of disability, so if she is awarded cash benefits, they would start five months after the month she applied. Medicare entitlement would begin 24 months later, 29 months after the month she applied.

Many individuals are unemployed or out of the labor force before applying for DI. As a second scenario, suppose that an individual separates from his employer, looks for work for at least 12 months, and then applies for DI. If his medical record indicates that he was impaired on the date his employment ended, his DI entry date can be made retroactive, up to a cap of 12 months before the application date. If his DI entry date was 12 months before applying, his Medicare entitlement would begin 12 months after the application date.

DI applicants who are initially denied can request a reconsideration; if unsuccessful at the reconsideration level, they can appeal the denial to an administrative law judge. Reconsiderations and appeals can take several months or even years. For example, French and Song (2014) show that over 60% of applicants who are initially denied are awarded benefits within 10 years through appealing their initial decision or reapplying for benefits. In the event of an eventual award, both DI and Medicare can be made retroactive. As a third scenario, suppose that 36 months after applying for DI, an individual is awarded DI with an entry date 5 months after the application date. Because the 24-month waiting period would have elapsed, he would gain 7 months of retroactive Medicare coverage and would thus enter Medicare 29 months after the application date.

Appendix Figure A.1 shows the distribution of months between DI application and entry using SSA data described in Section 3. The modes at -12 months and 5 months reflect the timelines exemplified above.

3 Data and Measures

3.1 SSA Data

Our analysis uses two supplemental data files from the SSA. The first is the Disability Analysis File Public Use File (PUF) for 2018, which contains individual-level data on DI program participation and benefits for a random 10% sample of individuals who have received disability benefits in any month in 1996–2018. The PUF reports the start date of DI benefit entitlement ("entry date"), the date the DI application was filed ("application date"), the start date of Medicare coverage, and date of birth. We limit the PUF sample to individuals gaining Medicare eligibility at ages 20–64 in 1993–2017, the Medicare sample period.

The PUF is useful in our analysis because the Medicare data, described below, do not contain a beneficiary's DI application date, the date at which we wish to measure unemployment. We primarily use the PUF to measure the distribution of DI application dates for beneficiaries who gained Medicare coverage in a given month. We also use the PUF sample to validate entry patterns observed in the Medicare sample and to compare how entry patterns vary with age at entry versus age at application.

The second SSA data file is a version of the Annual Statistical Report on the Social Security Disability Insurance Program (DI ASR) that covers all applications filed in 2008–2017 and reports outcomes by five-year age groups for ages 20–44 and by single year of age for ages 45–60. Because both the Medicare and PUF samples contain only successful applications, we use the DI ASR sample for supplemental analyses on overall application rates.

3.2 Medicare Data

Our primary analysis sample is derived from administrative Medicare data covering all beneficiaries in 1992–2017. We construct the sample to capture Medicare beneficiaries who entered DI at ages 20–60, an age range that excludes entry from age-18 redeterminations of childhood disability and from individuals nearing the early retirement age of 62. To measure age at DI entry, we use each individual's date of birth and Medicare coverage start date and take an individual's DI entry date to be 24 months (the duration of the Medicare qualifying period) before their Medicare coverage start date.[5] Using Medicare data on a beneficiary's original reason for Medicare entitlement and basis of eligibility for SSA programs, we fur-

[5]Program rules allow DI beneficiaries to gain Medicare coverage in fewer than 24 months with limited exceptions, including beneficiaries with end-stage renal disease and amyotrophic lateral sclerosis. In the PUF sample, which records both DI entry and Medicare coverage start dates, Medicare coverage starts exactly 24 months after DI entry for over 95% of beneficiaries and starts 20–28 months after DI entry for over 99% of beneficiaries.

ther exclude individuals who gained Medicare coverage due to end-stage renal disease and are unlikely to be eligible for DI (see the Online Appendix). Our final Medicare sample includes 15,790,262 beneficiaries gaining Medicare eligibility at ages 22–62 in 1993–2017, corresponding to DI entry at ages 20–60 in 1991–2015.

Using Medicare data to measure DI entry and health outcomes limits our focus to DI beneficiaries who become and remain eligible for Medicare. Based on the PUF, about 5% of DI entrants do not survive the two-year Medicare waiting period and thus do not appear in the Medicare sample.[6] When DI beneficiaries on Medicare reach age 65, their Medicare eligibility converts from being based on disability to being based on age. Thus, we generally observe DI beneficiaries on Medicare until the end of the sample period or death, with limited exceptions for those who return to work or medically improve before age 65.[7]

Our primary measure of health status is medical spending, observed for fee-for-service Medicare (FFS) beneficiaries in 1999–2017. Our measure of spending is the total allowed amount—the Medicare portion plus beneficiary cost-sharing—for all covered services.[8] For each beneficiary, we measure annual medical spending in each year they are enrolled only in FFS, beginning with the first calendar year after their Medicare coverage starts. We convert all spending values to 2017 dollars using the CPI-U for medical care.

Our secondary measure of health status is mortality, which we observe for all Medicare beneficiaries and in all years of the sample. For each beneficiary, we measure mortality as an indicator for death in each year they are enrolled in Medicare, beginning with the first calendar year after their Medicare coverage starts. To adjust for secular mortality trends, we deflate the death indicators by annual mortality among all US residents aged 20–84 relative to year 2017, analogous to the CPI adjustment for medical spending.

Finally, we measure for each beneficiary the initial county in which they are observed and annual indicators for enrollment in Medicare Advantage, Medicare Part B, and Medicaid. We use the initial county for measuring unemployment at application (described below), and

[6]Individuals who die during the Medicare waiting period represent a very small portion of the fiscal cost of DI. Over our sample period such individuals receive, on average, about $17,000 in lifetime DI benefits, while on average DI recipients receive approximately $25,000 in annual benefits ($12,000 in cash and $13,000 in Medicare) for each year in the program.

[7]DI exits occur predominantly for four reasons: death, conversion to normal retirement benefits, return to work, and medical improvement. Death and retirement conversions account for most DI exits. Beneficiaries younger than age 65 who return to work above the SGA level retain Medicare eligibility for at least 8.5 years (Social Security Administration, n.d.*a*). For those who experience a medical improvement, which may be established at a routine audit, Medicare eligibility ends the month after notification of the terminating event. Among DI beneficiaries in our final Medicare sample, about 0.1% exit each year for a reason other than death.

[8]Covered services include physician visits, inpatient hospitalizations, outpatient services such as imaging or outpatient surgeries, stays in skilled nursing or hospice facilities, and durable medical equipment. We exclude spending on outpatient prescription drugs, which were not covered by Medicare until 2006.

we use the insurance enrollment indicators in robustness checks to test whether enrollment in these programs can account for our main findings.

3.3 DI Entry and Unemployment at Application

A key aim of our analysis is to relate DI entry rates and entrant health status to local economic conditions at the time of application. We focus on the unemployment rate as our measure of economic conditions, both because it is the primary macroeconomic measure used in prior studies of DI entry cyclicality (e.g., Autor and Duggan, 2003; Cutler, Meara and Richards-Shubik, 2012) and because it is measured at both the county and national levels over a long time period. We obtain monthly unemployment at the national and county levels from the Bureau of Labor Statistics from 1990 to 2017.[9]

A challenge with assigning conditions at application to DI beneficiaries in our primary sample is that Medicare data do not report DI application dates. Instead, we use the PUF to calculate the fraction $p_{m\tau}$ of DI beneficiaries who gained Medicare coverage in month m (in 1993–2017) and applied for DI in month τ (in 1990–2017). We then calculate the average county unemployment rate at application for DI beneficiaries who gain Medicare coverage in month m and county[10] c as the average county unemployment rate $u_{c\tau}$ in all months τ, weighted by $p_{m\tau}$; that is,

$$[\textit{unemployment rate}]_{cm} = \sum_{\tau} p_{m\tau} u_{c\tau}.$$

We similarly measure national unemployment by repeating this calculation with $u_{c\tau}$ replaced by u_τ (national unemployment rate in month τ).

Appendix Figure A.2 shows the distribution of county and national unemployment rates at application, by month of entry, for our primary sample of DI recipients. Unemployment conditions vary substantially across counties and over time. The sample spans three periods of high unemployment followed by low unemployment, which is useful for disentangling secular trends from cyclical patterns in entry rates and entrant health characteristics.

Finally, we measure DI entry rates for each county, month, and age at entry (ages 20–60). The numerator for this rate is a count from the primary Medicare sample. The denominator is the population for that county, month, and age, obtained from CDC Wonder (Census

[9] In Appendix Section A.2 we explore the unemployment rate by age and education subgroups, and find similar levels of DI cyclicality.

[10] A beneficiary's county of residence at the time Medicare coverage begins could differ from the county in the month of application if the individual moves in response to high unemployment. Such a pattern could introduce measurement error in estimating the correlation of local unemployment and DI entry or spending (although it does not affect analyses of national unemployment). However, Halliday (2007) finds that individuals who self-report poor health do not respond to poor macroeconomic conditions by increases in moving, which would suggest this source of bias is modest in our application.

Bureau Population Estimates Program, n.d.). Age-specific population also serves as the weight for population-weighted summaries of the entry rate.

4 Descriptive Evidence on DI Entry and Health

In this section, we analyze how DI entry and the health outcomes of DI entrants, as captured by their medical spending and mortality, vary with local economic conditions at the time of DI application and the individual's age at entry.

4.1 Unemployment and DI Entry

We first show how national unemployment and DI entry vary over the sample period. In Figure 1a, the solid brown curve reports the population-weighted average monthly DI entry rate in each year. The dashed blue curve reports the average national unemployment rate at the time of DI application for entrants in each year. This figure reveals a pattern of countercyclical DI entry that persists across the three business cycles covered by our sample period, extending prior work documenting countercyclical DI entry in earlier periods (e.g., Autor and Duggan, 2003).

To formalize our measurement of cyclicality in DI entry, we adapt the regression model of Liebman (2015).[11] The age-specific entry rate is regressed on $[\textit{unemployment rate}]_{cm}$, calculated as in Section 3.3 to capture conditions for entrants in county c and month m at the time of application.[12] Specifically, we estimate

$$\textit{Entry}_{acm} = \alpha[\textit{unemployment rate}]_{cm} + [\textit{county FEs}]_c + \varepsilon_{acm}. \tag{1}$$

In our baseline specification, equation (1) includes county fixed effects, which account for persistent differences across counties, and isolate variation in local unemployment conditions that occurs over time. Thus, the key coefficient of interest, α, quantifies by how much DI entry tends to change over time within a county for each percentage point increase in the local unemployment rate. We weight the equation by the population of age a in county c for entry month m. Because we construct unemployment at application at the level of county by month of Medicare entry, we cluster our standard errors at this level in all analyses. This accounts for serial correlation in an individual's outcomes over time as well as any correlation

[11] In Appendix Table A.2, we instead estimate the model of Maestas, Mullen and Strand (2021) and find similar results. However, the Liebman model is easier to adapt for the health status outcomes that we investigate in the next section.

[12] The results are unchanged if we aggregate the age-specific entry rate to the county by entry month, the level of the unemployment rate. However, equations (5) and (6) both use the age-specific entry rate, so for simplicity we use it here as well.

across individuals joining Medicare at the same time and place. In Section 6, we demonstrate robustness to clustering at the county level.

We begin by estimating a version of equation (1) that, rather than imposing linearity, allows for an arbitrary relationship between DI entry and unemployment conditions at the time of DI application. To do so, we replace the unemployment rate variable with indicators for each ventile of the distribution of unemployment rates at application. Figure 2a reports the estimates, revealing an approximately linear relationship between DI entry rates and ventiles of the unemployment rate at application.

Table 1 reports the results of estimating equation (1). As shown in column (1) of Panel A, each percentage point increase in a county's unemployment rate corresponds to 13.2 additional DI entrants per million residents per month. This amounts to a 4.2% increase in DI entry, relative to the sample mean monthly DI entry rate of 313 monthly entrants per million residents.

We have chosen to use unemployment for the full population as our key measure of economic conditions. This measure has the advantage of being measured at the county-by-month level for our entire sample period. However, if we are willing to aggregate to a coarser unit of time (year) and consider only certain geographies and a more recent period, it is possible to instead examine unemployment rates that are specific to certain subpopulations. In Appendix Section A.2, we examine unemployment among two groups known to have high rates of work-limiting disability and DI enrollment: individuals with a high school degree or less and individuals aged 45-54. We find a similar relationship between those specific unemployment rates and DI entry, suggesting that the unemployment rate for the full population is a good proxy for economic conditions as experienced by likely DI applicants.

4.2 Unemployment and Health Status of DI Entrants

We extend this analysis to show the relationship between health outcomes (measured either as medical spending or mortality) for DI recipients and the unemployment rate at application.

We again begin with national trends, leveraging our 25-year panel of DI entrants. We measure the average medical spending or mortality associated with each year-of-entry cohort *coh*, which we estimate as the fixed effects of the following regression:

$$y_{it} = \delta_{coh(i)} + \gamma X_{it} + \varepsilon_{it}. \tag{2}$$

The dependent variable in this regression is a health measure for individual i in year t. We regress this individual's spending on a fixed effect $\delta_{coh(i)}$ for her annual entry cohort. To account for systematic differences in health by duration of disability, the control variables X_{it} in this specification include fixed effects for "years enrolled," i.e., the number of years since the individual's entry into Medicare.[13] A substantial share of DI beneficiaries die during their first years of Medicare coverage, and cohorts experience high average costs including those related to end-of-life care in their first years of Medicare coverage. Without fixed effects for years enrolled, the earlier cohorts (not observed in our data until their eighth year since DI entry) appear artificially inexpensive.

Figure 1b reports average spending by year of entry as estimated by the cohort fixed effects δ_{coh} from equation (2). Across the 24 cohorts entering between 1991 and 2014, the average cohort net spending ranges from about \$13,000 to \$13,900 (in 2017 dollars). The right axis again reports the average national unemployment rate at application for each entry cohort; it is apparent that the two series are negatively correlated. The cohort that entered in 2006 applied under an unemployment rate of 4.8%, the lowest of the macroeconomic cycle, at the time of their applications with average spending of \$13,900. Conversely, the cohort that entered in 2010 experienced an unemployment rate of 9.3%, the highest of the sample period, at the time of their applications but had the lowest spending of all cohorts. The swing in average spending between these cohorts was approximately \$700 per person per year, more than 5% of the mean.

Figure 1c repeats the analysis for mortality. The same pattern is evident: individuals who applied to DI when unemployment was high have lower subsequent mortality after joining the program.

We can adapt equation (2) to examine the correlation of health and local unemployment at application by simply replacing the cohort fixed effects with the unemployment rate, yielding the following regression equation:

$$y_{it} = \beta[unemployment\ rate]_{cm(i)} + \gamma X_{it} + \varepsilon_{it}. \tag{3}$$

The parameter β recovers the association between an individual's health outcome (medical spending or mortality) and the unemployment rate at application in i's county and entry month $cm(i)$. As in equation (2), the control variables X_{it} in our baseline specification include fixed effects for years enrolled, but we further interact these with county fixed effects to identify the relationship between unemployment and entrant health from cyclical fluctuations within counties rather than persistent differences across counties.

As before, we begin by estimating a version of equation (3) that allows for arbitrary relationships between entrant health outcomes and unemployment conditions at the time of DI application by changing the dependent variable to indicators for each ventile of the distribution of unemployment rates at application. Figure 2b reports the estimates of the relationship between unemployment ventiles and medical spending, and Figure 2c repeats the analysis for mortality. DI recipients who applied when local unemployment rates were

[13] Section 6 reports alternative specifications of all analyses.

low have higher medical spending and higher mortality rates. For medical spending, the relationship is nearly linear, while the relationship is measured with more noise for the mortality rate.

In Panel A of Table 1, columns (2)–(3) report the coefficient from equation (3) relating health outcomes to the unemployment rate at application. Each percentage point increase in the rate of unemployment at application is associated with a $43 (0.3%) decrease in subsequent annual medical spending and 0.47 fewer deaths per 10,000 person-years (a 0.2% reduction in mortality). One way to interpret the magnitude of these effects is to calculate the implied average spending and mortality of unemployment-induced marginal entrants under an assumption that there is no increase in health shocks during recessions. For the 4.2% increase in the entry rate alone to reduce average spending by 0.3%, individuals induced by one percentage point of unemployment must spend $12,235 on average, or 9% less than those who enter at mean unemployment.[14] The equivalent calculation for mortality implies that unemployment-induced marginals have a mortality rate 5% lower than individuals who join during mean unemployment.

The stylized fact that individuals who join DI during low unemployment are in better health does not on its own refute the hypothesis that DI entry increases because of health shocks. The two pathways—reduced entry costs and increased health shocks—would likely have offsetting effects on the health of DI entrants. Reduced entry costs will tend to induce the entry of individuals who are in better health than DI always-takers, while health shocks would imply that those individuals are in worse health than they would have been otherwise. Thus, we turn to a second source of variation to disentangle the two effects.

4.3 Health Status across the Age Discontinuity in DI Eligibility

As described in Section 2, DI eligibility relaxes discontinuously at ages 50 and 55. This discontinuity is evident in our data when we examine the age distribution of new Medicare entrants. Figure 3a demonstrates a sharp increase in the entry rate for individuals at ages 50 and 55. The entry rate spikes from 382 49-year-old entrants per million per month to 636 50-year-olds, an increase of 67%, before partially falling back to 525 51-year-old entrants. A similar spike and partial fallback can be seen at age 55.

We explore the application and award dynamics generating the age patterns in entry in Figure 4. In this figure, the solid brown curve indicates the raw number of annual entrants

[14] Average spending when unemployment increases by one percentage point is $13,311, which is a weighted average of spending by inframarginals (the overall mean, $13,354) and by marginals. The weights are determined by the entry equation: $96\%(= 313/(313 + 13))$ of the entrants at high unemployment are inframarginals, while 4% are induced.

by age at DI entry, showing the same spikes in entrants at ages 50 and 55 that we noted in Figure 3a. The short-dashed orange curve indicates the age at application for these same entrants. Beginning at age 47, we see the two curves diverge, indicating more (eventual) entrants applying at ages 47–49 than those entering in those years. Conversely, there are about 4,000 more entrants who join at age 50 than who apply at age 50. Thus, we find that the spike in entry at the threshold ages is driven by the entry of individuals who applied before reaching those ages. In Appendix Section A.3, we present evidence that this spike is due to individuals gaining DI eligibility in the first month after the age threshold is attained, suggesting their award was contingent on the use of the looser eligibility standards. We also find a longer duration between application and entry for individuals joining Medicare at age 50 compared to 49, consistent with a greater share of awards after the initial decision stage.

Figure 4 also reports (long-dashed blue curve) the number of annual applicants by age at application. Consistent with Deshpande, Gross and Su (2021), we find no discontinuity in applications at the age thresholds, although we do find evidence of a smooth swelling of applications in the preceding years as well as a local peak at ages 50 and 55. These application dynamics suggest individuals nearing the age threshold apply in advance of it to gain DI entry in the first possible month when they qualify. Thus, increased applications play a role in increased DI entry at the age discontinuity, just as they do in increased DI entry during recessions (Maestas, Mullen and Strand, 2021).

We next examine the health status of DI recipients across the age discontinuity. Figure 3b reports the average annual medical spending for individuals entering at each age. Specifically, the black curve plots the fixed effects for each age at entry a from the following equation:

$$y_{it} = \delta_{a(i)} + \gamma X_{it} + \varepsilon_{it}. \tag{4}$$

This equation mirrors equation (2) but estimates fixed effects for individual i's age at entry $a(i)$ instead of year of entry. As before, X_{it} simply includes a set of fixed effects for the number of years since Medicare entry. Average net spending gently rises for individuals who enter in their 30s and 40s; by contrast, clear, sharp reductions in average net spending are evidenced for those who enter at ages 50 and 55. For example, 49-year-old entrants have an average annual net spending of \$14,277, while entrants just above the first age discontinuity, at age 50, have an annual average net spending of \$13,800, a 3% reduction. Using mortality as the dependent variable (Figure 3c), we find a similar pattern, with mortality dropping sharply by about 2.5% at the age discontinuities. The improvements in average health observed after the age discontinuity imply that the extra individuals who join DI at age 50 spend about 8% less than 49-year-old entrants and experience 6% lower mortality rates.[15]

[15] This calculation relies on an assumption that comparable groups of individuals are admitted at both ages 49 and 50 under the entry pathways, such as listed impairments, that do not change with age. This

4.4 Sensitivity to Unemployment Across the Age Discontinuity

Over our time period, 50% of all entry occurs at ages 50 and above, under the looser eligibility rules that apply at those ages. Given the importance of this eligibility pathway in overall DI entry, a natural question is how the age discontinuity in eligibility interacts with the unemployment effects we document. It is straightforward to estimate equation (1) separately for each age at entry a to estimate the effect of local unemployment at application across the age distribution:

$$\text{Entry}_{acm} = \alpha_a[\textit{unemployment rate}]_{cm} + [\textit{county} \times \textit{age FEs}]_{ac} + \varepsilon_{acm}. \tag{5}$$

Figure 5 reports, for each age at Medicare entry, the effect of a 1 percentage point increase in the local unemployment rate at application on the age-specific DI entry rate (i.e., number of entrants at age a from county c in month m divided by the estimate of the population at age a from county c in month m). DI entry becomes sharply and substantially more sensitive to unemployment above the age discontinuities in eligibility. On average, 1 percentage point of unemployment would add only 5 new monthly entrants at each age for individuals younger than 50 but would add 27 new entrants at each age for individuals 50 and older. The area under the curve for ages 50–60 is equal to two-thirds of the total area (population weighted), indicating that the older ages account for two-thirds of total DI cyclicality.[16]

In our model in the following section, we will leverage the first age discontinuity in the DI grid rules, at age 50. Our comparisons between ages 49 and 50 show substantial differences—an increased entry rate, better health, and an increased sensitivity to unemployment. To examine this transition more closely, we repeat the analyses reported in Panel A of Table 1 but restrict the sample to individuals who entered DI at ages $a \in \{49, 50\}$. Specifically, we estimate the following regressions to estimate cyclicality in entry and health status:

$$\text{Entry}_{acm} = \alpha + \alpha^U \tilde{U}_{cm} + \alpha^{50}\mathbb{1}(a = 50) + \alpha^{50\times U}\mathbb{1}(a = 50)\tilde{U}_{cm} + [\textit{county FEs}]_c + \varepsilon_{acm}, \tag{6}$$

$$y_{it} = \beta + \beta^U \tilde{U}_{cm(i)} + \beta^{50}\mathbb{1}(a(i) = 50) + \beta^{50\times U}\mathbb{1}(a(i) = 50)\tilde{U}_{cm(i)} + \gamma X_{it} + \varepsilon_{it}. \tag{7}$$

In these equations, $\tilde{U}_{cm}$ is the county unemployment rate at application, demeaned using the person-weighted average to simplify interpretation of the constants. The parameters (αs and βs) together characterize DI entry and health among individuals entering Medicare before or after the age discontinuity under varying rates of unemployment. For example,

assumption follows directly from the ordering, independence, and relevance assumptions that are required for the treatment effects model we develop in Section 5. Note that this calculation can accommodate any pattern of application timing with respect to age, since it does not rely on a comparison of individuals admitted and denied to DI.

[16]In Appendix Figure A.3, we report the coefficients α_a as a percentage of the entry rate of age a over the time period. This normalization accounts for the fact that if the effect of unemployment is proportionally uniform, greater entry above age 50 would generate greater cyclicality when measured in levels. The figure shows that 1 percentage point in unemployment is associated with a 2.3% increase in the entry of 49-year-olds, but a 6.5% increase in the entry of 50-year-olds.

the regression constants α and β represent entry and spending for those entering at age 49 under conditions of mean unemployment (given the demeaning of the unemployment rate), while α^{50} and β^{50} measure the entry and health changes at the age discontinuity. Finally, we include a single set of county fixed effects since individuals at these ages are subject to the same county factors such as labor markets. As in equation (3), X_{it} contains fixed effects for the interaction of the number of years enrolled and county.

We report the results of this estimation in Panel B of Table 1. Column (1) reports the coefficients for entry. Consistent with the jump in entry at age 50 visible in Figure 3a, the estimated value of α indicates that entry jumps from 382 new 49-year-old entrants per million resident 49-year-olds to nearly 635 per million at age 50 ($382 + 253$). A 1 percentage point increase in the local unemployment rate at application from its mean (6%) increases entry for 49-year-olds by 7.8 per million. However, that same increase has a larger effect on 50-year-olds, increasing their entry rate by 41.8 per million (7.8 + 34.0).

Panel B, column (2) of Table 1 reports the impact of unemployment on medical spending for individuals entering at ages 49 and 50. The constant term (β) represents the average net medical spending for 49-year-olds who apply for DI under mean unemployment. The downward shift in spending for 50-year-olds that was clear in Figure 3b is represented by the negative estimate for β^{50}. We see that an increase in unemployment has no effect for 49-year-olds, as reflected by the estimate of β^{U}, but further reduces spending for 50-year-olds. Column (3) of Panel B shows that mortality falls for individuals who enter at age 50 relative to age 49. Those who enter at times of high unemployment also have lower mortality, with a larger effect for 50-year-olds.

Our empirical analysis has examined how macroeconomic conditions, DI eligibility rules, and their interaction affect DI entry and the medical spending and mortality of DI recipients. We find that the increases in DI entry associated with either greater unemployment or the age discontinuity in eligibility are accompanied by decreases in the larger group's health. Together, these results suggest that induced entrants—responsive to either higher levels of unemployment or to the more lenient age admission rules—are healthier than always-takers who would have joined the DI program regardless of either economic conditions or the shift in eligibility requirements. In the next section, we describe a graphical model of DI entry at varying ages and economic conditions.

5 Health Shocks and Entry Costs

As mentioned in Section 1, the literature has suggested two possible channels through which economic conditions might affect DI enrollment. First, deteriorating economic conditions could lead directly to a decline in health, increasing the number of individuals who meet the medical criteria for entry (the health-shock channel). Second, a worsening of economic conditions could lower the cost of entering DI among individuals who were already medically qualified for it by decreasing expected future earnings from remaining in the workforce (the entry-cost channel).[17] Both the entry-cost and health-shock channels could lead more and healthier individuals to enter DI during recessions.

A naïve approach to identifying the extent to which health shocks contribute to cyclical DI entry would compare the spending of individuals who enter at mean unemployment with that of individuals who enter at high unemployment. However, since unemployment simultaneously activates both the entry-cost and health-shock channels, this comparison cannot disentangle the two. In order to isolate the role of entry costs and health shocks in driving DI entry, we need to observe what the marginals' spending would have been if their entry had been driven solely by a change in one of these factors.

We address this issue using the age discontinuity, which admits additional entrants to DI via the entry-cost channel but does not directly affect health. We begin by using entry due to the age discontinuity to trace out how spending falls as a function of incremental entry. We then use this relationship to generate an estimate of what the marginal beneficiaries who enter DI due to a change in unemployment would have cost if they had been admitted only due to a change in entry cost. Finally, we compare the true spending of those induced into DI by unemployment and the health-held-constant predicted value. The difference between the two provides an estimate of the marginals' spending change due to the direct impact of an increase in unemployment on health, i.e., recessionary health shocks.

We describe the conceptual approach in Section 5.1. We then move on to the estimation and the translation of our estimates of average effects in Table 1 to the marginal effects discussed below.

5.1 Modeling the Medical Spending of Marginal DI Entrants

Our approach to estimating spending for individuals who enter DI due to the age discontinuity at different levels of unemployment draws on the framework employed in the marginal treatment effects literature (Heckman and Vytlacil, 2005; Kowalski, 2021; Brinch, Mogstad and Wiswall, 2017). In our case, the treatment in question is entry into DI, and the age discontinuity acts as an exogenous instrument that increases the likelihood of an individual being treated. However, our approach differs from much of the literature in that we do not

[17] Another possibility that would fall under the entry-cost channel would be if screening criteria are relaxed when fewer jobs are available. Although such behavior is explicitly prohibited by federal regulations, it could be incorporated into our model as described in Section 5.4.2.

attempt to estimate the impact of treatment. Indeed, we cannot do this in our setting since we do not observe outcomes for individuals who do not receive DI. Rather, our focus is on estimating what Kowalski (2021) calls the Marginal Treated Outcome function, i.e., medical spending for marginal entrants into DI.

Following the treatment effects literature, we assume that individuals differ according to an unobserved preference for DI, derived from idiosyncratic perceptions of the costs and benefits of program entry. An individual will choose to enter DI if their unobserved preference for DI exceeds a threshold value. Figure 6a depicts potential DI entrants in order of descending unobserved preference for DI. That is, individuals on the left have a high preference for DI and will always choose to enter, while individuals on the right have a low or negative preference for DI. Although changes in economic conditions may increase or decrease individuals' preference for DI, we assume that the ordering of individuals remains fixed. Following Kowalski (2021) and the literature, we assume a linear marginal medical spending function, depicted in Figure 6a as a solid orange line B.

To estimate the marginal medical spending function for a given level of unemployment, we leverage the exogenous "instrument" provided by the age discontinuity in eligibility at age 50.[18] We assume this instrument is both *relevant*—it makes uptake of treatment more likely—and *independent* of other factors that determine treatment. Our descriptive evidence and the nature of the eligibility discontinuity support the relevance of the instrument. Independence, which requires that the determinants of medical spending apart from their preference for DI are independent of the instrument (age), is a reasonable assumption because 49- and 50-year-olds are in similar health, face similar labor markets, and experience similar eligibility for other social safety net programs.

Assuming the relevance and independence of our instrument as well as a continuity assumption, we can infer that α inframarginals join DI under the strict rules at either age and α^{50} marginals join at the age of 50 under the looser guidelines. The solid black squares labeled W and X mark the marginal 49- and 50-year-old entrants and their medical spending given by $B(\alpha)$ and $B(\alpha+\alpha^{50})$ under average unemployment, and these two points determine the solid orange line, B, representing marginal Medicare spending at mean unemployment. Since 49- and 50-year olds are assumed to have similar health, movement along the solid orange line from W to X captures how spending changes with incremental entrants induced by the lower entry costs at the age discontinuity.

Next consider higher unemployment. At higher unemployment, we observe $\alpha + \alpha^U$ 49-year-olds entering (α inframarginals who enter at mean unemployment and α^U unemploy-

[18] We focus on the first age discontinuity in our analysis but repeat the exercise for the second age discontinuity affecting 55-year-olds in Section 6.

ment marginals); we mark the marginal 49-year-old entrant at higher unemployment and their spending using the open circle at point Y. Applying the age discontinuity a second time, we denote point Z the entry and spending of the marginal 50-year-old entrant at higher unemployment, with $\alpha^{50\times U}$ capturing the excess sensitivity of 50-year-olds to unemployment. These points define the line B^U representing the health status of DI recipients who enter at times of higher unemployment. If a change in unemployment has no direct impact on health, then lines B and B^U will coincide. On the other hand, if line B^U is above B, this indicates that for any level of unobserved preference for DI (x-axis), the individual entering Medicare at high unemployment would have worse health (i.e., higher medical spending).[19] We interpret this higher medical spending as evidence that individuals entering during recessions were subject to greater health shocks.

Now we can explain how we identify such health shocks using the data. Consider entry by 49-year-olds at mean unemployment (point W). An increase in unemployment would induce entry and a change in health care cost, moving to point Y. However, this change potentially involves entry due to a change in entry cost and health shocks. In order to isolate the two channels, we make use of point X, which indicates the expected spending of the marginal age-discontinuity entrant, who entered solely due to a change in entry cost. Under the assumptions that the ordering of individuals in terms of latent health status is not impacted by unemployment and that the benefit curve is approximately linear, we can characterize point Y', which tells us what the cost of the marginal individuals admitted to DI due to the change in unemployment *would have been* if they had been admitted only due to a change in entry cost. This counterfactual value is given by evaluating the marginal medical spending defined at mean unemployment, line B, at the entry level of high unemployment $\alpha + \alpha^U$. The magnitude of the health shock is therefore given by the vertical distance between points Y' and Y.

The empirical test we conduct below estimates the vertical distance between $B^U(\alpha+\alpha^U)$ and $B(\alpha + \alpha^U)$. Since in principle health dynamics may differ for those entering above the age discontinuity, we also test for a difference between $B^U(\alpha+\alpha^U+\alpha^{50}+\alpha^{50\times U})$ and $B(\alpha+\alpha^U+\alpha^{50}+\alpha^{50\times U})$.

[19]We draw B^U as an upwards shift from B – i.e., individuals entering at higher unemployment are sicker due to health shocks. We depict recession-associated health shocks (as opposed to recession-associated health improvements) in the figure because this is the recession health effect most often discussed in the DI literature. However, in estimation we allow the marginal medical spending function to move in any direction to accommodate countercyclical health patterns as in Ruhm (2000).

5.2 Estimating the Marginal Medical Spending Functions

We return to the data to parameterize the two marginal medical spending functions. First consider the marginal medical spending function at mean unemployment. According to Table 1, for every million residents per month, there are 382 49-year-old DI entrants and 253 DI entrants induced to join by the age discontinuity. Table 1 also reports average medical spending for 49 and 50-year-olds entering at mean unemployment, which we represent by β and $\beta + \beta^{50}$, respectively. The linear function B attains its average level over a range at its midpoint and so we apply the midpoint formula to find the slope and intercept of the marginal spending function B. Thus, $B\left(\frac{\alpha}{2}\right) = \beta$ and $B\left(\frac{\alpha+\alpha^{50}}{2}\right) = \beta + \beta^{50}$, implying that the slope of this function m is given by $m = 2\frac{\beta^{50}}{\alpha^{50}}$ and its intercept n is $n = \beta - \frac{\alpha\beta^{50}}{\alpha^{50}}$.

Next, we estimate the parameters of the marginal medical spending function implied by the entry and spending patterns of individuals entering when unemployment is higher by one percentage point.[20] We calculate the slope and intercept of B^U, following a similar logic: B^U reaches its average level over a given x-axis interval at the midpoint:

$$B^U\left(\frac{\alpha+\alpha^U}{2}\right) = \beta + \beta^U \qquad B^U\left(\frac{\alpha+\alpha^{50}+\alpha^U+\alpha^{50\times U}}{2}\right) = \beta + \beta^{50} + \beta^U + \beta^{50\times U}.$$

Thus we can calculate the slope m^U and intercept n^U as

$$m^U = 2\frac{\beta^{50}+\beta^{50\times U}}{\alpha^{50}+\alpha^{50\times U}} \qquad n^U = \beta + \beta^U - \frac{(\alpha+\alpha^U)(\beta^{50}+\beta^{50\times U})}{\alpha^{50}+\alpha^{50\times U}}.$$

Figure 6b depicts the marginal spending functions implied by the estimates in Table 1. We illustrate a 95% confidence interval (CI) for each line by estimating equations 6 and 7 using 500 resamplings of county $\times$ entry-month clusters (which yield 500 estimates of each of the four identifying points and lines B and B^U). The overlap of the two confidence intervals is in darker gray.

Our empirical test for whether the lines are statistically distinguishable is reported in Panel A of Appendix Table A.5. The level of the marginal medical spending function B^U at the x-value $\alpha + \alpha^U$ (entry at high unemployment for 49-year-olds) is equal to \$13,526, with a bootstrap CI from \$13,452 to \$13,602. When we evaluate the same x-value using the B function (i.e., point Y' in Figure 6a), we find that $B(\alpha + \alpha^U)$ is \$13,474 which lies in the CI for $B^U(\alpha + \alpha^U)$. The second column repeats the exercise for 50-year-olds, again

[20] Specifically, α^U and $\alpha^{50\times U}$ represent incremental entry for 49- and 50-year-olds when the unemployment rate is one percentage point above its mean level (about 6% in the sample). We denote this "higher unemployment" without loss of generality because we found in Figures 2a and 2b that both entry and spending are broadly linear in county unemployment at application.

finding that $B(\alpha + \alpha^U + \alpha^{50} + \alpha^{50\times U})$ is in the CI for $B^U(\alpha + \alpha^U + \alpha^{50} + \alpha^{50\times U})$ (point Z). Therefore, we conclude that individuals who applied to DI during high unemployment have similar spending patterns as those who applied during mean unemployment, implying that health shocks explain little of DI cyclicality.[21]

We have so far focused on the marginal medical spending function because we use it further in the full model in Section 5.4. But the same analysis can produce the marginal mortality functions for DI entrants at mean and high unemployment. Figure 6c shows the results, revealing a pattern similar to what we found for medical spending: there is little evidence for health shocks differentially affecting DI entrants at high unemployment.

Finally, while the focus of this paper is on the overall experience of DI recipients, in the Appendix we report these results by certain subgroups to examine the possibility of heterogeneity in the role of health shocks. Specifically, we estimate this model separately for males and females.[22]

5.3 Discussion

Our analysis concludes that the marginal spending functions at mean and higher unemployment are very similar: specifically, the incremental individuals entering at times of higher unemployment have spending patterns just like the incremental individuals entering after the age discontinuity (when adjusted for the size of the entry increase). Another way to see this similarity is to examine the algebraic expressions for the intercept of each line. Assume for the moment that the slopes of the two marginal spending functions are the same[23] such that we can substitute $\frac{\beta^{50}}{\alpha^{50}}$ for $\frac{\beta^{50}+\beta^{50\times U}}{\alpha^{50}+\alpha^{50\times U}}$. Then we can difference the two intercepts:

$$n^U - n\Big|_{m=m^U} = \beta + \beta^U - \frac{(\alpha+\alpha^U)\beta^{50}}{\alpha^{50}} - (\beta - \frac{\alpha\beta^{50}}{\alpha^{50}}) = \beta^U - \frac{\alpha^U\beta^{50}}{\alpha^{50}}.$$

The difference in intercepts would be zero if $\frac{\beta^U}{\alpha^U} = \frac{\beta^{50}}{\alpha^{50}}$. This is exactly what our empirical test comparing Y and Y' considers – do the individuals entering due to higher unemployment alter spending more (or less) than we would expect given the size of the entry increase? Our finding that the intercepts of the two functions are statistically indistinguishable means that recession marginals and age discontinuity marginals change spending to a similar extent.

[21]While we prefer to focus on the confidence intervals at the identifying points for inference, Appendix Table A.4 reports estimates and CIs for the slopes and intercepts of both marginal medical spending functions.

[22]Results for racial/ethnic subgroups can be found in Carey, Miller and Molitor (2024).

[23]In order for the two slopes m and m^U to be equal, $\frac{\beta^{50}}{\alpha^{50}}$ must be equal to $\frac{\beta^{50\times U}}{\alpha^{50\times U}}$. In words, the incremental entrants induced by the combined effect of the age discontinuity and unemployment, $\alpha^{50\times U}$, must alter spending in the same proportion as the incremental entrants induced by the age discontinuity alone α^{50}. We instead find a slightly flatter slope (see Appendix Table A.4), due to the fact that $\frac{\beta^{50\times U}}{\alpha^{50\times U}}$ is slightly above $\frac{\beta^{50}}{\alpha^{50}}$.

Comparing these intercepts shows how our analysis takes advantage of the assumption of a fixed ordering of individuals. Under this assumption, the spending of recession marginals can be compared to age discontinuity marginals. The fact that we consider two sources of variation expands the assumption from its usual meaning in the treatment effects literature. In our setting, the ordering assumption means that an individual who is on the DI margin (but not enrolled) at age 49 under mean unemployment will enter DI either when attaining age 50 or when unemployment rises.

To understand the implications of the ordering assumption, suppose individuals are lined up by their work capacity, with individuals with lower work capacity strictly more likely to join DI. Our assumption implies that individuals with the same work capacity have the same increased likelihood of entering DI as a result of an increase in unemployment. If there are characteristics of individuals (besides work capacity) that make them more likely to enter DI for a given percentage point of unemployment – e.g., their marital status – these characteristics must be independent of health (medical spending and mortality). Our analysis would be biased if there were characteristics that made an individual more sensitive to unemployment *and* systematically increased (or decrease) their medical spending. In that case, our recession marginals would have systematically higher (or lower) spending than our age discontinuity marginals due to composition alone, and we could not interpret the vertical distance between Y and Y' as evidence for health shocks.

In our empirical implementation, our ordering assumption need not hold unconditionally, but must hold conditional on controls. Of course, we do not see all relevant characteristics that could affect both responsiveness to unemployment and spending; for example, we do not observe an individual's industry or occupation. However, we condition on county fixed effects since geography is a strong correlate of these dimensions of potential heterogeneity.

We support our ordering assumption in two ways. First, suppose for a moment that there is substantial variation across counties in the sensitivity of DI entry to unemployment – either because of heterogeneity by industry or by any other factor. We expect that removing or adding controls – as we do in our robustness – would greatly change our results. However, in Section 6 when we evaluate models with and without county fixed effects, we do not find large changes.

A second piece of evidence supporting our ordering assumption can be found in the descriptive findings in Section 4.4. Figure 5 shows that the two sources of variation—unemployment and the age discontinuity—interact to create greater entry than either source on its own. If unemployment and the age discontinuity induced the entry of completely disjoint sets of individuals, there is no reason to think that entry would become discontinuously more sensitive at ages 50 and 55. Finally, we find that increased entry from either source arises from the same underlying mechanism—increased applications.

Our analysis relies on a further assumption, which is that there is no heterogeneity in the effect of receiving DI on health outcomes. In the treatment effects literature, any difference in a treated outcome—e.g., a drop in spending after age 50—can be due either to differences in the underlying health of compliers, or by differences in the response of the compliers to the "treatment" of DI and Medicare.[24] For example, suppose that DI recipients induced by recessions or the age discontinuity received lower cash benefits from the DI program. Then the lower spending among these groups could be, in part, due to the lower spending we might expect from a lower-income group exposed to Medicare's relatively high cost-sharing. This "treatment effect heterogeneity" would contaminate our use of spending to infer underlying health.

We argue that treatment effect heterogeneity is likely to be modest in our setting. First, we find very similar results for both of our health measures, medical spending and mortality, even though mortality is less likely to be affected by differences in DI recipients' experience of DI or Medicare. Second, we can empirically rule out a number of potential channels for heterogeneous treatment effects. We first examine the example mechanism of varying cash benefits by estimating equations (2) and (4) with annual cash benefits as the dependent variable. In Appendix Figure A.4, we show that cash benefits are not related to unemployment at application or age at entry. We also examine differential enrollment in Medicaid, Medicare Advantage, or Medicare Part B. Enrollment in these programs potentially affects our measure of medical spending: Medicaid enrollees face limited cost-sharing, while we do not observe medical spending for individuals enrolled in Medicare Advantage or all spending on physician services for individuals not enrolled in Part B. We find that 39% of person-years are dually eligible for Medicaid, 22% are enrolled in Medicare Advantage, and 92% elect Part B. If enrollment in these programs is correlated with unemployment at application, our findings could be confounded by these programs. We examine the possibility of differential enrollment in these programs by again adapting equations (2) and (4). In Appendix Figure A.5, we demonstrate no relationship between these outcomes and national unemployment at enrollment (represented by the dashed blue curve) or age at entry.

Finally, we hypothesize health shocks of the type described in Grossman (1972) that cause a reduction in health capital and thus a *permanent* increase in medical spending. If

[24] That is to say, the Marginal Treated Outcome function is the sum of two component functions: the Marginal Untreated Outcome function (which reports how the outcome would vary with the unobserved preference for treatment in the absence of treatment) and the Marginal Treatment Effect function (which reports the magnitude of the treatment effect as a function of the unobserved preference for treatment). Given that we only observe the outcome (medical spending) among the treated (DI recipients), we cannot separately identify the component functions.

recession-associated health shocks only temporarily reduce health capital, these effects may not be observable in our Medicare data due to the two-year waiting period. We note that the DI eligibility criteria require that the work limitation be "permanent" so that the temporary effects of recessions on health should not result in greater DI eligibility. In addition, we cannot rule out the presence of recession-associated health shocks that do not affect medical spending. Health shocks could leave medical spending unchanged due to barriers to accessing care or because the health shock is not amenable to medical care.

5.4 Full Model of DI Entry

5.4.1 Costs and Benefits of DI Entry

We now embed our marginal spending functions in a full model of DI entry among 49- and 50-year-olds at mean and higher unemployment rates. Our full model incorporates institutional details of the DI program and illustrates the entry-cost channel in cyclical DI entry. We use the full model to determine the share of recession-associated DI entry that is attributable to health shocks, and to examine the welfare impact of recession-associated DI entry.

We begin by redefining the x-axis. While the treatment effects literature defines an "unobserved preference for treatment", in our full version of the model we instead characterize individuals by their residual work capacity. As shown in Figure 7a, the lowest range corresponds to individuals who are found to have "less than sedentary" work capacity, which is the lowest category of work capacity for individuals without a listed impairment.[25]

Next, we redefine what is represented by the functions B and B^U. Previously, these functions represented medical spending for marginal DI entrants. We now redefine those functions to represent the marginal *benefit* of DI. Our marginal benefit concept includes the utility of cash benefits as well as the value of eligibility for Medicare. Cash benefits depend only on an individual's earnings history and are independent of work capacity; consequently, we interpret our marginal benefit function as identified up to an unknown constant. We proxy the value of Medicare eligibility using medical spending (ignoring the insurance value of Medicare). Defining the benefit of DI as a function of work capacity reflects research showing a strong correlation between the level of disability (measured by limitations in activities of daily living) and medical spending (Wolff et al., 2019; Koroukian et al., 2017).

There are age-specific costs to establishing disability and obtaining DI benefits in the form of foregone expected earnings and costs incurred during the application process, such

[25] We focus on individuals whose DI applications are adjudicated by the grid rules (Step 5 in Section 2). Individuals with listed impairments are not subject to the age discontinuity in eligibility and show very little cyclicality in DI entry (Maestas, Mullen and Strand, 2021).

as the cost of a disability lawyer or clinical documentation of health status (Maestas, Mullen and Strand, 2013; Autor et al., 2015). We denote these costs as C.[26] The cost of DI entry for a 49-year-old is depicted by the red curve with circle markers in Figure 7a. Applicants who have significant work-limiting disabilities that leave them incapable of undertaking even sedentary work on a sustained basis likely have low or zero expected earnings, and it is likely to be relatively easy for any individual in this range to document and prove their disability to the SSA. Consequently, the cost curve is low and flat over this range of severe work-limiting disability.

Once the individual's residual work capacity increases to the point where they are capable of sustained sedentary work, the cost of establishing eligibility for DI benefits begins to increase for two reasons. First, as individuals' work capacity increases, new jobs become available to them, causing their earnings expectations to rise.[27] Second, SSA guidelines recommend that most 49-year-olds with a sedentary work capacity be found not disabled. While this recommendation can be overcome, doing so involves extensive and costly documentation of health conditions (Autor et al., 2015) and commonly involves a costly appeal process. Thus the cost of establishing disability is larger for 49-year-olds capable of sedentary work and increases rapidly as work capacity further increases. We depict this in the model by the steep, upward-sloping segment on the red curve (marked with circles) beginning when individuals reach the level of sustained sedentary work capacity.

The green curve (marked with squares) in Figure 7a depicts entry cost for 50-year-olds. Compared to 49-year-olds, 50-year-olds with sedentary work capacity face relaxed eligibility criteria, especially those with low education levels and unskilled work histories. This reduces the cost of DI entry for this group relative to their younger counterparts. The result is that while the green function also increases once individuals reach a sedentary work capacity, it does so more slowly, capturing that both the cost of establishing disability and the slope of this cost in work capacity is lower for 50-year-olds than 49-year-olds.

Individuals whose work-limiting disability is such that the benefit of entering DI exceeds its cost will apply for and be awarded DI benefits. Thus, α 49-year-olds to the left of the intersection of the red cost function and the benefit function will enter DI, and α^{50} additional age discontinuity marginals with sedentary work capacity join DI as a result of the age discontinuity.

[26] For ease of exposition, we assume that the cost function includes the cost of *successfully* applying for DI so that individuals are always admitted whenever the benefits exceed the costs. Probabilistic admission, where the probability of admission is decreasing in residual work capacity, could be incorporated into the model without changing its qualitative implications.

[27] Deshpande and Li (2019) find that the "hassle" costs of DI applications among eventual enrollees are larger for those with milder disabilities, supporting an upward sloping cost curve.

5.4.2 Effects of Unemployment in the Full Model

In the full model, we represent both potential channels by which unemployment induces higher DI entry. As before, recession-associated health shocks potentially shift the benefits function outward from B to B^U, representing an increase in medical spending for DI recipients of any given work capacity.

We also directly represent the second potential channel, a reduction in the cost of DI entry. In Figure 7a, the lowered dashed curves represent the cost functions for 49- and 50-year-olds in high unemployment.[28] This shift arises from the negative impact of increased unemployment on expected earnings, which is consistent with the work of Lindner, Burdick and Meseguer (2017). The reduction in the entry cost of DI moves the intersection of the cost and benefit functions to the right. Thus, benefits exceed costs for a slightly larger group, and DI entry increases.

Because 49- and 50-year-olds experience similar labor markets, we assume unemployment reduces C^{49} and C^{50} similarly and draw the same downward shift in the cost function for 50-year-olds (to the dashed green curve). However, the flatter slope of the cost function among 50-year-olds means that a 1 percentage point increase in the unemployment rate induces a greater entry response among 50-year-olds than among 49-year-olds. Thus, the model predicts greater sensitivity to unemployment for 50-year-olds than for 49-year-olds, as we showed empirically in Section 4.4.

5.4.3 Estimation

To complete the model, we turn to estimation of the cost functions. In the previous section we identified the benefits functions by exploiting the age discontinuity in eligibility, which generates movement along the benefits function. We do not have a similar source of variation identifying the slope of the cost functions; instead, each of the four points that we characterize in the data are associated with different cost functions: C_{49}, C_{49}^U, C_{50}, and C_{50}^U. However, assuming that the cost functions are piecewise linear and that unemployment reduces costs similarly for both 49- and 50-year-olds, the sloped portion of the cost functions can be characterized with five parameters: the slope (m_{49}) and intercept (n_{49}) for 49-year-olds under mean unemployment, the slope (m_{50}) and intercept (n_{50}) for 50-year-olds under mean unemployment, and the cost change associated with unemployment (ΔC).

While the five cost function parameters are underidentified by the four points the functions pass through, we can calculate the slopes and intercepts given a value for ΔC. In

[28]For simplicity, we model the fall as independent of work capacity; the model's qualitative findings are unchanged if the shift depends on work capacity as long as the changes are the same for 49- and 50-year-olds.

Appendix Section A.4, we present equations for the slopes and intercepts of the two cost functions as a function of ΔC and the slopes and intercepts of the benefit functions. We focus on a low-to-moderate scenario in which ΔC is equal to \$5000, and test sensitivity to a very low cost scenario in which ΔC is set equal to \$1000.[29]

For $\Delta C = -\$5000$, we draw our full model in Figure 7b and report the slope and intercept of the cost functions in Panel B of Appendix Table A.4. The dashed red and green curves represent the reduced entry costs in a recession, intercepting the vertical axis at \$5,000 less than the the solid curves.[30] The data imply a flatter slope for the cost function for 50-year-olds, which in turn means that the same vertical shift in the intercept generates a larger entry response for 50-year-olds than for 49-year-olds. We find similar estimates for $\Delta C = -\$1000$ (Appendix Figure A.6), suggesting that our cost function parameters are not very sensitive to the choice of ΔC.

5.4.4 Entry Under a Counterfactual of No Health Shocks

The parameterized cost functions allow us to illustrate the magnitude of the small outward shift in the benefits function that we saw in Figure 6b. Consider a counterfactual in which unemployment reduces entry costs but has no effect on health, such that the benefits curve B does not shift outward whatsoever. In this counterfactual (and assuming $\Delta C = -\$5000$), one percentage point of unemployment would increase DI entry by 98.5% of the observed value. Thus, the small outward shift of the benefits curve accounts for only 1.5% of actual DI cyclicality, with a confidence interval of 0.1% to 3.2%. If we instead assume that ΔC is \$1000, unemployment accounts for 92.8% of the true recession associated effect. Thus, under a scenario in which one percentage point of unemployment only alters entry costs by about one week of earnings, we would still conclude that these small entry costs alone generate 92.8% of observed recession-associated DI entry increases. We report these estimates and their CIs in Appendix Table A.5.

The full model highlights a third potential channel by which unemployment could change the number and health status of DI entrants: SSA examiners could be systematically more likely to award benefits when unemployment is high, which we refer to as "screening effects." To evaluate the scope for this channel, we first note that SSA screening criteria are based only on whether an individual has the ability to do a job; the criteria explicitly prohibit the evaluation of cases based on the availability of jobs (20 C.F.R. §404.1566). If screening effects

[29] For scale, \$1000 is between one and two weeks of wages for individuals with high school degrees over our sample period (Bureau of Labor Statistics, n.d.). Higher estimates of ΔC would simply imply that the small outward shift of the benefits curve is even less important in countercyclical DI than our low-to-moderate and very low cost scenarios.

[30] In the figure, we have normalized all costs to be non-negative by shifting them up by about \$25,000.

nonetheless exist, they can be represented in our framework as a change in the slope of the cost curves during recessions. Much as the relaxation of screening criteria between ages 49 and 50 is represented by the flatter slope of the green cost curve relative to the red cost curve, a less-stringent criterion would allow slightly more people at any given level of work capacity. As discussed above, we cannot parameterize our model without assuming the same slopes at mean and higher unemployment levels. However, we note that any alternative cost curves we consider would still pass through the four points identified by the solid squares and hollow circles in Figure 7b and that these points along the marginal medical spending functions were determined in Section 5.2 without any reference to cost curves. Thus, we conclude that while the presence of screening effects would alter our interpretation of why more and healthier DI entrants join during high unemployment, it would not alter our conclusion that unemployment-related health shocks do not play a role.

5.5 Welfare Implications of Entry Sensitivity

Even though the DI entry criteria are not supposed to depend on economic conditions, the fact that the program does allow, for whatever reason, more people to enter when economic conditions worsen, conveys benefits to those who enter the program. Figure 7a illustrates these benefits for 49- and 50-year olds following a 1 percentage point increase in the unemployment rate. In the case of 49-year olds, when unemployment increases, the cost curve shifts down, admitting α^U additional beneficiaries. Each of these marginal beneficiaries earns positive surplus from being admitted to the program equal to the distance between the benefit and cost curves. The aggregate benefit to all marginal beneficiaries is equal to the area of the red triangle. For 50-year olds, $\alpha^U + \alpha^{U\times 50}$ additional beneficiaries are admitted, and the aggregate benefit is given by the area of the gray triangle.

To determine the relative welfare impact of DI entry sensitivity, we can compare the areas of the two triangles. To do so, we require a further assumption: that the benefit curves B and B^U have the same slope. As we report in Appendix Table A.4, this is approximately true in our case. Given this assumption, the heights of the two triangles are the same, since the cost curves shift equivalently for 49- and 50-year-olds. Therefore the ratio of the areas of the two triangles is equal to the number of marginal entrants of each age.

Thus, the fact that DI entry sensitivity approximately doubles after age 50 implies that DI provides approximately double the welfare benefit to individuals in their 50s versus individuals in their 40s. The welfare gain is particularly disparate between 49- and 50-year-olds due to the entry spike discussed in Section 4.4. Figure 5 reports entry sensitivity as a function of age for all ages, which suggests that the welfare benefit of DI entry sensitivity is fairly low below 40 and concentrated at older ages. As a caution, comparisons between ages rely on an assumption that the recession experiences of the two groups are similar.

6 Robustness

In this section, we demonstrate that the key results of our analysis are unchanged under a number of alternative specifications. We reexamine three core findings: the correlation between unemployment and the health status of DI entrants, the increased sensitivity to unemployment above the age discontinuity, and the model-based analysis that rejects unemployment-related health shocks. These results are unchanged when we use fixed effects to net out components of the identifying variation or adjust for known determinants of health, or cluster standard errors at alternative levels.

6.1 Unemployment and Health Status

Figure 1b shows that the average spending of DI entrants is negatively correlated with the national unemployment rate at DI application. That analysis controlled for the number of years enrolled to correct for the fact that each entry-year cohort is observed over a different set of years in the program (e.g., the 1993 cohort is not observed until their sixth year in the program). Appendix Figure A.7 shows how our findings change when adding controls for known determinants of spending such as county, age, sex, and year of observation. The inclusion of county has almost no effect. When controlling for age and sex, we measure age in two ways: at entry and at observation, due to the patterns we find in age at entry. In recent years, DI entrants have become older; thus, the medical spending of recent DI entrants is measured to be somewhat lower after adjusting for the extra spending associated with the older ages. Conversely, the cohorts that entered in the 1990s are measured to have somewhat higher spending once adjusting for their relatively young ages. However, the overall pattern of spending net of age-sex controls is similar to the baseline specification. The inclusion of a fixed effect for the observation year (i.e., t in equation (2)) controls for the evolution of medical technology over our 18 years of spending data, and when interacted with county, it accounts for the availability of that technology by county.[31] We find that the cyclical pattern is still evident in the presence of those controls.

We also measure the correlation between county unemployment and health status (equation (3) and Table 1). We examine this correlation under various fixed effects in Appendix

[31]When included with year-of-entry fixed effects as in Appendix Figure A.7, we require a second omitted year; we choose 2014.

Table A.6. The first row repeats the baseline results, while the next four rows add the controls just discussed to account for known determinants of spending, showing modest reductions in the correlation when correcting for demographics and year of observation.

Our baseline model measuring the correlation between county unemployment and health status includes county fixed effects, which identify the correlation using deviations from the average county unemployment rate. However, county fixed effects net out the portion of the correlation related to counties with persistently high unemployment and a persistently high entry of healthier DI recipients. Dropping the county fixed effects, as in the fifth row of Appendix Table A.6, reveals a stronger correlation between unemployment and health.

Our use of local unemployment rates enables a specification that includes an entry month fixed effect. This specification shifts identification from entirely within county to entirely between county, leveraging the fact that in any given month unemployment is high in some counties and low in others. An advantage of this specification is that it accounts for any national-level changes in the DI program over our 25-year period. The last row of Appendix Table A.6 reports that within a set of individuals who joined Medicare in the same month and have been in the program the same number of years, those who joined from counties with higher unemployment are in better health.

Finally, we also consider how inference changes when we cluster our standard errors at a higher level. For estimating the effect of unemployment on entry and health, our baseline analysis clusters standard errors at the county × entry-month level, following the recommendation of Abadie et al. (2022) to cluster at the level at which the "treatment" (the local unemployment rate) is assigned. However, Appendix Table A.7 shows that inference is substantively unchanged when we cluster at the county level; in fact, some standard errors in Panel B are actually smaller when clustering at the county level. To further evaluate the robustness of our core conclusions to clustering at the county level, we replicate Figures 6b and 6c with the 95% confidence intervals generated from a bootstrap of county clusters instead of the county × entry-month clusters used in the baseline analysis. The resulting confidence intervals, reported in Appendix Figure A.10, are slightly larger than but substantively similar to those based on county × entry-month clusters.

6.2 Cyclical Entry by Age

Our finding that sensitivity to unemployment jumps discontinuously at the age thresholds for relaxed eligibility is unchanged when we change the variation used to identify it. Appendix Figure A.8 reports the age-specific coefficients estimated in equation (5) in the presence of county × entry-age fixed effects (our baseline), entry-age fixed effects alone, and entry-month

$\times$ entry-age fixed effects alone. Our finding persists whether we limit ourselves to within- or between-county variation in unemployment rates or if we use all variation.

6.3 No Evidence for Unemployment-Associated Health Shocks

Finally, we test the sensitivity of the findings of our model of DI entry and spending. To do so, we vary the samples and specifications used to estimate equations (6) and (7), which generate the parameters of the marginal spending functions at mean and high unemployment. We first apply our methodology to the second age discontinuity, which relaxes eligibility further at age 55. For equation (6) predicting entry, our baseline specification exploited within-county variation (e.g., county fixed effects); we additionally report alternatives using between-county variation (entry-month fixed effects) or all variation (no fixed effects). For equation (7) predicting spending, we use the same fixed effects reported in Appendix Table A.6, except for the additional controls for age, which are collinear given our indicator for entering DI at age 50 and our control for years enrolled.

Appendix Figure A.9 and Appendix Table A.5 demonstrate that across samples and specifications, we consistently find no evidence for unemployment-associated health shocks. Panel (a) uses our baseline fixed effects in combination with individuals aged 54 and 55, exploiting the second age discontinuity in eligibility. Panel (b) returns to the first age discontinuity but adds richer controls for spending, while Panels (d) and (f) also vary the spending equation by exploiting between-county or all variation in county unemployment rates, respectively. Panels (c) and (e) explore alternative specifications for our entry equation that remove county fixed effects and, in Panel (c) replace those with entry-month fixed effects (both panels use the baseline spending specification and our sample of 49- and 50-year-olds). The marginal spending functions at mean (solid lines) and high (dashed lines) unemployment are always very similar. Appendix Table A.5 reports our empirical test for each specification, which confirms our interpretation that these lines are not statistically distinguishable and that any outward shift of the benefits curve is economically small.

7 Conclusion

This paper examines the mechanisms driving increased Social Security Disability Insurance (DI) enrollment during recessions. Using Medicare administrative data, we find that recession-induced DI entrants have substantially better health, as measured by lower medical spending and mortality, than those entering under better macroeconomic conditions. To disentangle whether this pattern reflects health changes or reduced entry costs, we exploit age-based discontinuities in DI's Medical-Vocational Guidelines. These guidelines relax eligibility criteria at ages 50 and 55 without directly affecting health, allowing us to isolate the causal effect of entry costs. We find that the health of marginal DI entrants remains similar across unemployment levels. Thus, countercyclical DI enrollment stems overwhelmingly from reduced opportunity costs during economic downturns, with no detectable role for health shocks. This finding suggests inadequate safety net support for individuals with functional limitations during economic downturns, and that temporary disability benefits or employer accommodations may better serve their needs than permanent DI awards.

Our study further reveals how these age-based guidelines fundamentally shape the DI program's response to economic downturns. While unemployment increases DI entry at all ages, the effect jumps 2–4 fold precisely at ages 50 and 55. Workers over 50 account for half of all DI awards but generate two-thirds of recession-induced entry, demonstrating that the age-based changes in eligibility rules drive most of DI's cyclical sensitivity. Our welfare analysis quantifies the distributional consequences: workers over 50 receive approximately double the insurance value from DI's countercyclical protection compared to younger workers.

References

Abadie, Alberto, Susan Athey, Guido W Imbens, and Jeffrey M Wooldridge. 2022. "When Should You Adjust Standard Errors for Clustering?" *The Quarterly Journal of Economics*, 138(1): 1–35.

Aizawa, Naoki, Soojin Kim, and Serena Rhee. 2020. "Labor Market Screening and Social Insurance Program Design for the Disabled." National Bureau of Economic Research Working Paper 27478.

Alon, Titan, Sena Coskun, Matthias Doepke, David Koll, and Michèle Tertilt. 2021. "From Mancession to Shecession: Women's Employment in Regular and Pandemic Recessions." *NBER Macroeconomics Annual 2021, volume 36*, 83–151. University of Chicago Press.

Armour, Philip, and Claire O'Hanlon. 2019. "How Does Supplemental Medicare Coverage Affect the Disabled under-65 Population?: An Exploratory Analysis of the Health Effects of States' Medigap Policies for SSDI Beneficiaries." National Bureau of Economic Research Working Paper 25564.

Autor, David H., and Mark G. Duggan. 2003. "The Rise in the Disability Rolls and the Decline in Unemployment." *The Quarterly Journal of Economics*, 118(1): 157–206.

Autor, David H., Nicole Maestas, Kathleen J. Mullen, and Alexander Strand. 2015. "Does Delay Cause Decay? The Effect of Administrative Decision Time on the Labor Force Participation and Earnings of Disability Applicants." National Bureau of Economic Research Working Paper 20840.

Black, Dan, Kermit Daniel, and Seth Sanders. 2002. "The Impact of Economic Conditions on Participation in Disability Programs: Evidence from the Coal Boom and Bust." *American Economic Review*, 92(1): 27–50.

Brinch, Christian N., Magne Mogstad, and Matthew Wiswall. 2017. "Beyond LATE with a Discrete Instrument." *Journal of Political Economy*, 125(4): 985–1039.

Browning, Martin, and Eskil Heinesen. 2012. "Effect of job loss due to plant closure on mortality and hospitalization." *Journal of Health Economics*, 31(4): 599–616.

Bureau of Labor Statistics. n.d.. "Median usual weekly earnings of full-time wage and salary workers by sex."

Cabral, Marika, and Marcus Dillender. 2024. "Gender Differences in Medical Evaluations: Evidence from Randomly Assigned Doctors." *American Economic Review*, 114(2): 462–99.

Carey, Colleen, Nolan H. Miller, and David Molitor. 2024. "Racial and Ethnic Disparities in SSDI Entry and Health." National Bureau of Economic Research Retirement and Disability Research Center NB23-04.

Census Bureau Population Estimates Program. n.d.. "Census U.S. Intercensal County Population Data, 1970–2014." *Last accessed February 2021*.

Charles, Kerwin Kofi, Yiming Li, and Melvin Stephens Jr. 2018. "Disability Benefit Take-Up and Local Labor Market Conditions." *Review of Economics and Statistics*, 100(3): 416–423.

Chen, Susan, and Wilbert Van der Klaauw. 2008. "The Work Disincentive Effects of the Disability Insurance Program in the 1990s." *Journal of Econometrics*, 142(2): 757–784.

Coile, Courtney C., Phillip B. Levine, and Robin McKnight. 2014. "Recessions, Older Workers, and Longevity: How Long Are Recessions Good for Your Health?" *American Economic Journal: Economic Policy*, 6(3): 92–119.

Crost, Benjamin, and Andrew Friedson. 2017. "Recessions and Health Revisited: New Findings for Working Age Adults." *Economics & Human Biology*, 27: 241–247.

Cubanski, Juliette, Tricia Neuman, and Anthony Damico. 2016. "Medicare's Role for People under Age 65 with Disabilities." Kaiser Family Foundation Issue Brief.

Cutler, David M., Ellen Meara, and Seth Richards-Shubik. 2012. "Unemployment and Disability: Evidence from the Great Recession." National Bureau of Economic Research.

Davidson, Kate. 2020. "Trump Administration Weighs Tighter Requirements for Disability Payments." *Wall Street Journal*.

Deshpande, Manasi, and Lee Lockwood. 2022. "Beyond Health: Non-Health Risk and the Value of Disability Insurance." *Econometrica*, 90(4).

Deshpande, Manasi, and Yue Li. 2019. "Who Is Screened Out? Application Costs and the Targeting of Disability Programs." *American Economic Journal: Economic Policy*, 11(4): 213–248.

Deshpande, Manasi, Tal Gross, and Yalun Su. 2021. "Disability and Distress: The Effect of Disability Programs on Financial Outcomes." *American Economic Journal: Applied Economics*, 13(2): 151–178.

Duggan, Mark, Perry Singleton, and Jae Song. 2007. "Aching to Retire? The Rise in the Full Retirement Age and Its Impact on the Social Security Disability Rolls." *Journal of Public Economics*, 91(7): 1327–1350.

Eliason, Marcus, and Donald Storrie. 2009. "Does Job Loss Shorten Life?" *The Journal of Human Resources*, 44(2): 277–302.

Finkelstein, Amy, Matthew J Notowidigdo, Frank Schilbach, and Jonathan Zhang. 2025. "Lives Versus Livelihoods: The Impact of the Great Recession on Mortality and Welfare." *The Quarterly Journal of Economics*, qjaf023.

French, Eric, and Jae Song. 2014. "The Effect of Disability Insurance Receipt on Labor Supply." *American Economic Journal: Economic Policy*, 6(2): 291–337.

Gelber, Alexander, Timothy J. Moore, and Alexander Strand. 2017. "The Effect of Disability Insurance Payments on Beneficiaries' Earnings." *American Economic Journal: Economic Policy*, 9(3): 229–261.

Grossman, Michael. 1972. "On the Concept of Health Capital and the Demand for Health." *Journal of Political Economy*, 80(2): 223–255.

Halliday, Timothy J. 2007. "Business Cycles, Migration, and Health." *Social Science and Medicine*, 64(7).

Hawkins, Amelia, and Salla Simola. 2021. "Paying for Disability Insurance?: Firm Cost Sharing and Its Employment Consequence." Working Paper.

Heckman, James J., and Edward Vytlacil. 2005. "Structural Equations, Treatment Effects, and Econometric Policy Evaluation." *Econometrica*, 73(3): 669–738.

Kearney, Melissa S., Brendan M. Price, and Riley Wilson. 2021. "Disability Insurance in the Great Recession: Ease of Access, Program Enrollment, and Local Hysteresis." *AEA Papers and Proceedings*, 111: 486–90.

Koroukian, Siran M., Nicholas K. Schlitz, David F. Warner, Jiayang Sun, Kurt C. Stange, Charles W. Given, and Avi Dor. 2017. "Multimorbidity: Constellations of Conditions across Subgroups of Midlife and Older Individuals, and Related Medicare Expenditures." *Journal of Comorbidities*, 7(1): 33–43.

Kostøl, Andreas Ravndal, and Magne Mogstad. 2014. "How Financial Incentives Induce Disability Insurance Recipients to Return to Work." *American Economic Review*, 104(2): 624–655.

Kowalski, Amanda E. 2021. "Reconciling Seemingly Contradictory Results from the Oregon Health Insurance Experiment and the Massachusetts Health Reform." *The Review of Economics and Statistics*, 1–45.

Liebman, Jeffrey B. 2015. "Understanding the Increase in Disability Insurance Benefit Receipt in the United States." *Journal of Economic Perspectives*, 29(2): 123–150.

Lindner, Stephan. 2016. "How Do Unemployment Insurance Benefits Affect the Decision to Apply for Social Security Disability Insurance?" *Journal of Human Resources*, 51(1): 62–94.

Lindner, Stephan, Clark Burdick, and Javier Meseguer. 2017. "Characteristics and Employment of Applicants for Social Security Disability Insurance over the Business Cycle." *The B.E. Journal of Economic Analysis & Policy*, 17.

Low, Hamish, and Luigi Pistaferri. 2019. "Disability Insurance: Error Rates and Gender Differences." National Bureau of Economic Research Working Paper 26513.

Maestas, Nicole, Kathleen J. Mullen, and Alexander Strand. 2013. "Does Disability Insurance Receipt Discourage Work? Using Examiner Assignment to Estimate Causal Effects of SSDI Receipt." *American Economic Review*, 103(5): 1797–1829.

Maestas, Nicole, Kathleen J. Mullen, and Alexander Strand. 2021. "The Effect of Economic Conditions on the Disability Insurance Program: Evidence from the Great Recession." *Journal of Public Economics*, 199.

McInerney, Melissa, and Jennifer M. Mellor. 2012. "Recessions and Seniors' Health, Health Behaviors, and Healthcare Use: Analysis of the Medicare Current Beneficiary Survey." *Journal of Health Economics*, 31(5): 744–751.

Mueller, Andreas I., Jesse Rothstein, and Till M. von Wachter. 2016. "Unemployment Insurance and Disability Insurance in the Great Recession." *Journal of Labor Economics*, 34(S1): S445–S475.

Pattison, David, and Hilary Waldron. 2013. "Growth in new disabled-worker entitlements 1970-2008." *Soc. Sec. Bull.*, 73: 25.

Prinz, Daniel, and Bastian Ravesteijn. 2021. "Employer Responsibility in Disability Insurance: Evidence from the Netherlands." Working Paper.

Ruhm, Christopher J. 2000. "Are Recessions Good for Your Health?" *The Quarterly Journal of Economics*, 115(2): 617–650.

Ruhm, Christopher J. 2003. "Good Times Make You Sick." *Journal of Health Economics*, 22(4): 637–658.

Ruhm, Christopher J. 2005. "Healthy Living in Hard Times." *Journal of Health Economics*, 24(2): 341–363.

Ruhm, Christopher J. 2015. "Recessions, Healthy No More?" *Journal of Health Economics*, 42: 17–28.

Schaller, Jessamyn, and Ann Huff Stevens. 2015. "Short-run effects of job loss on health conditions, health insurance, and health care utilization." *Journal of Health Economics*, 43: 190–203.

Schwandt, Hannes. 2018. "Wealth Shocks and Health Outcomes: Evidence from Stock Market Fluctuations." *American Economic Journal: Applied Economics*, 10(4): 349–77.

Schwandt, Hannes, and Till M. von Wachter. 2020. "Socioeconomic Decline and Death: Midlife Impacts of Graduating in a Recession." National Bureau of Economic Research Working Paper 26638.

Social Security Administration. 2017. "Annual Statistical Report on the Social Security Disability Insurance Program, 2016." Social Security Administration, Office of Retirement and Disability Policy, SSA Publication No. 13-11826, Washington, DC.

Social Security Administration. 2022. "Annual Statistical Report on the Social Security Disability Insurance Program." SSA Publication No. 13-11826.

Social Security Administration. n.d.*a*. "HI 00820.025 Termination of Disability HI (D-HI)." *https://www.ssa.gov/policy/docs/ssb/v77n3/v77n3p15.html*, Accessed: March 2022.

Social Security Administration. n.d.*b*. "Policy Interpretation Ruling Titles II and XVI: Determining Capability to Do Other Work: Implications of a Residual Functional Capacity for Less Than a Full Range of Sedentary Work." *https://www.ssa.gov/OP_Home/rulings/di/01/SSR96-09-di-01.html. Last Accessed April 2021.*

Stevens, Ann H., Douglas L. Miller, Marianne E. Page, and Mateusz Filipski. 2015. "The Best of Times, the Worst of Times: Understanding Pro-cyclical Mortality." *American Economic Journal: Economic Policy*, 7(4): 279–311.

Strand, Alexander, and Matthew Messel. 2019. "The Ability of Older Workers with Impairments to Adapt to New Jobs: Changing the Age Criteria for Social Security Disability Insurance." *Journal of Policy Analysis and Management*, 38(3): 764–786.

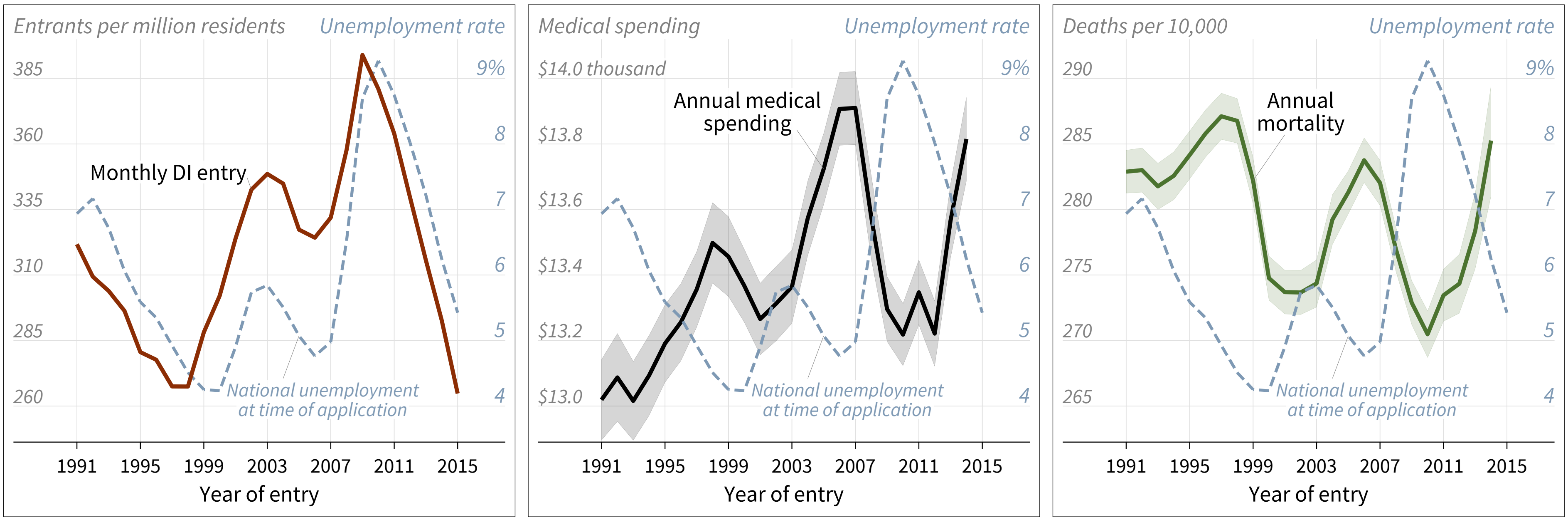
Sullivan, Daniel, and Till von Wachter. 2009. “Job Displacement and Mortality: An Analysis Using Administrative Data.” *The Quarterly Journal of Economics*, 124(3): 1265–1306.

von Wachter, Till, Jae Song, and Joyce Manchester. 2011. “Trends in Employment and Earnings of Allowed and Rejected Applicants to the Social Security Disability Insurance Program.” *American Economic Review*, 101(7): 3308–29.

Wolff, Jennifer L., Lauren H. Nicholas, Amber Willink, John Mulcahy, Karen Davis, and Judith D. Kasper. 2019. “Medicare Spending and the Adequacy of Support with Daily Activities in Community-Living Older Adults with Disability: An Observational Study.” *Annals of Internal Medicine*, 170(12): 837–844.

Figures and Tables

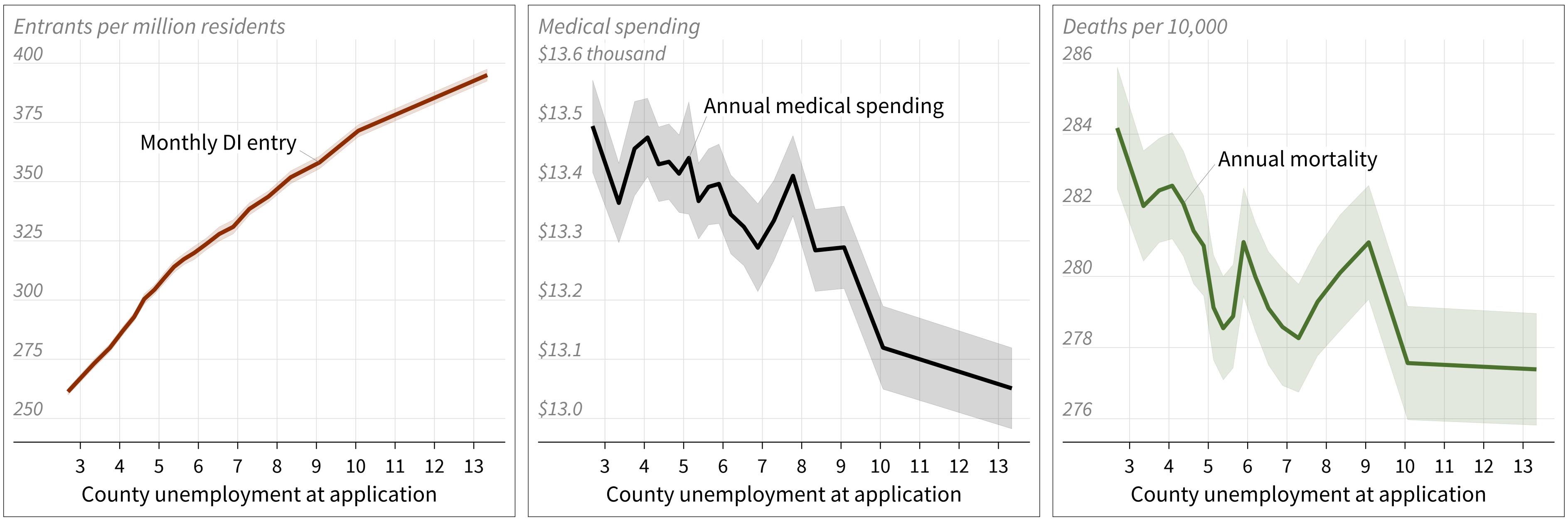
Figure 1: DI entry, medical spending, and mortality, by year of entry



(a) DI entry **(b)** Medical spending **(c)** Mortality

Notes: The figure reports DI entry, medical spending, and mortality in our primary sample, by year of DI entry. In all panels, the dashed blue curve reports the average national unemployment rate at the time of DI application for entrants in each year. In panel (a), the solid brown curve reports the population-weighted average monthly DI entry rate for years 1991–2015. Entry is measured for each county, month, and age as the number of entrants per million same-aged residents at the time of DI application. In panels (b) and (c), the solid black and green curves report the average subsequent annual medical spending and mortality, respectively, for each year of entry in 1991–2014, as estimated by equation (2). These regressions use person-year observations and include fixed effects for years enrolled. Medical spending is measured among traditional fee-for-service Medicare enrollees, and mortality is measured for all Medicare beneficiaries. Shaded regions reflect the 95% confidence intervals on the estimates, calculated from standard errors clustered on the county by month of entry.

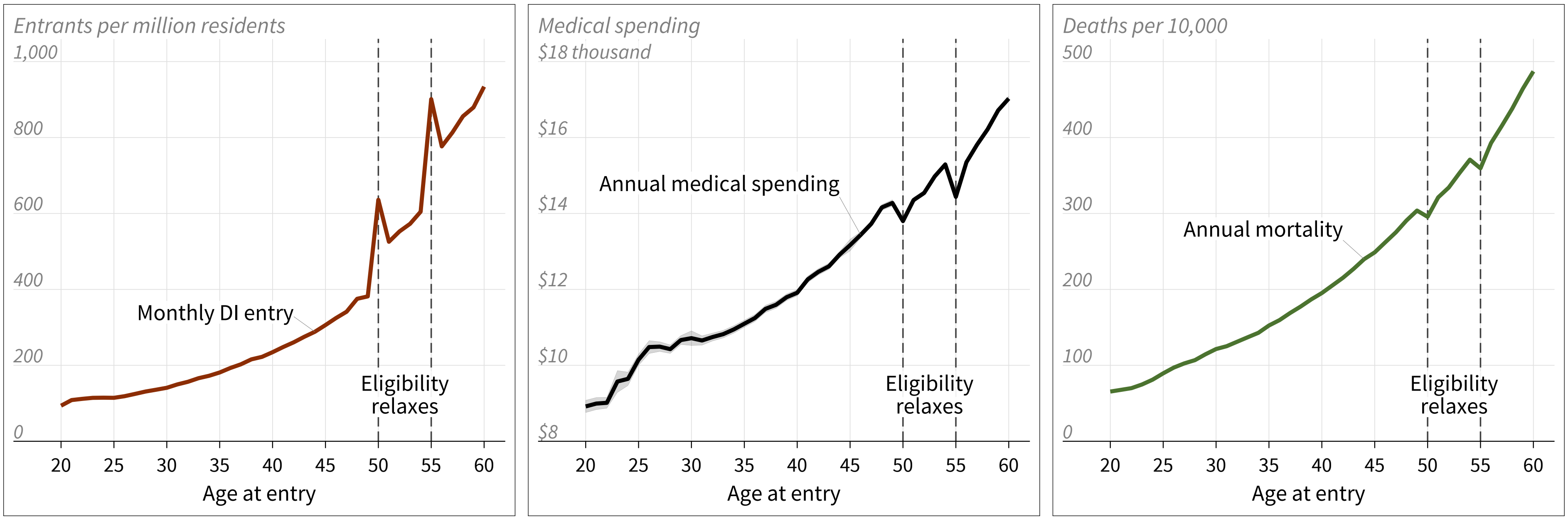
Figure 2: DI entry, medical spending, and mortality, by unemployment at application



(a) DI entry **(b)** Medical spending **(c)** Mortality

Notes: The figure reports how DI entry, medical spending, and mortality in our primary sample vary with the county unemployment rate at the time of DI application. In panel (a), the solid brown curve reports average monthly DI entry by ventile of unemployment, as estimated by equation (1). Entry is measured for each county, month, and age as the number of entrants per million same-aged residents at the time of DI application. The entry regression includes county fixed effects and uses population weights. Panels (b) and (c) report similar estimates but where the outcomes are subsequent annual medical spending and mortality, respectively, of DI entrants. These regressions, described by equation (3), use person-year observations and include fixed effects for initial county by years enrolled. Medical spending is measured among traditional fee-for-service Medicare enrollees, and mortality is measured for all Medicare beneficiaries. In all panels, shaded regions reflect the 95% confidence intervals on the estimates, calculated from standard errors clustered on the county by month of entry.

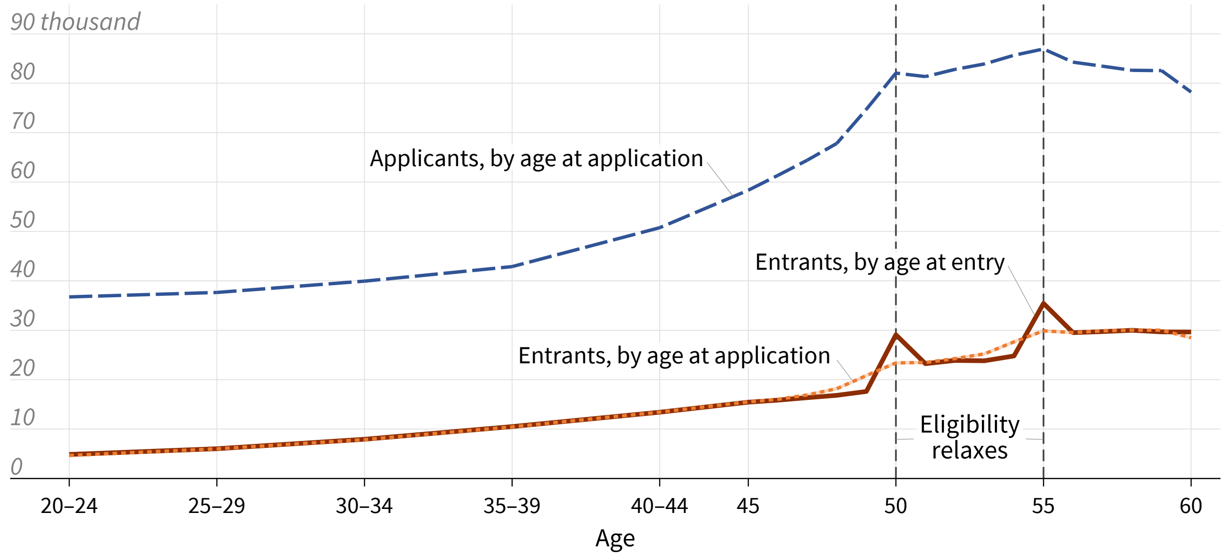
Figure 3: DI entry, medical spending, and mortality, by age at entry



(a) DI entry **(b)** Medical spending **(c)** Mortality

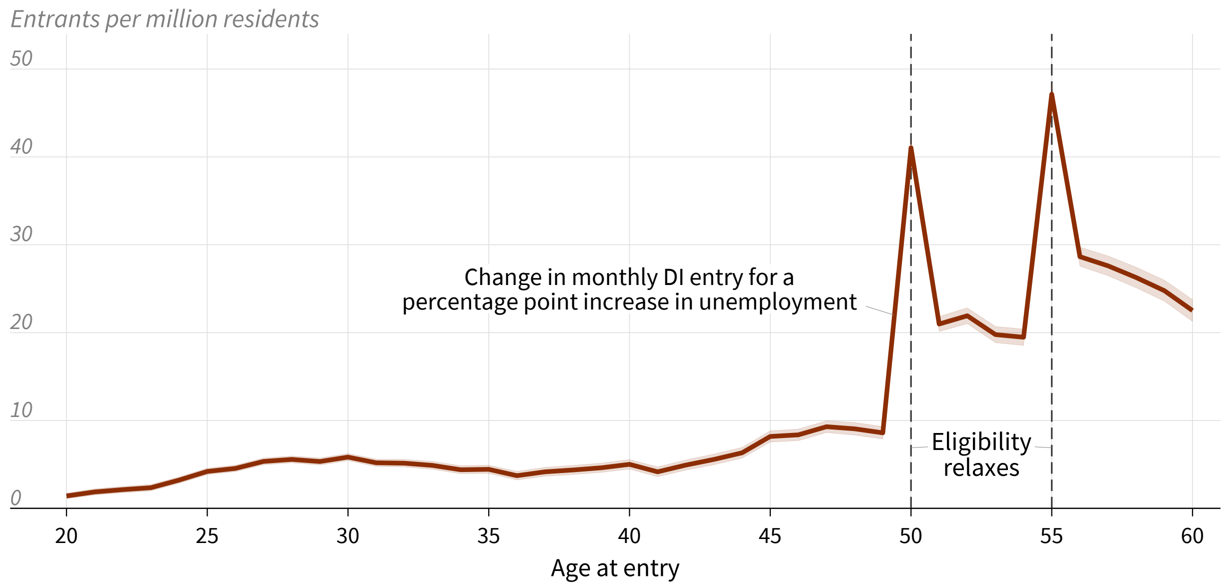
Notes: The figure reports DI entry, medical spending, and mortality in our primary sample, by age at DI entry. In panel (a), the solid brown curve reports the population-weighted average monthly DI entry for ages 20–60. Entry is measured for each county, month, and age as the number of entrants per million same-aged residents at the time of DI application. In panels (b) and (c), the solid black and green curves report the average subsequent annual medical spending and mortality, respectively, for each age of entry, as estimated by equation (4). These regressions use person-year observations and include fixed effects for years enrolled. Medical spending is measured among traditional fee-for-service Medicare enrollees, and mortality is measured for all Medicare beneficiaries. Shaded regions reflect the 95% confidence intervals on the estimates, calculated from standard errors clustered on the county by month of entry.

Figure 4: Annual number of DI applicants and entrants, by age



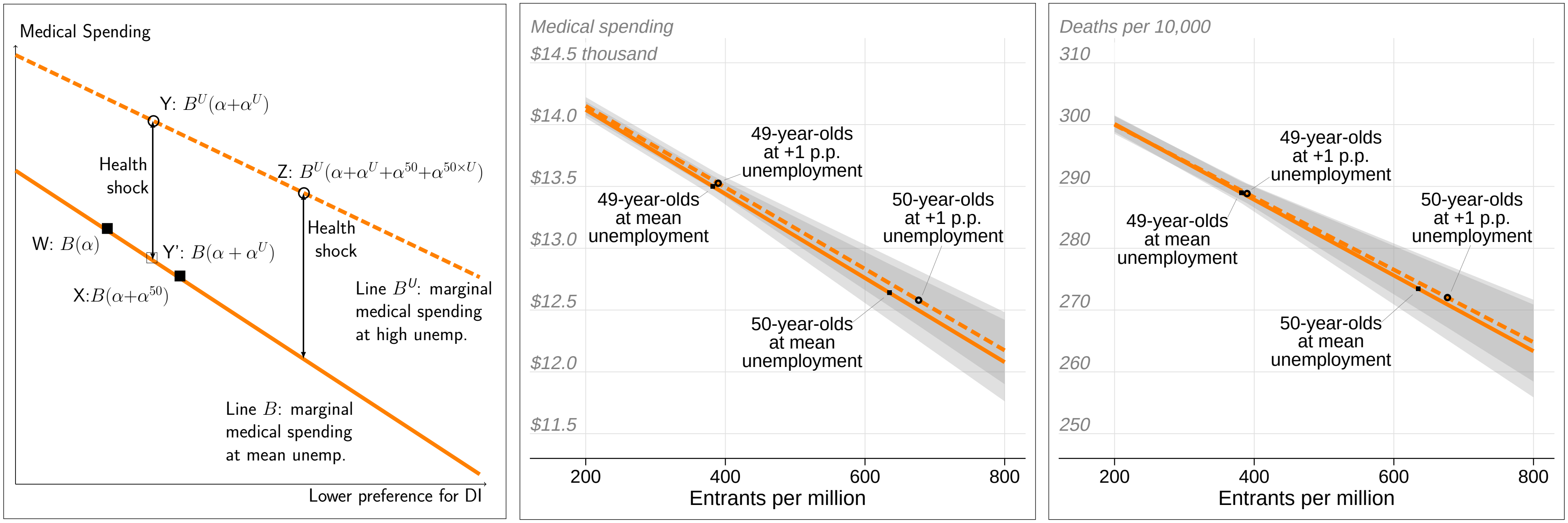
Notes: The figure reports the annual number of DI applicants and entrants per year of age. Data on the number of DI applicants come from a custom version of the Annual Statistical Report on the Social Security Disability Insurance Program (DI ASR) that covers applications filed in 2008–2017 and reports outcomes by five-year age groups for ages 20–44 and by single year of age for ages 45–60. The number of applicants is reported by age at application filing (long-dashed blue curve). Data on the number of entrants come from the Disability Analysis File Public Use File (PUF) and are based on DI recipients who enter Medicare before age 65 in the period 1993–2017. The number of entrants is reported both by age at DI entry (solid brown curve) and by age at DI application (short-dashed orange curve), using the same age groupings as the DI ASR sample.

Figure 5: Cyclicality of DI entry, by age at entry



Notes: The figure shows the cyclicality of DI entry in our primary sample by age at entry, as estimated by equation (5). Entry is measured for each county, month, and age as the number of entrants per million same-aged residents. The curve's height reflects the change in monthly DI entry at a given age associated with a 1 percentage point increase in the county unemployment rate at the time of DI application. The shaded region reflects the 95% confidence intervals on the estimates, calculated from standard errors clustered on the county by month of entry.

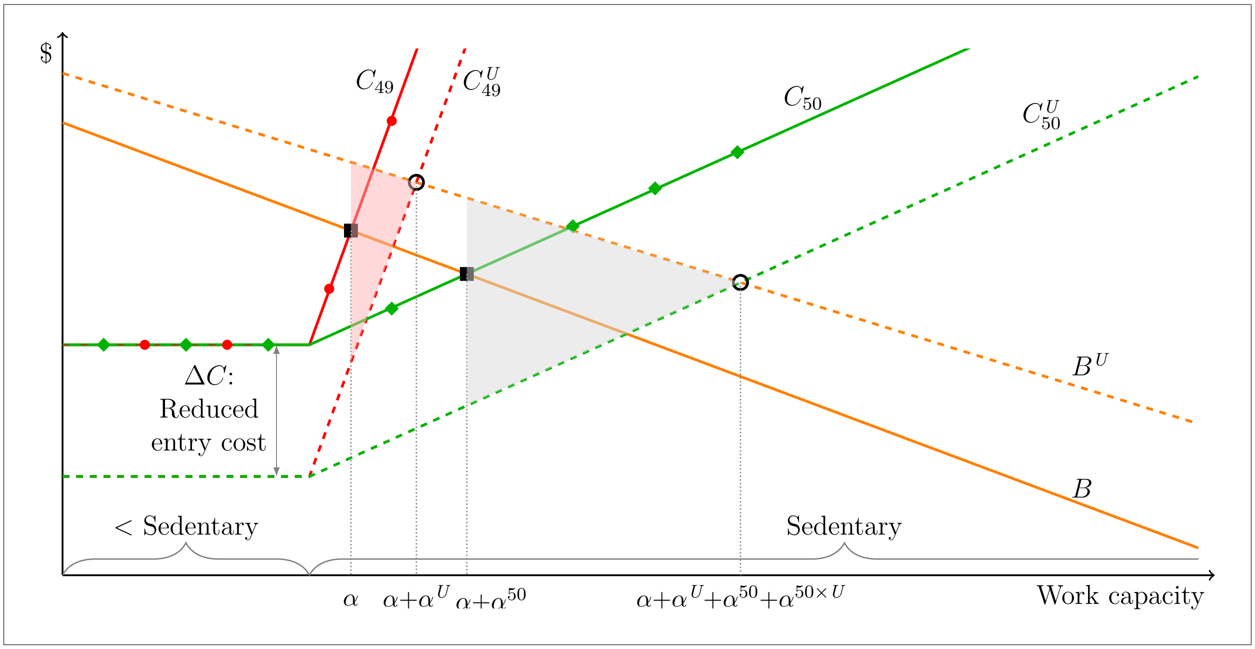
Figure 6: Health characteristics of marginal DI entrants



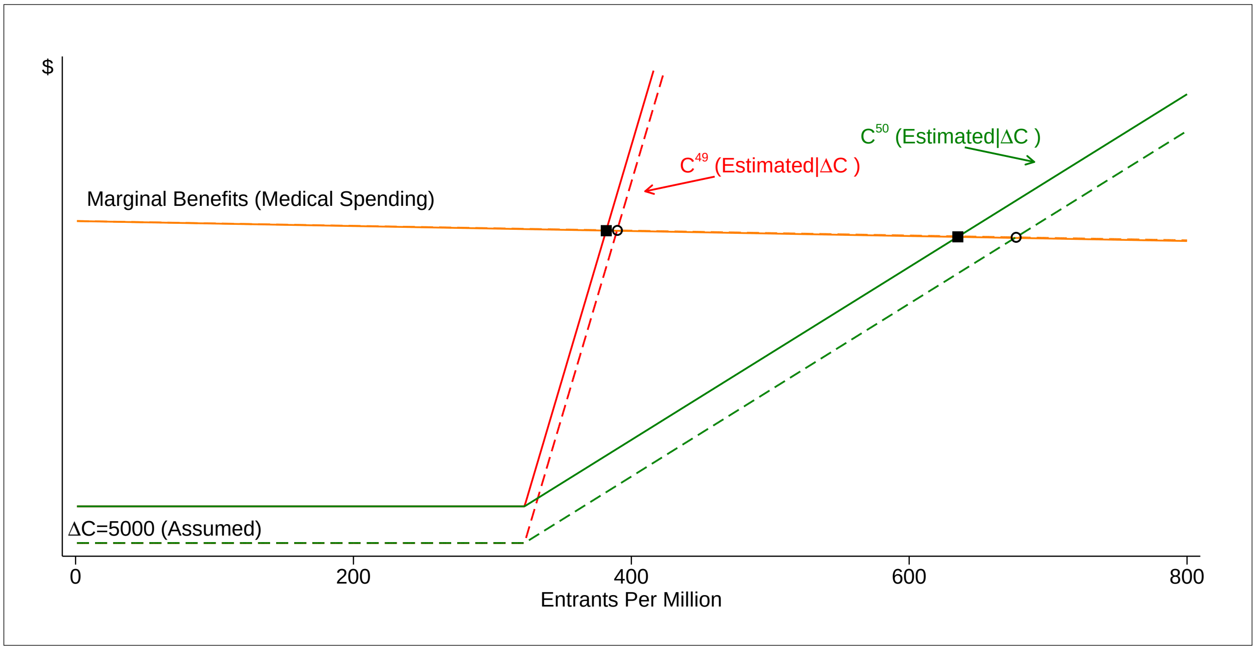
(a) Model: Health of marginal entrants **(b)** Data: Entrant medical spending **(c)** Data: Entrant mortality

Note: Panel (a) represents our identification of the marginal medical spending functions for DI entrants. The y-axis measures medical spending and the x-axis represents the unobserved preference for DI. The marginal medical spending function at mean unemployment is represented by the solid line B, with entry of 49 and 50 year olds marked by the solid squares. The marginal medical spending function at higher unemployment is represented by the dashed line B^U, with entry of 49 and 50 year olds marked with open circles. See Section 5 for discussion. Panel (b) represents the marginal spending functions implied by the data, using the slopes and intercepts calculated in Section 5.2. We bootstrap a confidence interval for the functions by reestimating equations (6) and (7) on 500 resamplings of county × entry-month clusters. Light gray denotes a single confidence interval, while darker gray represents overlap in confidence intervals from both lines.

Figure 7: Full Model of DI Entry: Benefits and Costs at Mean and Higher Unemployment



(a) Model: Benefits and age-specific costs as a function of work capacity



(b) Data: Benefits and costs at mean (solid) and +1pp (dashed) unemployment, $\Delta C = -\$5000$

Note: Panel (a) represents our full model of DI entry. The y-axis measures the costs and benefits of DI entry, measured in dollars, and the x-axis measures residual work capacity. The benefits of DI entry at mean and higher unemployment are represented by B and B^U. The costs of DI entry at mean unemployment are represented by the red and green lines for individuals entering at ages 49 and 50, respectively. High unemployment reduces the entry cost of DI entry, represented by the downward shift of the cost functions to the dashed lines. High unemployment potentially also shifts the benefits function upward and outward to B^U (dashed). Panel (b) represents the parameterization of the full model under an assumption that the cost curves shift downward by \$5000, using the slopes and intercepts calculated in Section 5.

Table 1: Cyclicality of DI entry, medical spending, and mortality

	(1)	(2)	(3)
	Entrants per million residents	Annual medical spending ($)	Annual mortality (deaths per 10,000)
A. Cyclicality of DI entry and cohort outcomes (main sample)			
Unemployment rate at application	13.47***	–43.13***	–0.47***
	(0.13)	(4.16)	(0.09)
Fixed effects	County	County × Years enrolled	County × Years enrolled
Dependent variable mean	319.79	13,354.31	280.13
Observations	38,436,824	101,825,663	140,407,837
B. Cyclicality of DI entry and cohort outcomes, by age at entry (49–50)			
Intercept	381.92***	14,150.80***	300.66***
	(0.69)	(41.40)	(0.85)
Age 50 at entry	253.01***	–430.43***	–7.75***
	(1.03)	(50.76)	(1.09)
UR (demeaned unemployment rate)	7.84***	17.18	–0.39
	(0.36)	(17.08)	(0.37)
UR × Age 50 at entry	34.03***	–42.55**	–0.66*
	(0.48)	(17.03)	(0.35)
Fixed effects	County	County × Years enrolled	County × Years enrolled
Dependent variable mean	507.61	13,892.97	295.97
Observations	1,874,972	7,471,112	10,508,228

Notes: The table reports how DI entry and subsequent health status relate to unemployment at the time of DI application. Each column in a panel reports coefficients and their standard errors (in parentheses) from a separate regression. Outcomes are indicated by the column label. In Panel A, column (1) reports results from equation (1), measuring the association of unemployment at the time of application, calculated in Section 3.3, and DI entry, calculated as the number of individuals entering Medicare on the basis of disability as a share of the working-age population in a county and month. Results from equation (3) measuring the association of unemployment at the time of application with health status are reported for medical spending (column (2)) and mortality (column (3)), where column (2) is limited to fee-for-service enrollees observed in calendar years 1999–2017. Panel B reports results from estimating equations (6) and (7) based on the subset of DI entrants entering at ages 49–50. Standard errors are clustered at the level of county by month of Medicare entry. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and *** respectively.

Online Appendix

Why Does Disability Insurance Enrollment Increase During Recessions? Evidence from Medicare

Colleen Carey, Nolan Miller, & David Molitor

Table of Contents

A.1 Details of Sample Construction

Our Medicare data were accessed via the National Bureau of Economic Research. Our measures are derived from the Denominator File for years 1993–1998 and 2000–2005 and its successor file, the Master Beneficiary Summary File for years 1999 and 2006–2017.

We define the month of Medicare entry by primarily using Medicare's reported coverage start date (*covstart*). This variable is reported for all Medicare enrollees who enrolled in the years 1999 or 2006–2017, and we directly observe it for 96% of our sample. For individuals in our sample of DI entrants who do not appear in Medicare in either 1999 or in any year 2006–2017, we measure the month of Medicare entry using the monthly Part A enrollment variables in the first year in which they appeared in the data.

To obtain a sample of DI recipients in Medicare, we begin with all Medicare beneficiaries who are below age 65 in their first year in Medicare. However, some of these individuals may be entitled to Medicare because of end-stage renal disease (ESRD). In order to exclude individuals who do not receive DI benefits, we combine information on an individual's original reason for entitlement (*OREC*) and current basis for eligibility (*BIC*).

Our sample criteria is individuals who entered Medicare below age 65 who ever have "DIB" (DI benefits) as an original reason for entitlement *or* ever have an eligibility basis related to DI. We combine the two variables because the original reason for entitlement commonly transitions from "ESRD" to "DIB & ESRD"; of individuals who join Medicare before age 65 whose first-recorded OREC is "ESRD", 43% eventually have an OREC of "DIB & ESRD". These transitions could be due to SSA eventually awarding retrospective DI benefits, or due to lags in communication between CMS and other agencies. For individuals who enter Medicare in the later years of our sample (e.g., 2016–2018), some share of these will eventually transition to "DIB & ESRD", but have not by the end of our panel. Thus, relying purely on the OREC variable understates the population of DI recipients in the final years of our sample (as compared to the population of DI recipients reported in the Disability Analysis File Public Use File).

Because of the limitations of the OREC variable, we also include individuals who have a disability-related eligibility basis. We determined the disability-related eligibility bases by limiting to the codes that have greater than 98% overlap with an OREC status of "DIB" or "DIB & ESRD". We cannot use this method for our full time period because this variable is not reported in the MBSF files for the years 2002–2005.

These methods indicate that about 1.5% of individuals entering Medicare before age 65 are exclusively eligible due to ESRD; we exclude them from all analyses.

A.2 Alternative Measures of Unemployment

Our core measure of the unemployment rate is the Local Area Unemployment Statistics (LAUS) collected by the Bureau of Labor Statistics (BLS), which is available for county-months from 1990–2017. However, for age and education subgroups, BLS produces only national estimates.

Therefore, we turned to the American Community Survey (ACS) in order to measure unemployment rates among subgroups. We note that the ACS-based unemployment rate differs somewhat in concept and measurement from the LAUS.[1] In addition, the ACS microdata only reports county for 475 large counties representing about one-third of the US population, and only exists for the last 10 years of our sample period. Still, using the ACS we developed unemployment rates for the full population (to compare with the LAUS), those aged 45-54, and those with a high school degree or less for 475 counties over the years 2008–2017.

Appendix Table A.3 repeats Table 1 varying the measure of unemployment. Column (1) repeats the first column of Table 1, predicting monthly DI entry per million residents using the LAUS county-month unemployment rate. Column (2) scales those estimates by 12 to compare with Column (3), which predicts annual DI entry per million residents using the LAUS county-year unemployment rate. We conclude that aggregating to the annual level has little impact on our estimates for a fixed geography-time subsample.

[1]See https://www.bls.gov/lau/acsqa.htm

Next, in column (4) we use the LAUS county-year measures using only the 4750 county-year observations for which we observe the ACS unemployment rate. We find a slightly higher rate of cyclicality for this geography-time subsample. Column (5) uses the ACS-based unemployment measure on this same subsample, and demonstrates that the LAUS and ACS return similar measures of DI cyclicality.

Finally, in columns (6) and (7), we turn to our age- and education-specific unemployment measures. For both measures, we find a somewhat lower response. However, the muted response is proportional to the correlation between these measures and the LAUS measure for overall unemployment. In Panel B, we report the relationship between the LAUS measure (as the dependent variable) and these age- and education-specific unemployment measures (as the independent variable). Returning to Equation 1, we find:

$$Entry_{ct} = 178.89[unemployment\ rate]_{ct}^{LAUS} + [county\ FEs]_c + \varepsilon_{ct}$$

We can substitute in using predicted values for $unemployment\ rate_{ct}^{LAUS}$ from Panel B:

$$Entry_{ct} = \underbrace{178.89 * 0.898}_{=160.64}[unemployment\ rate]_{ct}^{ACS\ 50} + [county\ FEs]_c + \varepsilon_{ct}$$

Note the similarity between 160.64 and the result from column (6): 162.11.

We find something similar when we consider the unemployment rate for those with a high school degree or less:

$$Entry_{ct} = \underbrace{178.89 * 0.633}_{=113.23}[unemployment\ rate]_{ct}^{ACS\ HSD} + [county\ FEs]_c + \varepsilon_{ct}$$

Column (7)'s estimate, 119.43, is very similar to the 113.23 we get from this calculation.

Panel C reports the same analysis when all unemployment rates have been standardized to Z-scores. This panel clarifies that one standard deviation in unemployment rates tends to have a similarly-sized impact on DI entry, whether unemployment is measured overall or for the subgroups where DI is most prevalent. In particular, one standard deviation in unemployment rates tends to raise DI enrollment by 455 individuals using the overall unemployment rate, 403 using the unemployment rate for those near age 50, and 439 when using the unemployment rate for those with a high school education or less.

Our conclusion from this exercise is that, at least for these age- and education-specific unemployment measures, we do not find a substantially different DI cyclicality. The variance of the subgroup-specific unemployment rates is higher (i.e., a one percentage point change in the unemployment rate for these subgroups is associated with a less than one percentage point change in the overall unemployment), and the relationship between the measure and our entry outcome is proportionally lower. But accounting for the higher variance, as we do in the previous paragraphs or in Panel C, reveals a quantitatively similar result.

A.3 Descriptive Evidence on the Source of the Spike in Entry at the Age Discontinuity

Figure 3a shows that entry rate of DI recipients spikes at the ages discontinuity thresholds before partially falling back at the following ages. In this section, we present evidence that this spike is due to some applications received when the applicants are in their 40s being approved with an exact eligibility date of age 50.

Appendix Figure A.11a reports the number of entrants by age at entitlement (i.e., the black line in Figure 4) but measures age in months rather than years. In addition, this figure uses both Medicare data (black solid line) and the PUF (gray line) to demonstrate the concordance of the two datasets. This figure shows that the spike in DI entry is driven by individuals entering DI at ages 50.5 and 55.5 after beginning the 5-month DI waiting period in the month they attain the higher age – e.g., at age 50 and 0 months or 55 and 0 months.[2] In each year, about 4000 individuals join DI at ages 50.5 and 55.5, comparable to the size of the spike in entry at the age thresholds that is visible in Figure 4.

The precision of this spike suggests that the applications of individuals who applied before attaining the age of relaxed eligibility were eventually awarded with a disability onset date of the month they attained the higher age. For example, an individual who applied at 48 could be initially denied at age 49, then awarded benefits at the reconsideration or hearing level after their 50th birthday; if they qualified only under the looser eligibility guidelines, their five-month waiting period would begin at age 50. This example is supported by the analysis of Deshpande, Gross and Su (2021) (in their Appendix Figure A15), who find that among those initially denied while below the age threshold, about two in five gain eligibility in the subsequent two years. While some will gain eligibility due to a reevaluation of their application and others may experience a deterioration in health while appealing their initial denials, the fact that entry spikes right at the exact month of attaining the older age suggests that some are admitted precisely when they are subject to the relaxed eligibility thresholds.

If some individuals entering at age 50 applied long before, the duration of months between application and DI entry should be longer for those entrants. Appendix Figure A.11b reports

[2]There is a smaller spike in entry at exactly age 50, which arises because of flexibility in the guidelines allowing disability examiners to apply the looser guidelines to anyone within six months of attaining the higher age (as discussed in Deshpande, Gross and Su (2021)), while the small spike at age 48 relates to special rules for widows and widowers.

a histogram of the number of months between application and DI eligibility for those entering at age 49 (gray) and 50 (red). We find that applications among those entering right in the first year of relaxed eligibility spent more months in adjudication.

A.4 Parameters of Cost Curves

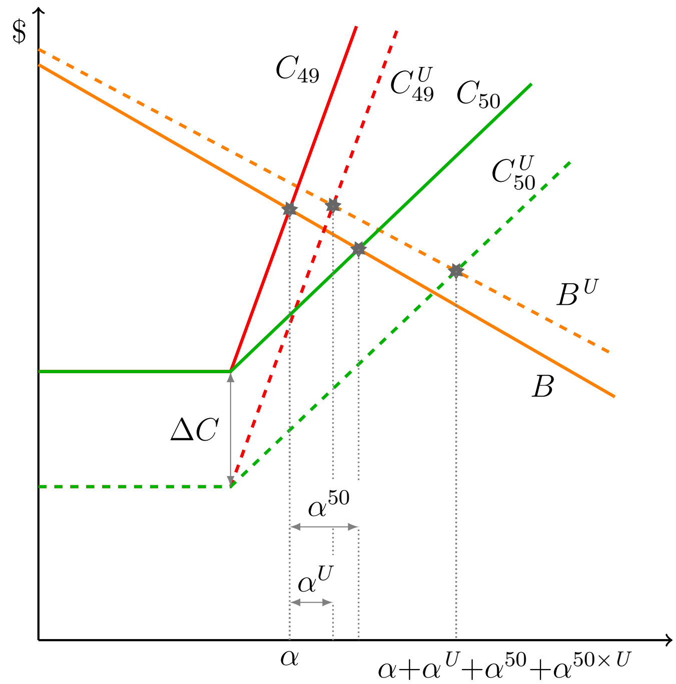


Figure A.1: Cost Curve Parameters

To determine the slopes and intercepts of the cost curves, we first begin with the points of intersection that will identify them, identified by gray stars. The benefit function for mean unemployment has slope m and intercept n. It intersects the cost curve for 49 year olds at x-axis value α. Define the slope for the cost function for 49 year olds as m_{49}^{C} and its intercept n_{49}^{C}. Thus, our first equation is

$$m_{49}^{C}\alpha + n_{49}^{C} = m\alpha + n$$

When unemployment is high, the benefits function B^{U} and cost function C_{49}^{U} intersect at x-axis value $\alpha + \alpha^{U}$. The slope m^{U} and intercept n^{U} of B^{U} were found in Section 5.2. By assumption, the intercept of C_{49}^{U} is $n_{49}^{C} + \Delta C$. Thus, we can write a second equation:

$$m_{49}^{C}(\alpha + \alpha^{U}) + n_{49}^{C} + \Delta C = m^{U}(\alpha + \alpha^{U}) + n^{U}$$

Subbing the first equation into the second

$$m_{49}^{C}(\alpha+\alpha^{U})+m\alpha+n-m_{49}^{C}\alpha+\Delta C=m^{U}(\alpha+\alpha^{U})+n^{U}$$

$$m_{49}^{C}=(-\Delta C-m\alpha-n+m^{U}(\alpha+\alpha^{U})+n^{U})/\alpha^{U}$$

And similarly, we can find n_{49}^{C} in terms of known parameters:

$$n_{49}^{C}=m\alpha+n-(-\Delta C-m\alpha-n+m^{U}(\alpha+\alpha^{U})+n^{U})\frac{\alpha}{\alpha^{U}}$$

A similar exercise can be done for the cost curves for 50 year olds. The cost curve for 50 year olds in good economic times intersects B at $\alpha+\alpha^{50}$.

$$m_{50}^{C}(\alpha+\alpha^{50})+n_{50}^{C}=m(\alpha+\alpha^{50})+n$$

And in times of high unemployment, the dashed curves intersect at $\alpha+\alpha^{U}+\alpha^{50}+\alpha^{50\times U}$.

$$m_{50}^{C}(\alpha+\alpha^{U}+\alpha^{50}+\alpha^{50\times U})+n_{50}^{C}+\Delta C=m^{U}(\alpha+\alpha^{U}+\alpha^{50}+\alpha^{50\times U})+n^{U}$$

We can again combine the equations to solve for m_{50}^{C} and n_{50}^{C} in terms of ΔC. Subbing the first equation into the second:

$$m_{50}^{C}(\alpha+\alpha^{U}+\alpha^{50}+\alpha^{50\times U})+(m-m_{50}^{C})(\alpha+\alpha^{50})+n+\Delta C=m^{U}(\alpha+\alpha^{U}+\alpha^{50}+\alpha^{50\times U})+n^{U}$$

$$m_{50}^{C}=\frac{-\Delta C+m^{U}(\alpha+\alpha^{U}+\alpha^{50}+\alpha^{50\times U})-m(\alpha+\alpha^{50})+n^{U}-n}{\alpha^{U}+\alpha^{50\times U}}$$

And the intercept is expressed as

$$n_{50}^{C}=m(\alpha+\alpha^{50})+n-\frac{(-\Delta C+m^{U}(\alpha+\alpha^{U}+\alpha^{50}+\alpha^{50\times U})-m(\alpha+\alpha^{50})+n^{U}-n)(\alpha+\alpha^{50})}{\alpha^{U}+\alpha^{50\times U}}$$

A.5 Heterogeneity in Role of Recession-Associated Health Shocks by Sex

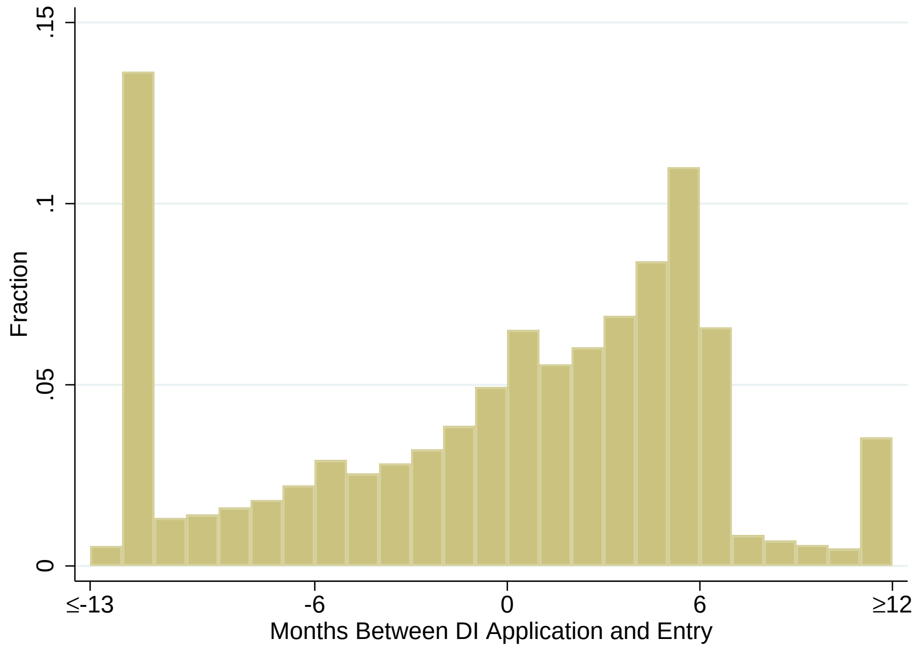
In this section, we estimate our marginal medical spending functions separately by sex to determine whether recession-associated health shocks play a different role in DI entry for men and women. Heterogeneity by sex could arise due to differences in chronic disease burden, recession experience, or disability determination (Cabral and Dillender, 2024; Low and Pistaferri, 2019; Alon et al., 2021).

We are cautious about comparing the levels of entry for men and women because the large increase in labor force attachment among women over our sample period also greatly increased women's DI eligibility (Pattison and Waldron, 2013). However, Appendix Figure A.12 reveals important differences between males and females. First, males show a much stronger health-entry gradient, specifically a much more negative slope of the marginal medical spending function. This pattern arises due to a strong disparity in medical spending between males entering at ages 49 and 50, whereas 49 and 50 year old female entrants have more similar spending.

Second, our point estimates for the impact of recessions on health indicate a different sign for men and women – i.e, negative health shocks for men, health improvements for women. As is reported in Appendix Table A.4 (Response Table A.5), we find that for men the B^U function for high unemployment lies above the confidence interval for B. Using the counterfactual exercise in Section 5.4 we can estimate the share of unemployment-associated entry increases that is attributable to health shocks. Applying that counterfactual to men and assuming that unemployment reduces entry costs by \$5000, we find that the outward shift of the benefits curve implies that 6.5% of the true entry increase at higher unemployment is due to health shocks, and even more when entry costs are assumed to be lower. By contrast, the marginal medical spending functions for women are statistically indistinguishable. In terms of magnitude, we find that the marginal medical spending function for women shifts inward, implying health improvements, although these are small under either entry cost assumption. These findings indicate that the relationship between unemployment, DI entry, and health differs for males and females.

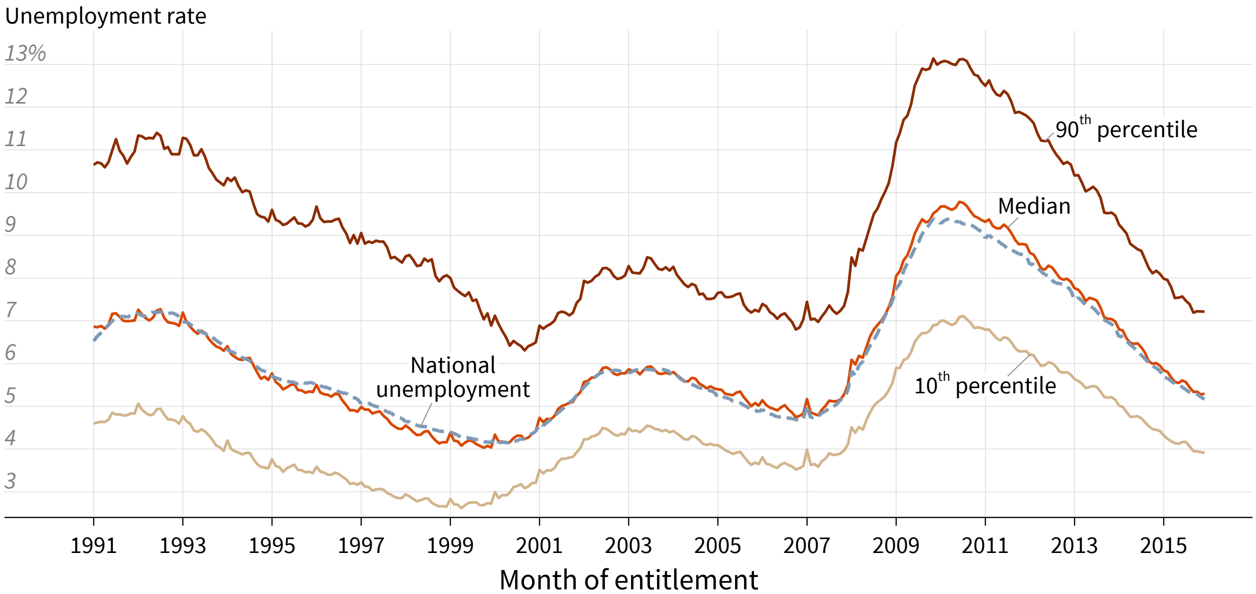
Appendix Figures and Tables

Figure A.1: Distribution of months between DI application and entry



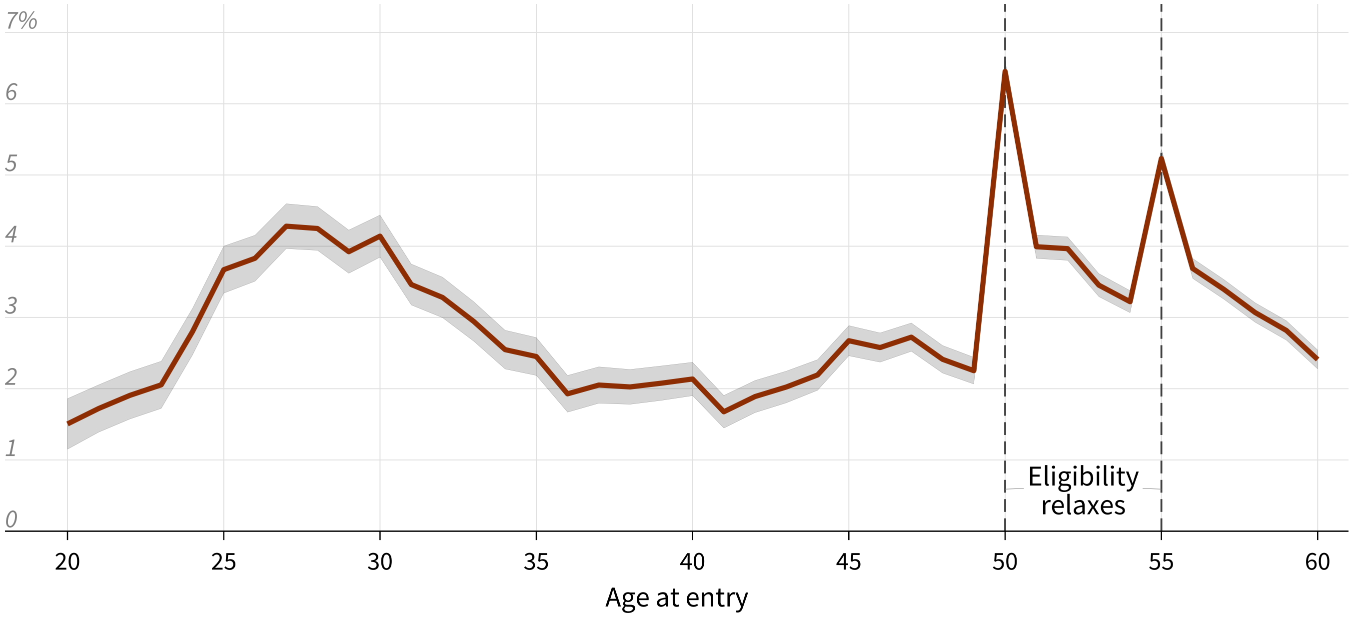
Notes: Figure represents the distribution of months between DI application and entry for individuals entering DI between 1991 and 2015, bottom- and top-coded at −13 months and 12 months, respectively. Source: Disability Analysis File Public Use File.

Figure A.2: Unemployment at application, by month of entry



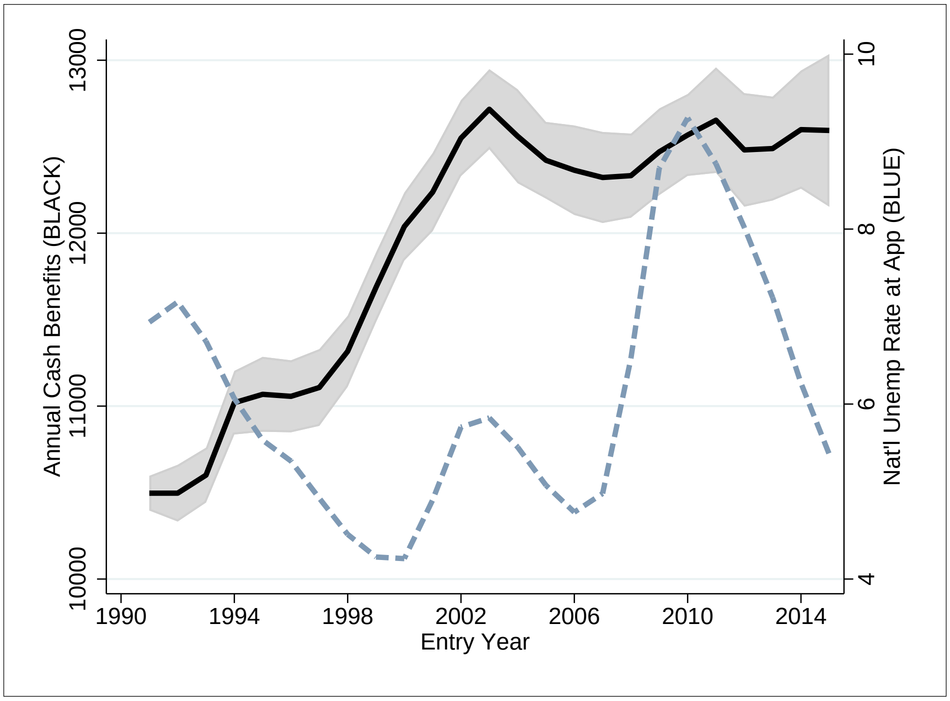
Notes: The figure summarizes county and national unemployment rates at the time of DI application among our primary sample of disability recipients ($N = 15,790,262$). Month of entitlement to DI benefits is taken to be two years prior to the month in which Medicare coverage began. Beneficiaries are assigned to their initial county of residence observed in Medicare. Section 3.3 describes the calculation of county unemployment at the time of application. Brown, orange, and tan curves indicate the 90^{th}, 50^{th}, and 10^{th} percentiles, respectively, of county unemployment rates at the time of application. The average national unemployment rate at the time of application is depicted by the dashed blue line.

Figure A.3: Cyclicality of DI entry as a percentage of total entry, by age at entry

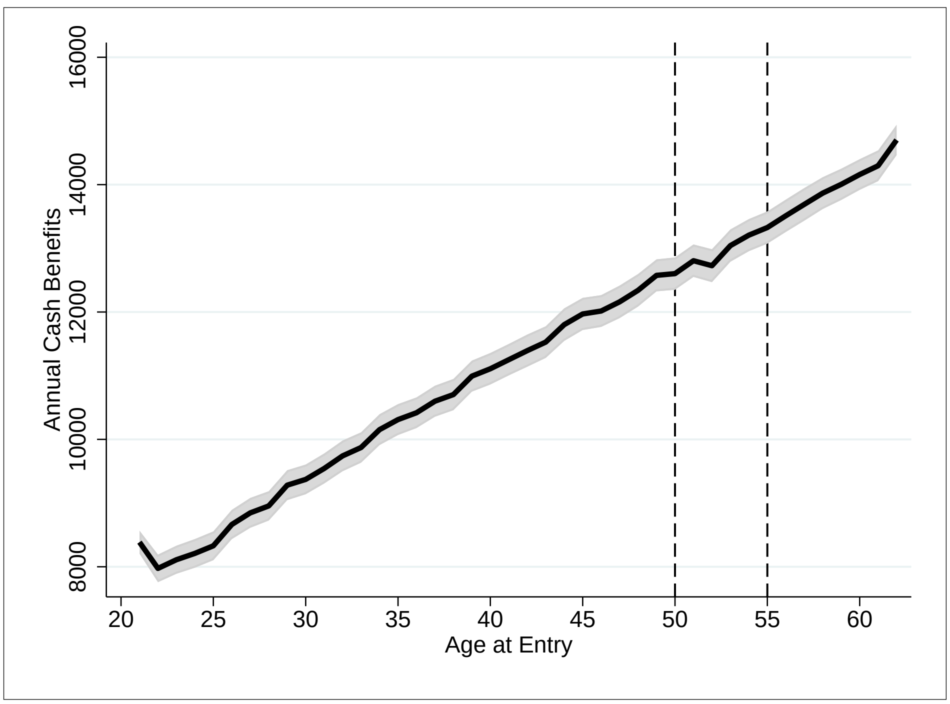


Notes: The figure shows the coefficients and confidence intervals from Figure 5 as a percentage of total DI incidence at each age of entry (reported in Figure 3a).

Figure A.4: Annual cash benefits, by year of entry and age at entry



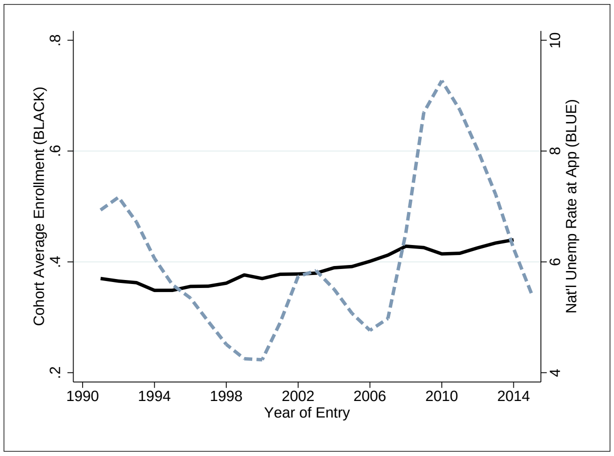
(a) Year of entry



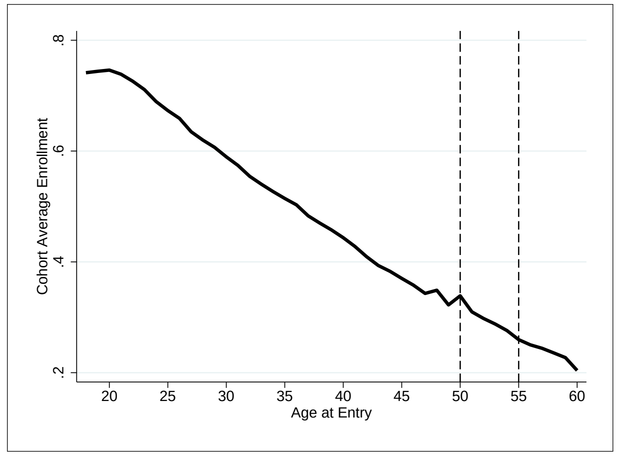
(b) Age at entry

Notes: Panel (a) reports coefficients from estimation of equation 2, where the dependent variable is annual cash benefits as measured in the PUF for DI entrants 1991–2015. The fixed effect associated with each year of entry is depicted in the black line (left axis) in each figure, while national unemployment at application for each year of entry is depicted in blue dashes (right axis). Panel (b) reports estimation of equation 4, again varying the dependent variable. The fixed effect associated with each age of entry is depicted in the black line. 95% CIs estimated from standard errors clustered on the entry month are reported in gray.

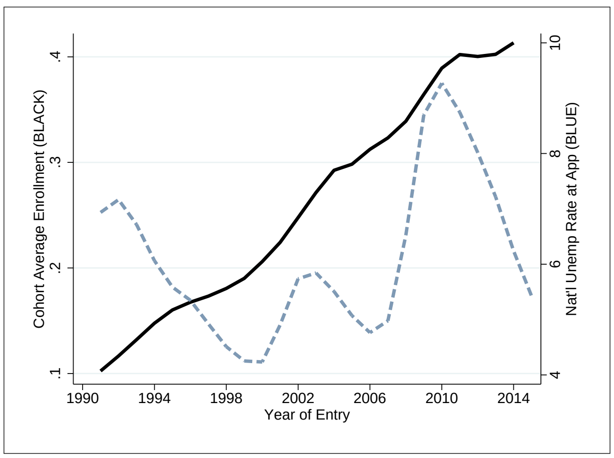
Figure A.5: Medicaid, Medicare Advantage, and Part B enrollment



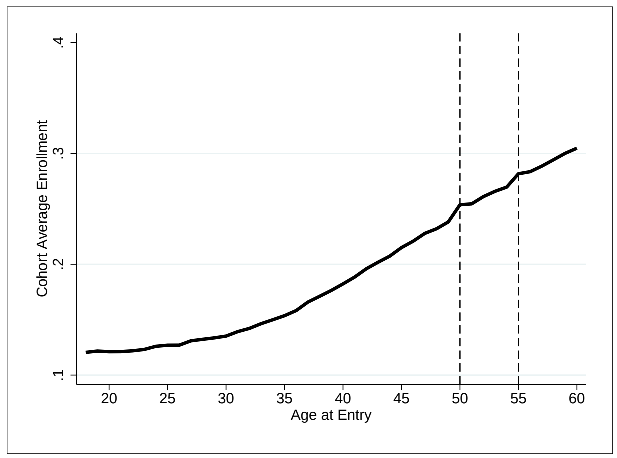
(a) Medicaid, by year of entry



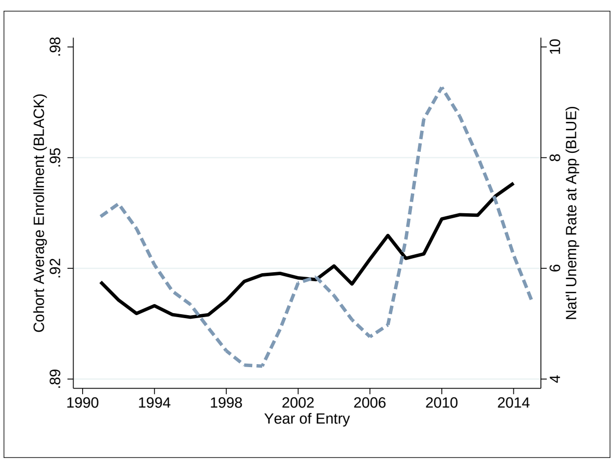
(b) Medicaid, by age at entry



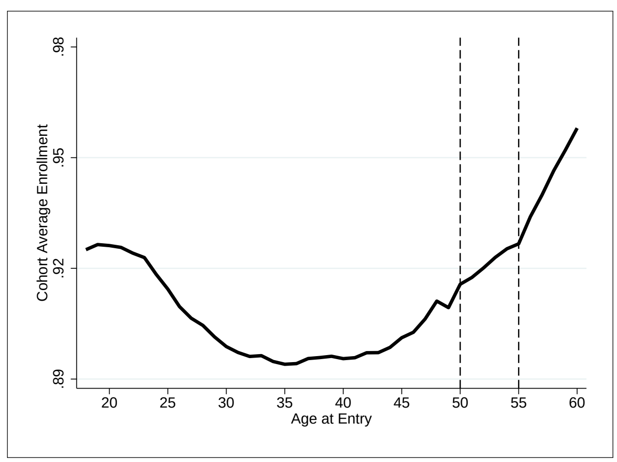
(c) Medicare Advantage, by year of entry



(d) Medicare Advantage, by age at entry



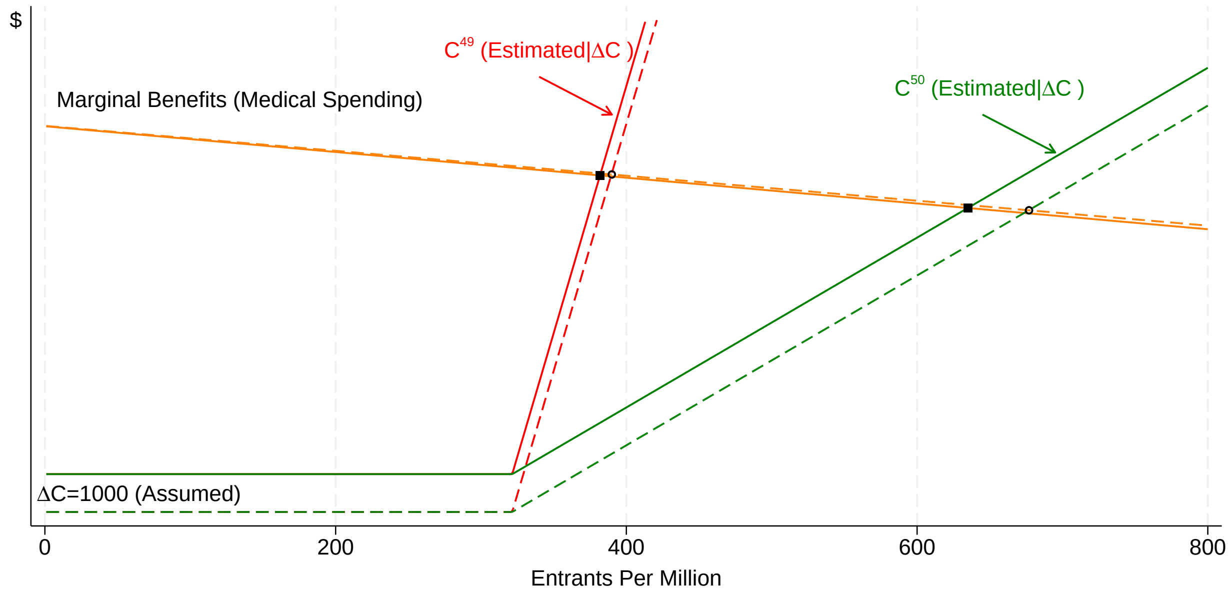
(e) Medicare Part B, by year of entry



(f) Medicare Part B, by age at entry

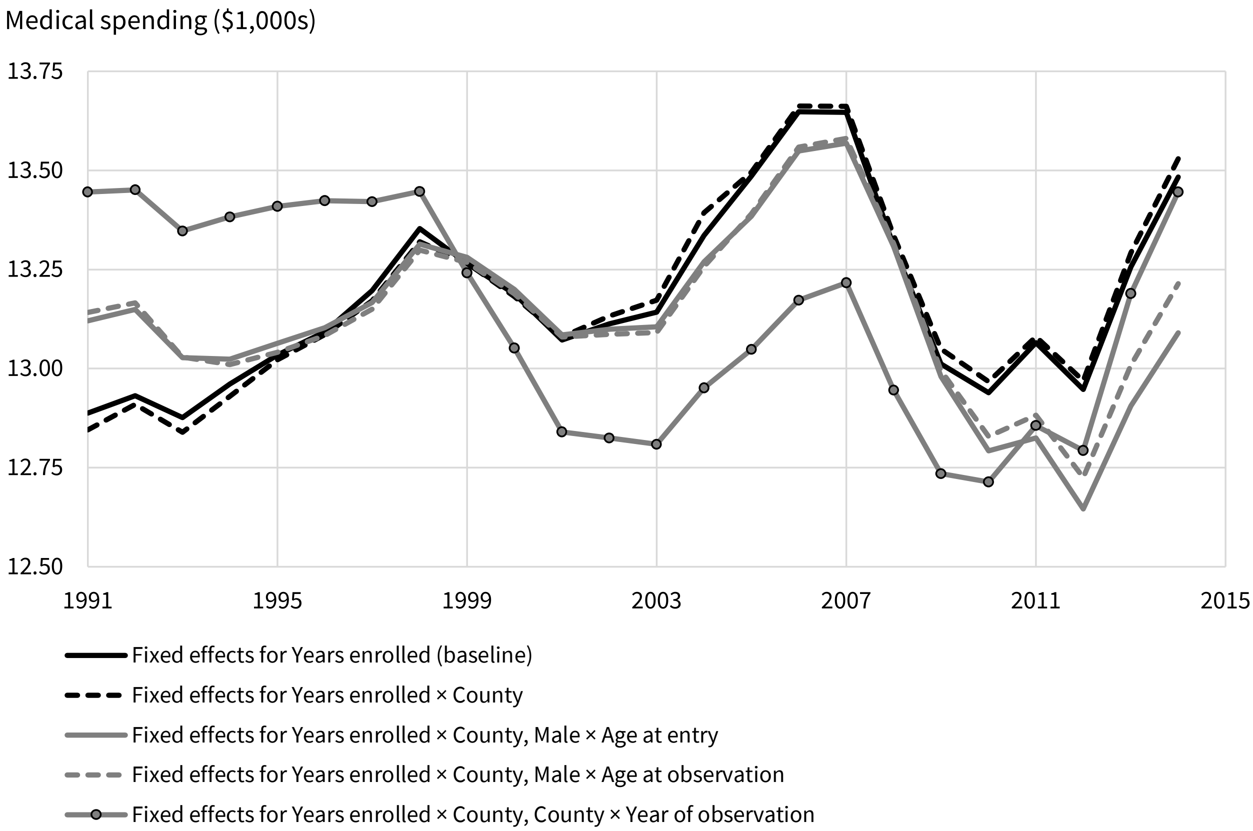
Notes: Panels (a), (c), and (e) report coefficients from estimation of equation 2, where the dependent variable is an individual-year indicator of enrollment in Medicaid, Medicare Advantage, or Medicare Part B. The fixed effect associated with each year of entry is depicted in the black line (left axis) in each figure, while national unemployment at application for each year of entry is depicted in blue dashes (right axis). Panels (b), (d), and (f) represent estimation of equation (4), again varying the dependent-variable. The fixed effect associated with each age of entry is depicted in the black line. 95% CIs estimated from standard errors clustered on the county by entry month are reported in gray.

Figure A.6: Estimates of model parameters when $\Delta C = -\$1000$



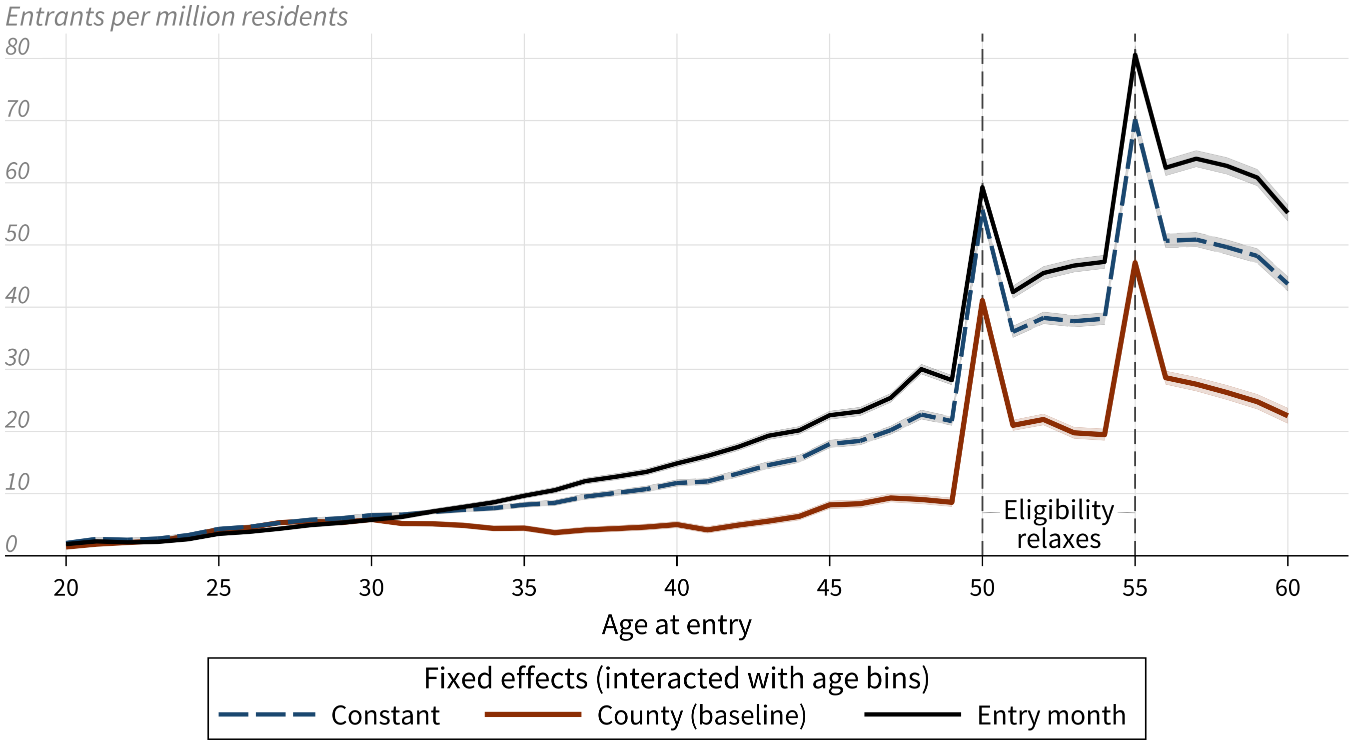
Notes: Figure represents elements of the conceptual model, using parameters estimated from the data using the specification in the first column of Appendix Table A.4. Model elements at average unemployment are represented by solid lines, and model elements associated with a one percentage point increase in unemployment are represented by dashed lines. The benefits functions B and B^U have the slopes and intercepts shown algebraically in Section 5.2. The cost functions C_{49}, C_{49}^U, C_{50}, and C_{50}^U have the slopes and intercepts shown in Appendix Section A.4 when ΔC is assumed equal to -\$1000.

Figure A.7: DI medical spending, by year of entry: alternative specifications



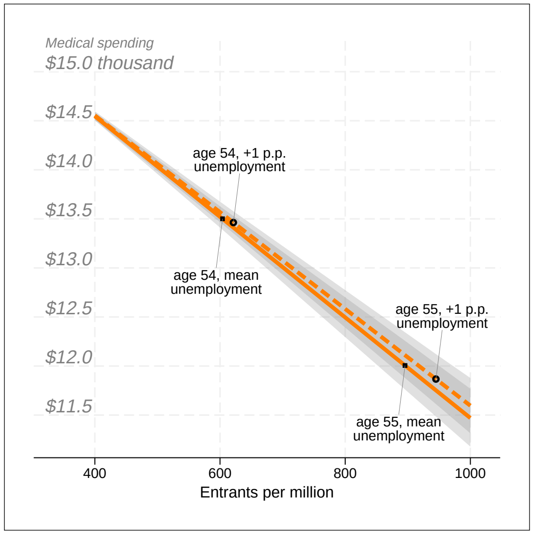
Notes: The figure reports results of estimating equation (2) under various controls specifications. The fixed effects included in each specification are defined in Appendix Table A.6. The solid black curve reports the baseline specification from Figure 1b.

Figure A.8: Cyclicality of DI entry, by age at entry: alternative specifications

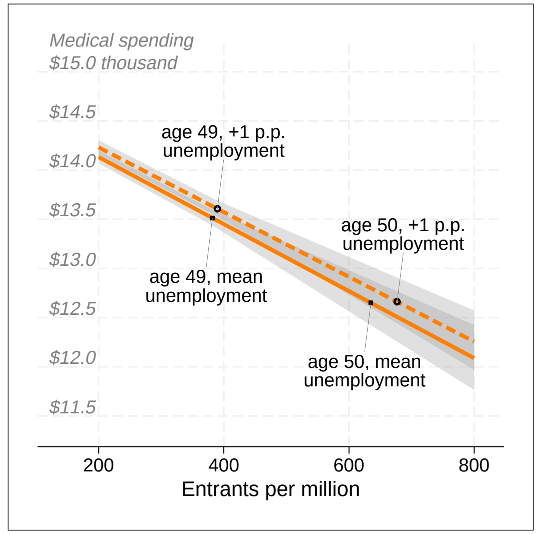


Notes: The figure shows the cyclicality of DI entry in our primary sample by age at entry, as estimated by equation (5) using three alternative sets of controls. Entry is measured for each county, month, and age as the number of entrants per million same-aged residents. The curve's height reflects the change in monthly DI entry at a given age associated with a 1 percentage point increase in the county unemployment rate at the time of DI application. The shaded regions reflect 95% confidence intervals on the estimates, calculated from standard errors clustered on the county by month of entry. The baseline coefficients (solid brown curve) are the same as those shown in Figure 5.

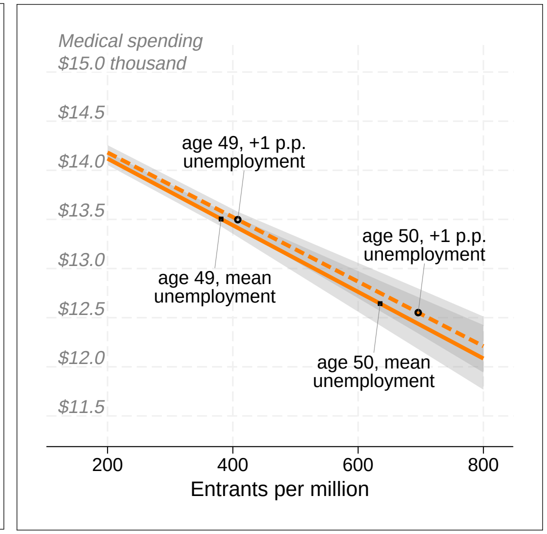
Figure A.9: Marginal medical spending functions: alternative specifications



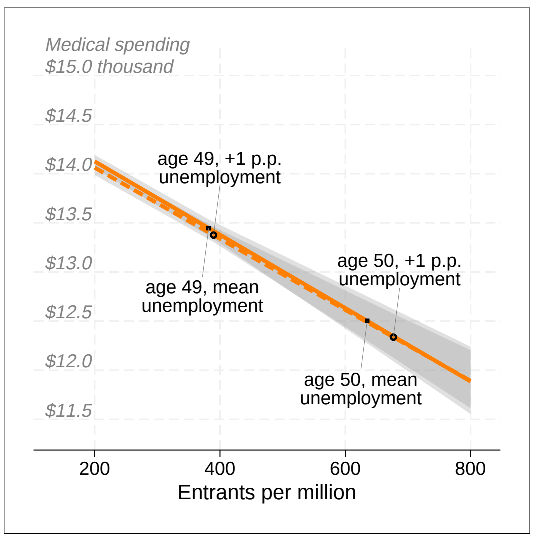
(a) Sample: 54 and 55 year olds
Entry: County
Spending: Years enrolled × County



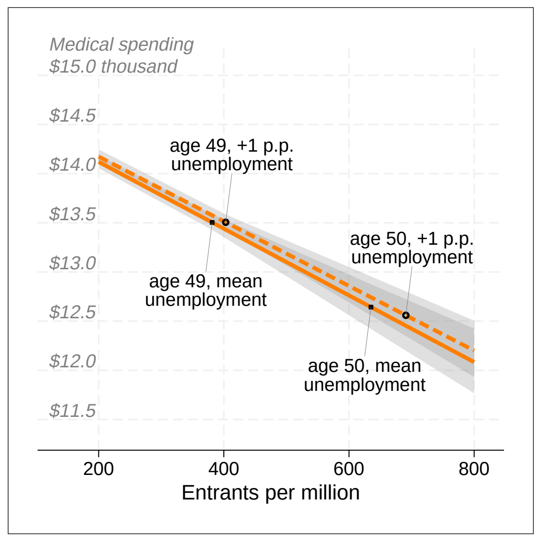
(b) Entry: County
Spending: Years enrolled × County,
County × Year of observation



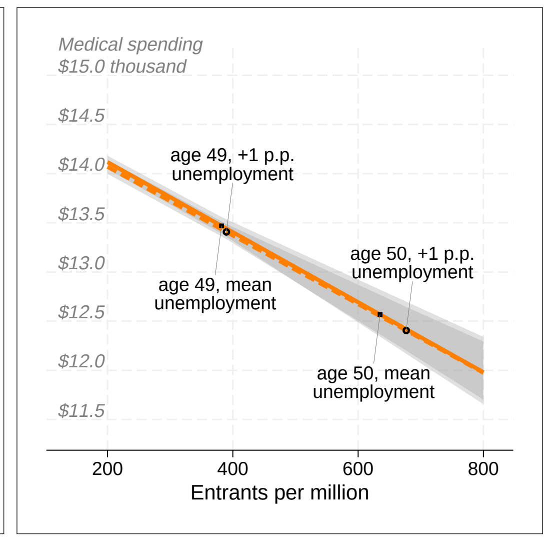
(c) Entry: Entry-month
Spending: Years enrolled × County



(d) Entry: County
Spending: Years enrolled × Entry-month



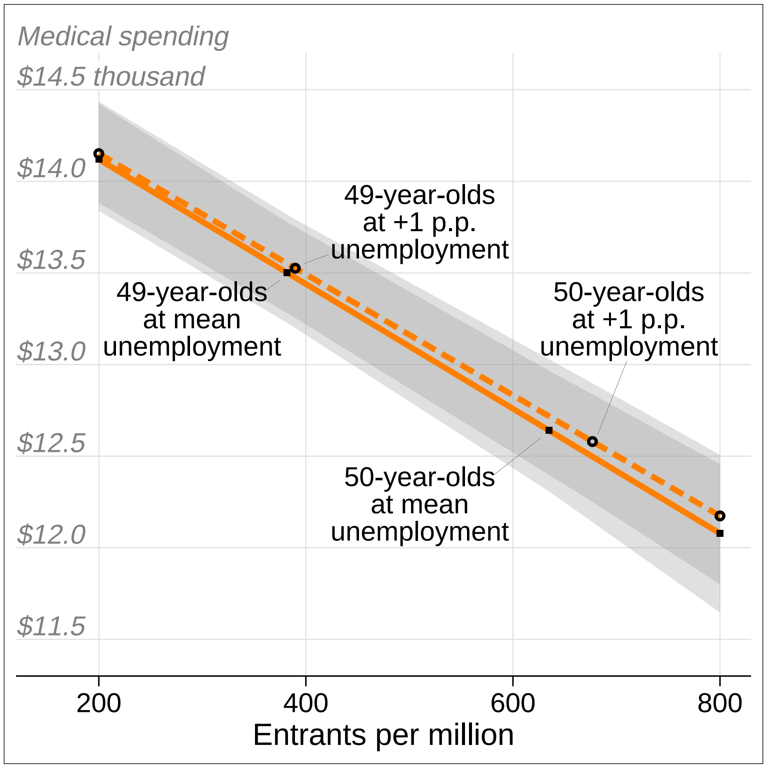
(e) Entry: ∅
Spending: Years enrolled × County



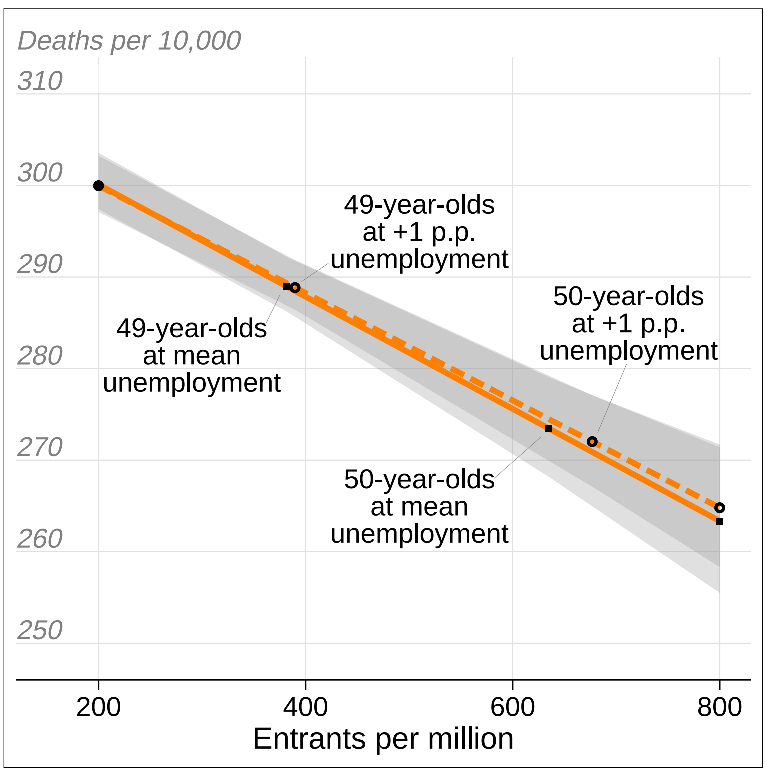
(f) Entry: County
Spending: Years enrolled

Notes: This model repeats Figure 6b under alternative specifications. Panel (a) repeats our baseline specification but uses 54 and 55 year olds entering near the second age discontinuity in eligibility. Panels (b) through (f) return to our baseline sample of 49 and 50 year olds. Panels (c) and (e) differ in the fixed effects included in equation (6), predicting entry. Panels (b), (d), and (f) differ in the fixed effects included in equation (7), predicting spending. The marginal medical spending at mean unemployment is denoted by a solid line while the dashed line reflects high unemployment. We bootstrap a confidence interval for the functions by reestimating equations 6 and 7 on 500 resamplings of county × entry-month clusters. Light gray denotes a single confidence interval, while darker gray represents overlap in confidence intervals from both lines.

Figure A.10: Health characteristics of marginal DI entrants: county clusters



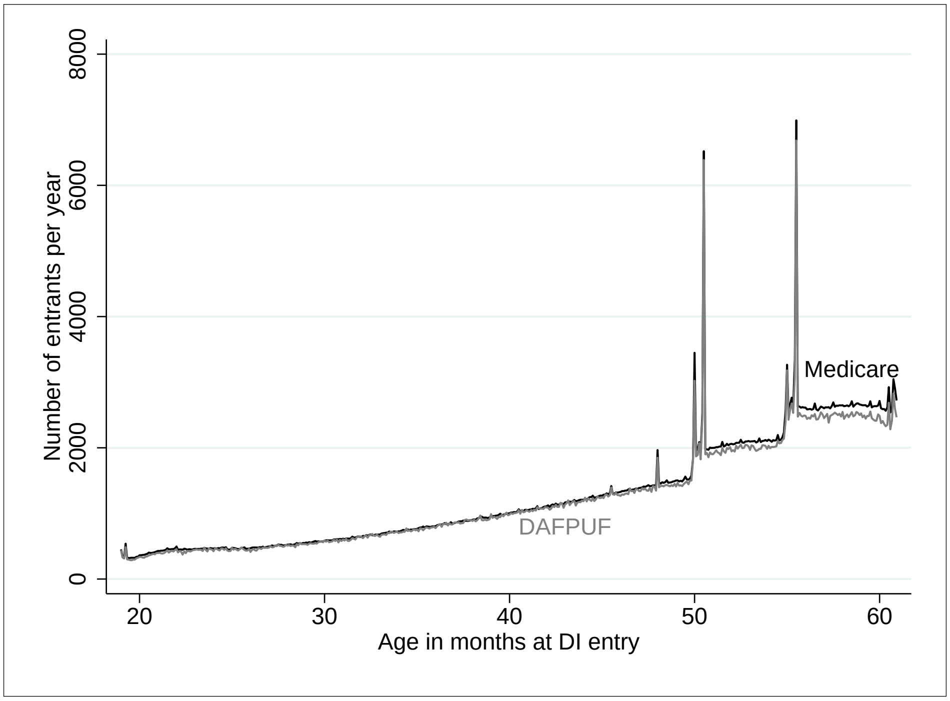
(a) Entrant medical spending: county clusters



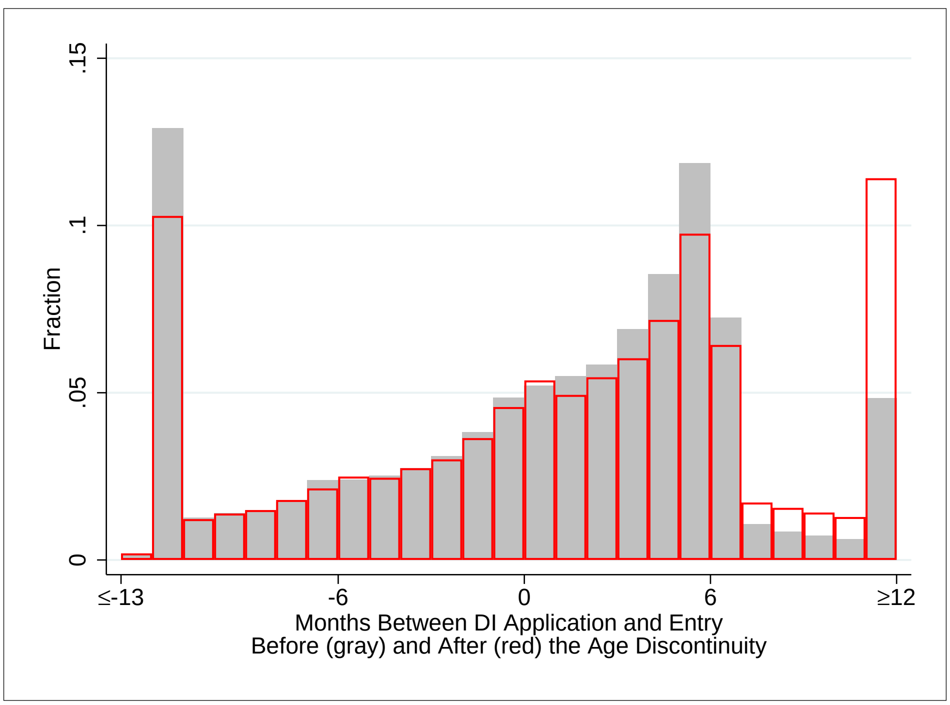
(b) Entrant mortality: county clusters

Notes: This figure replicates Figures 6b and 6c with the confidence intervals generated from 500 resamplings of county clusters (rather than county × entry-month clusters). Light gray denotes a single confidence interval, while darker gray represents overlap in confidence intervals from both lines

Figure A.11: Entry patterns near the age discontinuities



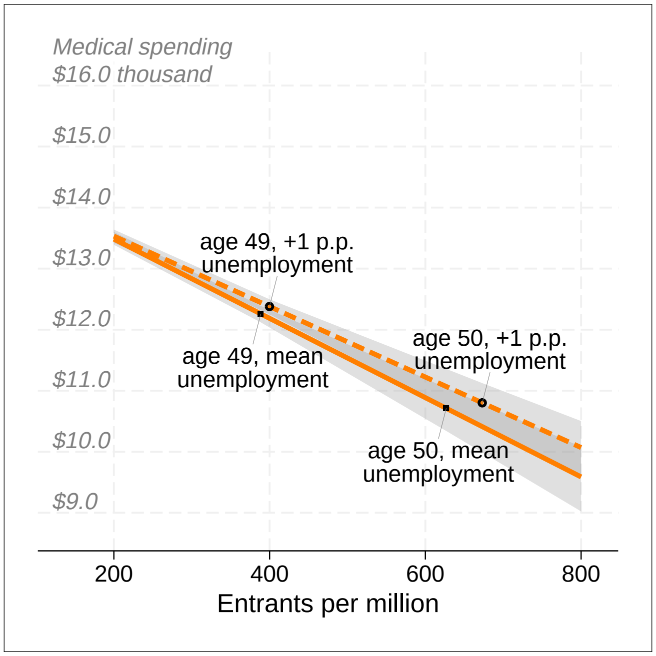
(a) Number of entrants, by age (in months) at entry



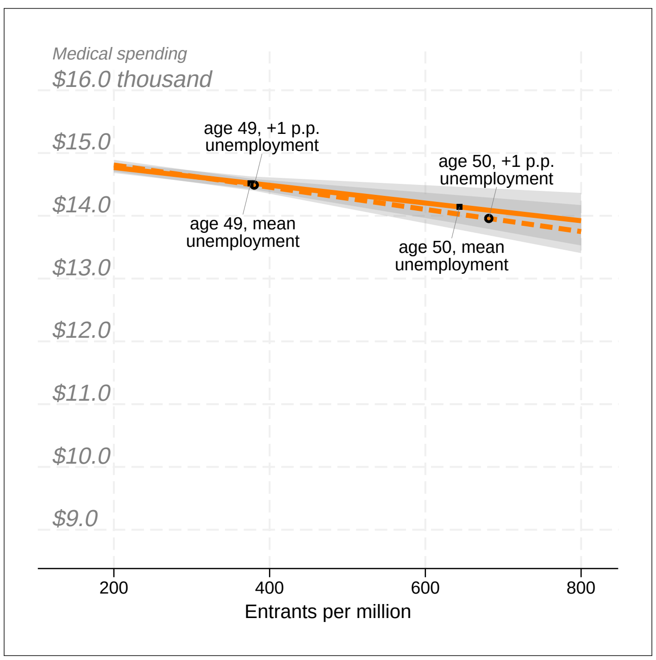
(b) Months between DI application and entry near the age-50 discontinuity

Notes: The top panel reports the annual number of new Medicare entrants at each age, calculated in months, for individuals entering Medicare 1991-2015, as measured in Medicare (black) and the DAFPUF (gray, upweighted by 10). The bottom panel reports the distribution of months between DI application and Medicare entry (bottom- and top-coded at -12 months and 12 months, respectively) for individuals entering Medicare at age 49 (gray) and 50 (red).

Figure A.12: Medical Spending of Male and Female Marginal DI Entrants



(a) Entrant Medical Spending, Males



(b) Entrant Medical Spending, Females

Notes: This figure repeats Figure 6b for males and females. The y-axis measures medical spending and the x-axis represents DI entry. The marginal medical spending function at mean unemployment is represented by the solid line, with entry of 49 and 50 year olds marked by the solid squares. The marginal medical spending function at higher unemployment is represented by the dashed line, with entry of 49 and 50 year olds marked with open circles. See Section 5 for discussion. We bootstrap a confidence interval for the functions by reestimating equations 6 and 7 on 500 resamplings of county × entry-month clusters. Light gray denotes a single confidence interval, while darker gray represents overlap in confidence intervals from both lines

Table A.1: Age discontinuities in the SSA Vocational Grids

MSWC	Education	Previous Work Experience	Outcome
Sedentary	Illiterate	Unskilled or none	Not disabled at 44, disabled at 45
Sedentary	Less than HS grad	Unskilled or none	Not disabled at 49, disabled at 50
Sedentary	Less than HS grad	Nontransferable skills	Not disabled at 49, disabled at 50
Sedentary	Less than HS grad	Transferable skills	Not disabled
Sedentary	HS grad – no direct entry into skilled work	Unskilled or none	Not disabled at 49, disabled at 50
Sedentary	HS grad – no direct entry into skilled work	Nontransferable skills	Not disabled at 49, disabled at 50
Sedentary	HS grad – no direct entry into skilled work	Transferable skills	Not disabled
Sedentary	HS grad – provides for direct entry into skilled work	Unskilled or none, nontransferable skills, or transferable skills	Not disabled
Light	Illiterate	Unskilled or none	Not disabled at 49, disabled at 50
Light	Less than HS grad	Unskilled or none	Not disabled at 54, disabled at 55
Light	Less than HS grad	Nontransferable skills	Not disabled at 54, disabled at 55
Light	Less than HS grad	Transferable skills	Not disabled
Light	HS grad – no direct entry into skilled work	Unskilled or none	Not disabled at 54, disabled at 55
Light	HS grad – no direct entry into skilled work	Nontransferable skills	Not disabled at 54, disabled at 55
Light	HS grad – no direct entry into skilled work	Transferable skills	Not disabled
Light	HS grad – provides for direct entry into skilled work	Unskilled or none, nontransferable skills, or transferable skills	Not disabled

Notes: "MSWC" signifies Maximum Sustained Work Capacity. "HS grad" signifies high school graduate. Individuals with MSWC medium or above are excluded; there are few to no age discontinuities for these groups.

Table A.2: Number of DI entrants versus number of unemployed: alternative specification

	(1)	(2)	(3)
Dependent variable: Number of DI entrants			
Unemployment Rate	5557***	2157***	2048***
	(599)	(357)	(340)
Fixed Effects		County	County, Entry month
N (County $\times$ entry month)	937,500	937,500	937,500

Notes: The table reports the results of estimating the DI entry model in Maestas, Mullen and Strand (2021) for the time period 1993–2017. The dependent variable is the number of DI entrants by county and Medicare entry month. In the regression, the independent variable is the number of unemployed individuals in the county during the applications of individuals entering Medicare in this entry month, constructed as in Section 3.3. Following the authors, we report the regression results as the implied effect of 1pp in unemployment on the number of monthly DI entrants by multiplying by the average size of the labor force over the time period. Standard errors are clustered by county. Statistical significance at the 10%, 5%, and 1% levels are indicated by *, **, and ***, respectively.

Table A.3: Cyclicality of DI entry, medical spending, and mortality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
sample	Baseline		Baseline	ACS subsample	ACS subsample	ACS subsample	ACS subsample
measure	LAUS cty×month	Col(1)*12	LAUS cty×yr	LAUS cty×yr	ACS overall	ACS 45-54	ACS HS
year range	1990–2017		1990–2017	2008–2017	2008–2017	2008–2017	2008–2017
Panel A: Entrants Per Millions Residents							
UR	13.47	161.64	156.92	178.89	171.22	162.11	119.43
	(0.13)	(1.56)	(3.22)	(7.52)	(6.28)	(5.84)	(4.04)
unit	age×cty×month		cty×yr	cty×yr	cty×yr	cty×yr	cty×yr
N	38,436,824		78,124	4,750	4,750	4,750	4,750
Panel B: "First stage": LAUS cty×yr as dependent variable							
UR					0.916	0.898	0.633
					(0.01)	(0.01)	(0.01)
Panel C: UR as Z-score							
UR (Z-score)	43.08	516.96	495.74	452.10	455.40	403.02	438.59
	(0.42)	(5.04)	(10.16)	(19.01)	(16.70)	(14.52)	(14.83)

Notes: This table reports how DI entry responds to various measures of the rate of unemployment. The first column of Panel A repeats the top-left estimates in Table 1 for Equation 1. The second column aggregates from months to years by multiplying by 12. The third column uses an annual measure of unemployment. The fourth column uses that same annual measure of unemployment, for the ten-year 475-county subsample for which we can obtain county-level unemployment rates from the American Communities Survey (ACS). The fifth column uses that ACS measure. The sixth and seventh measure use ACS-derived unemployment rates for those aged 45-54 and those with a high school degree or less. Panel B reports the correlation between our baseline (Local Area Unemployment Statistics) measure and various ACS measures. Panel C uses the dependent variables transformed to Z scores, reflecting the impact of one standard deviation increase in unemployment rate from the mean. Standard errors are clustered at the level of county by month of Medicare entry.

Table A.4: Estimates of DI entry model parameters

	(1)
A. Parameters of Benefits Functions	
slope of B: m	-3.40 (0.39)
intercept of B: n	14,801 (110)
slope of B^{UR}: m^{UR}	-3.30 (0.35)
intercept of B^{UR}: n^{UR}	14,810 (106)
difference in slopes: $m^{UR} - m$	0.11 (0.13)
difference in intercepts: $n^{UR} - n$	10 (38)
B. Parameters of Cost Functions, Assuming ΔC=-$5000	
slope of C_{49} and C_{49}^{UR}: m_{49}	641 (29)
intercept of C_{49}: n_{49}	-231,139 (11,117)
slope of C_{50} and C_{50}^{UR}: m_{50}	118 (2)
intercept of C_{50}: n_{50}	-62,257 (1,112)
Entry fixed effects	County
Spending fixed effects	County × Years enrolled, Age at observation × Sex

Notes: The table reports estimates and bootstrapped standard errors (in parentheses) of parameters of model elements. Panel A reports the slopes and intercepts of benefits functions B and B^U using the equations in Section 5.2. Panel B reports the slopes and intercepts of cost functions using the equations in Appendix Section A.4 and an assumption on ΔC. To bootstrap standard errors, we resample county × entry-month units with replacement 500 times, estimating regression parameters (αs and βs) and calculating model parameters for each sample.

Table A.5: Inference and Magnitude for Marginal Medical Spending Functions

age:	49	50	Health shock share of true entry change	
x-axis value	$\alpha+\alpha^U$	$\alpha+\alpha^U+\alpha^{50}+\alpha^{50\times U}$	ΔC =\$5000	ΔC =\$1000
Spec: Baseline, Medical Spending (Figure 6b)				
B^U	13526	12580	0.015	0.072
95% CI	(13452, 13602)	(12373, 12820)	(0.001, 0.032)	(0.006, 0.141)
B	13474	12498		
Spec: 54 and 55 year olds (Appendix Figure A.10a)				
B^U	13463	11867	0.019	0.089
95% CI	(13354, 13577)	(11612, 12122)	(0.003, 0.033)	(0.016, 0.146)
B	13412	11752		
Spec: Add County × Year of Observation Fixed Effects to Spending Equation (Appendix Figure A.10b)				
B^U	13606	12661	0.029	0.129
95% CI	(13528, 13689)	(12441, 12907)	(0.016, 0.045)	(0.074, 0.190)
B	13486	12508		
Spec: Use Entry-Month Fixed Effects in Entry Equation (Appendix Figure A.10c)				
B^U	13498	12552	0.021	0.095
95% CI	(13419, 13578)	(12339, 12797)	(0.007, 0.036)	(0.035, 0.158)
B	13414	12437		
Spec: Use Years enrolled × Entry-Month Fixed Effects in Spending Equation (Appendix Figure A.10d)				
B^U	13375	12337	-0.003	-0.015
95% CI	(13304, 13459)	(12128, 12576)	(-0.018, 0.016)	(-0.100, 0.072)
B	13418	12346		
Spec: Remove County Fixed Effects in Entry Equation (Appendix Figure A.10e)				
B^U	13506	12560	0.019	0.088
95% CI	(13428, 13585)	(12349, 12803)	(0.006, 0.035)	(0.027, 0.152)
B	13430	12454		
Spec: Remove County Fixed Effects in Spending Equation (Appendix Figure A.10f)				
B^U	13407	12405	-0.003	-0.018
95% CI	(13334, 13488)	(12200, 12644)	(-0.019, 0.014)	(-0.102, 0.067)
B	13442	12419		
Spec: Males, Medical Spending (Appendix Figure A.4a)				
B^U	12379	10801	0.065	0.257
95% CI	(12253, 12498)	(10431, 11124)	(0.046, 0.089)	(0.194, 0.325)
B	12186	10411		
Spec: Females, Medical Spending (Appendix Figure A.4b)				
B^U	14490	13958	-0.024	-0.136
95% CI	(14398, 14585)	(13689, 14290)	(-0.048, -0.000)	(-0.300, -0.001)
B	14514	14089		

Notes: Each panel of this table reports on a separate specification of our marginal medical spending functions. In the first column, we report the level of the marginal medical spending function B^U at the x-value $\alpha + \alpha^U$ (entry at higher unemployment for 49 year olds), its bootstrapped 95% confidence interval (CI), and the level of the marginal medical spending function B, representing spending among those entering at mean unemployment, evaluated at the same x-value (point Y' in Figure 6a). The second column evaluates the functions at the x-value $\alpha + \alpha^{50}$ (entry at higher unemployment for 50 year olds). The third and fourth columns report the share of true entry increases that would occur if unemployment did not change entry costs but only shifted the marginal medical spending function from B to B^U, for entry costs ΔC of \$5000 and \$1000, as well as bootstrapped 95% CIs.

Table A.6: Cyclicality of DI medical spending and mortality: alternative specifications

	(1)	(2)
Specification	Annual medical spending ($)	Annual mortality (deaths per 10,000)
Baseline: Years enrolled × County	-43.13***	-0.47***
	(4.16)	(0.09)
Years enrolled × County, Male × Age at entry	-42.24***	-1.63***
	(4.14)	(0.09)
Years enrolled × County, Male × Age at observation	-35.40***	-1.22***
	(4.13)	(0.09)
Years enrolled × County, Years of obs × County	-18.91***	-0.45***
	(4.80)	(0.10)
Years enrolled	-68.02***	-4.78***
	(4.08)	(0.06)
Years enrolled × Entry month	-56.22***	-5.58***
	(4.61)	(0.07)

Notes: The table reports results from equation (3), which measures the association of unemployment at the time of application with health status, under different control specifications. The first specification is the baseline reported in Table 1, Panel A, columns (2)–(3). Statistical significance at the 10%, 5%, and 1% levels are indicated by *, **, and ***, respectively.

Table A.7: Cyclicality estimates under county-level clustering

	(1)	(2)	(3)
	Entrants per million residents	Annual medical spending ($)	Annual mortality (deaths per 10,000)
A. Cyclicality of DI entry and cohort outcomes (main sample)			
Unemployment rate at application	13.47***	–43.13***	–0.47**
	(0.72)	(8.46)	(0.20)
Fixed effects	County	County × Years enrolled	County × Years enrolled
Dependent variable mean	319.79	13,354.31	280.13
Observations	38,436,824	101,825,663	140,407,837
B. Cyclicality of DI entry and cohort outcomes, by age at entry (49–50)			
Intercept	381.92***	14,150.80***	300.66***
	(3.36)	(32.10)	(0.65)
Age 52 at entry	253.01***	–430.43***	–7.75***
	(6.76)	(53.74)	(1.08)
UR (demeaned unemployment rate)	7.84***	17.18	–0.39
	(0.95)	(17.66)	(0.41)
UR × Age 52 at entry	34.03***	–42.55**	–0.66**
	(2.65)	(17.73)	(0.33)
Fixed effects	County	County × Years enrolled	County × Years enrolled
Dependent variable mean	507.61	13,892.97	295.97
Observations	1,874,972	7,471,112	10,508,228

Notes: The table reports results from the same regressions as in Table 1 except that standard errors are clustered at the county level. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and *** respectively.