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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 and fall in expansions, especially for older adults. Using Medicare administrative data for DI entrants between 1991 and 2015, we provide new evidence on the health of DI recipients who enter at different ages and points in the business cycle. We find that each percentage point increase in unemployment at the time of application corresponds to 4.2% more awards and 0.4% lower Medicare spending among new entrants. We then investigate whether this relationship is driven by changes in health, with deteriorating economic conditions making individuals less healthy, or by changes in the cost of entering DI. To separate these two channels, we leverage a feature of the DI determination process that sharply relaxes the eligibility criteria at ages 50 and 55. We find that marginal DI entrants have similar spending regardless of whether they were induced to enter by poor economic conditions or by the age discontinuities in the eligibility criteria. The findings suggest that changes in entry costs can fully account for cyclical DI entry.

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1 Introduction

Poor macroeconomic conditions are associated with increased admissions into Social Security Disability Insurance (DI), the federal safety net program for individuals who have work-limiting disabilities (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 the health of DI entrants across the business cycle and what role health plays in driving countercyclical entry. If recessions directly increase the number of workers with disabling medical conditions, DI serves its primary aim when it admits these additional individuals. If instead the increased entry is a response to diminished labor market opportunities, countercyclical enrollment can increase the insurance value of DI by providing cash benefits to individuals whose earnings prospects have declined (Deshpande and Lockwood, 2021). However, DI was not designed or intended for this purpose, and the program's de facto permanence and strict limits on earnings make it a costly and incomplete form of insurance against temporary downturns.[1] Understanding the sources of DI cyclicality can illuminate the program's role in the social safety net and guide policy decisions on how best to meet the needs of individuals in a recession.

We consider two broad channels through which countercyclical DI enrollment may arise (Cutler, Meara and Richards-Shubik, 2012). The first, the "health shocks" channel, captures entry by those whose health worsens during a recession, such as due to the sequelae of job loss (Sullivan and von Wachter, 2009; Schaller and Stevens, 2015) or uncertainty and stress (Coile, Levine and McKnight, 2014), leading them to meet the medical criteria for disability. The second, the "entry cost" channel, captures entry by those who were already medically qualified but who join DI during a recession due to reduced program entry costs, such as the opportunity cost of remaining unemployed during the application process and foregone earnings while in the program.

Attempts to identify the roles of health shocks and entry costs in cyclical DI enrollment face two main challenges. The first is one of measurement: illuminating how the health

[1] Indeed, 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).

status of DI entrants varies with economic conditions at application requires more detailed data on health than is available through the Social Security Administration (SSA), which administers the DI program. The second is an identification challenge: since both channels could yield marginal entrants who are healthier than inframarginal ones, disentangling the health-shock and entry-cost channels requires isolating variation in a single channel.

We overcome these challenges through a novel use of health data 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. To separately identify the health-shock and entry-cost channels, we exploit a feature of the DI determination process called the Medical-Vocational Guidelines ("grid rules") that sharply relaxes the eligibility criteria at ages 50 and 55. These age-based discontinuities effectively reduce entry costs for those with a low work capacity but do not directly affect health. We then compare the health characteristics of DI entrants who join when unemployment increases to those who join due to the age discontinuities to isolate the extent to which health shocks explain countercyclical DI entry.

We first evaluate the degree of cyclicality in DI entry across multiple business cycles and establish new descriptive evidence on the health of DI recipients who applied for DI under different economic conditions. We link DI recipients entering the program in 1991–2015 to the county unemployment rate at the time of their application to DI. We find that recipients who applied under high unemployment subsequently had lower Medicare spending than those who applied when unemployment was low. In our baseline specification, each percentage point increase in local unemployment corresponds to a 0.4% reduction in average spending among DI entrants. We confirm that this finding captures the relationship between economic conditions and health—as opposed to variation in prices or other supply-side determinants of medical spending—by documenting a similar relationship between unemployment and subsequent mortality among DI entrants. Because economic conditions may affect both the composition and health of DI entrants, these findings alone are insufficient to distinguish the relative roles of entry costs and health shocks in driving cyclical DI entry.

To identify the effects of these two channels, we study how DI entry and entrant characteristics vary with age at entry. We find that DI entry increases sharply at ages 50 and 55, when the eligibility criteria relax. 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 cutoffs. We also find that the average medical spending and mortality for DI recipients who enter just above these age thresholds are about 3% lower than for those entering at slightly younger ages, reflecting a change in the composition of new entrants. 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 illuminate whether and how cyclicality in DI entry relates to the age discontinuities, we evaluate how entry responds to unemployment at each age. We find that DI entry becomes sharply more cyclical at the age discontinuities. Individuals subject to the looser eligibility guidelines account for half of DI entry but two-thirds of DI cyclicality. This finding reveals a close link between cyclical DI entry and the age discontinuities: the responsiveness of DI entry to unemployment is itself partly due to the relaxed eligibility criteria at older ages.

To determine the relative roles of entry costs and health shocks in driving cyclical DI entry, we develop a model of DI entry where individuals differ in their work capacity (degree of disability) and enter DI if the benefits exceed the costs. Benefits include the value of Medicare coverage and decrease with work capacity, while costs increase with work capacity since to receive DI, individuals must forego earnings and document 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). Motivated by the model, we argue that the age discontinuity, which induces DI entry via a change in entry cost only, admits a similar group of people as would a change in unemployment, which may work through both the health-shock and entry-cost channels (Lindner, Burdick and Meseguer, 2017; Grossman, 1972).

Using the model, we derive an empirical test for the presence of health shocks in driving cyclical DI entry based on whether DI entrants induced by unemployment have higher spending than those induced by the age discontinuities. We parameterize our model using reduced-form estimates of the entry increases and medical spending decreases associated with the age discontinuity, high unemployment, and their combination. We estimate the benefits function to be downward sloping, consistent with marginal entrants being healthier than inframarginal entrants. However, we estimate the benefits function to be nearly identical in periods of high and low unemployment, reflecting nearly identical medical spending between a marginal entrant induced by unemployment versus the age discontinuities. Consequently, we conclude that unemployment-associated changes in entry costs can fully account for the patterns of cyclical DI entry in our sample period.

Our paper makes a series of advances to understanding 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 paper contributes to this work in three primary ways. First, 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), which are directly relevant to the cost of Social Security programs and complement the prior work evaluating health status based on conditions documented in the DI application. Second, we characterize the health status of DI entrants, not applicants, which takes into account the role of screening in DI entry. Third, we propose and implement a novel research design for disentangling the channels through which cyclical DI entry arises.

Our findings also shed new light on the importance of the age discontinuities in DI entry, which have come under scrutiny in recent proposals to reform DI (Davidson, 2020). Recent evidence on the role of the age discontinuities comes from Chen and Van der Klaauw (2008) and Deshpande, Gross and Su (2021), who use a regression discontinuity approach to evaluate the effects of disability allowance on labor force participation and financial distress, respectively. Both papers show that the share of applications awarded benefits, by age at the date of initial decision, jumps sharply at the age cutoffs. This jump is likely to understate the effect of the age discontinuities on DI entry since some who are initially denied at a younger age may appeal and ultimately be found to meet the definition of disability under the relaxed criteria, with the DI entry month set to the corresponding age cutoff. We confirm this in an analysis of the application dynamics near the age discontinuity: entry rates by age not only jump upon reaching an age cutoff but also spike sharply and precisely at these cutoffs, with the excess mass corresponding to individuals who applied before reaching an age cutoff. Thus, we find that increased entry at the age discontinuities comes partly from applications that are dispersed over the years leading up to the age discontinuities.

Our paper is also the first to reveal the key role of the grid rule age discontinuities in driving cyclical DI entry. Our finding that DI entry becomes sharply and substantially more cyclical at the age discontinuities spotlights how the relaxed eligibility criteria at these ages explains previous findings that DI cyclicality is strongest among older workers and those with mild impairments, low skill, and low education (Cutler, Meara and Richards-Shubik, 2012; Maestas, Mullen and Strand, 2021; Lindner, 2016; Autor and Duggan, 2003; Duggan, Singleton and Song, 2007). Moreover, our finding that the impact of the age discontinuities on DI entry grows with unemployment reveals how studies that produce a single average effect of the age discontinuities are likely to understate their role in the social safety net during economic downturns.

Our finding that recessions neither worsen nor improve long-run health among individuals with marginal work-limiting disabilities also contributes to the literature on the relationship between recessions and health. Despite folk wisdom that a weakening of the economy should worsen health due to decreased income and access to health care, the empirical evidence has been mixed. Early work in this area found mortality to be procyclical, suggesting that recessions could be good for health (Ruhm, 2000, 2003, 2005, 2012), but more recent work has found the opposite pattern (McInerney and Mellor, 2012; Ruhm, 2015), especially among the working-age population (Crost and Friedson, 2017; Schwandt and von Wachter, 2020).

The extent to which fluctuations in entry costs versus shifts in long-run health status drive cyclical DI entry has important policy implications for the design of DI and other social safety net programs. The DI program is primarily designed to insure against permanent disability and not cyclical or other temporary shocks. Our finding that entry costs can fully account for cyclical DI entry suggests that existing elements of the safety net are not adequately supporting individuals with functional limitations during economic downturns. For example, 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 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.

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).[2]

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

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

[2] 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.

respiratory or cardiovascular diseases. Each listed impairment is defined by particular elements of the medical evaluation (e.g., medical lab values).[3]

4. **Can the individual do the work they did previously?** In this step, the SSA assesses the most 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.

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, applicants' step 4 work assessments are used to determine a categorical "maximum sustained work capacity" (MSWC): less than sedentary, sedentary, light, medium, heavy, or very heavy.[4] 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). In recent years, 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 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" are usually denied benefits, but those with the same sedentary work capacity who are

[3]While listed impairments are thought to have objective definitions, Hoynes, Maestas and Strand (2021) find that legal representation for DI applications increases the share of applications initially awarded from 32% to 55%, primarily by successfully categorizing individuals' mental impairments as listed.

[4]MSWC is intended to capture work capacity based on the exertion involved. Individuals may also have other impairments (e.g., mental, postural, visual, or environmental conditions that affect their ability to work) unrelated to exertion per se. While these are not captured by MSWC, disability determinations are allowed to take such limitations into consideration. Thus, some applicants with an MSWC of "heavy" or "very heavy" are awarded benefits because of significant non-exertional limitations (e.g., mental disorders, memory problems, sight or hearing impairments) that prevent them from doing sustained work that they can otherwise physically do (Rule 204.00 of 20 C.F.R. §404 Subpart P, Appendix 2).

aged 50–54 may be awarded benefits.[5] 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.[6] 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 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 Part A and Part B benefits via a Medicare managed care plan (Medicare Advantage).

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

[5] For applicants assigned a “sedentary” work capacity, the SSA determines the set of occupations a person could actually perform on a sustained basis by examining a list 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 more likely to be awarded benefits (Social Security Administration, n.d.*b*).

[6] 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.

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.[7] Using Medicare data on a beneficiary's original reason for Medicare entitlement and basis of eligibility for SSA programs, we further 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. 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.[8]

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.[9] 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

[7]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.

[8]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.

[9]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.

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 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.

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,

[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.

weighted by $p_{m\tau}$; that is,

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

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 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 and medical spending, 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

$$Entry_{acm} = \alpha[\textit{unemployment rate}]_{cm} + [\textit{county FEs}]_c + \varepsilon_{acm}. \quad (1)$$

In our baseline, 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 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 across individuals joining Medicare at the same time and place.

We begin by estimating a version of equation (1) that 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

[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.

DI entry, relative to the sample mean monthly DI entry rate of 313 monthly entrants per million residents.

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:

$$y_{it} = \delta_{coh} + X_{it} + \varepsilon_{it}. \tag{2}$$

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 for her annual entry cohort: δ_{coh}. In our baseline specification, X_{it} contains a set of fixed effects for the number of years since the individual's entry into Medicare. We control for number of years enrolled because a substantial share of DI beneficiaries die during their first years of Medicare coverage, and thus cohorts experience high average costs (likely related to end-of-life care) in their first years of Medicare coverage. Without this fixed effect, the earlier cohorts (not observed in our data until their eighth year since DI entry) appear artificially inexpensive. We exclude each cohort's first (partial) year of spending because otherwise the influence of this partial year dominates the cohort fixed effect for recent cohorts.

Figure 1b reports the average spending (net of fixed effects) for each year-of-entry cohort (e.g., 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 2007 applied under an unemployment rate of 5.0%, the lowest of the macroeconomic cycle, at the time of their applications but had the highest spending of all entry cohorts. 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.

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, yielding the following regression equation:

$$y_{it} = \beta[\textit{unemployment rate}]_i + X_{it} + \varepsilon_{it}. \tag{3}$$

In this case, β recovers the correlation of an individual's health outcome (medical spending or mortality) with the unemployment rate at application for i's county and entry month. In our core specification, X_{it} contains fixed effects for the interaction of the number of years enrolled and county. The inclusion of the county fixed effect means we are identifying our effect using cyclical fluctuations within counties rather than the persistent differences in counties that could independently affect health.

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 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 \$47 (0.4%) decrease in subsequent annual medical spending and 0.49 fewer deaths per 10,000 person-years (a 0.2% reduction in mortality).

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 indicate 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 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.2, 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 longer durations 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 solid black curve plots the fixed effects estimated for each age at entry a from the following equation:

$$y_{it} = \delta_a + X_{it} + \varepsilon_{it}. \tag{4}$$

This equation mirrors equation (2) but estimates fixed effects for age at entry 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.

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.[13]

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:

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

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

In these equations, $\tilde{U}_{cm}$ is the county unemployment rate at application, demeaned to simplify interpretation of the coefficients. 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, the regression constants α and β represent

[13] 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.

entry and spending for those entering at age 49 under conditions of mean unemployment, 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 for explicitly comparing entrants induced by unemployment or the age discontinuity.

5 Health Shocks versus Entry Costs

As mentioned in Section 1, the literature has suggested two possible channels through which economic conditions might affect DI enrollment. 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-shocks channel), or such 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-costs channel), leading more of them to enter DI.[14] In this section, we explain our strategy for separately identifying the impact of health shocks and entry cost shifts by comparing the medical spending of two groups of people: those who enroll in DI due to a change in unemployment (following the terminology of Angrist, Imbens and Rubin (1996), "recession compliers") and those who enter only due to the looser eligibility rules that apply at older ages (i.e., "age discontinuity compliers").

5.1 Conceptual Framework

Consider the simple model of entry into DI depicted in Figure 6a. Importantly, this is a model of *successful entry* into DI, not applications. Individuals are characterized by their level of work capacity d and are sorted along the x-axis, with those with a lower work capacity (i.e., their disabilities limit their ability to work to a greater degree) toward the left and those with a greater work capacity toward the right. An assumption embedded in our x-axis is that individuals can be continuously ordered by work capacity, with entry increases induced by unemployment or the age discontinuity sequentially admitting individuals with progressively greater work capacities. We further discuss this assumption in Section 5.4. Our focus here is on individuals who enter DI via the grid rules in step 5 of the application process since qualification in the earlier stages due to a listed impairment is significantly less sensitive to economic conditions (Maestas, Mullen and Strand, 2021).

We posit that eligible individuals obtain an expected benefit from receiving DI equal to

[14] A third possible mechanism is that the SSA becomes more likely to approve applicants when job prospects are bad. However, 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).

$B(d)$, where $B(d)$ includes the value of cash benefits and Medicare. Our analysis focuses on the utility of Medicare, which we proxy using medical spending (ignoring the insurance value of Medicare). The benefits function 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). Consistent with the assumption that the value of Medicare decreases as work capacity increases, we draw $B(d)$ as downward sloping. However, our analysis does not rely on this assumption.

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 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 $C(d)$.[15]

The cost functions vary with age. The cost of DI entry for a 49-year-old is depicted by the red curve with circle markers in Figure 6a. 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 $C(d)$ 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. Second, while SSA guidelines allow 49-year-olds with a less-than-sedentary work capacity to be found disabled, the rules recommend that 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 and the exact nature of the applicant's disability (Autor et al., 2015). Many such individuals are denied benefits on their initial application, and benefits are awarded only after successfully completing a costly appeal process. Thus the cost of

[15] 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.

establishing disability is larger for individuals capable of sustained sedentary work and, due to the narrow path toward establishing disability via the grid rules for individuals in this range, 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. This cost quickly rises to a level that, for all practical purposes, precludes establishing DI eligibility.

Our cost function is consistent with the evidence developed in Deshpande and Li (2019) in their analysis of the closure of nearby SSA administrative offices. While the authors do not categorize applicants by work capacity or age, they find that the "hassle" costs of DI applications among eventual enrollees are larger for those with milder disabilities and individuals who will need to appeal as compared to those with severe disabilities.

The green curve (marked with squares) in Figure 6a depicts entry cost for 50-year-olds, which follows the same general pattern as entry cost for 49-year-olds. However, for those with a sedentary work capacity, the discontinuity in eligibility at age 50 provides greater scope to establish disability and a lower cost of doing so. 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.

At either age, 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, 49-year-olds to the left of the intersection of the red cost function and the benefit function will enter DI. This level of entry is denoted by α. As depicted, the relaxation in eligibility standards for 50-year-olds with a sedentary work capacity admits α^{50} additional age discontinuity compliers into DI. Note that the model predicts lower spending among this group, just as we found in Section 4.3.

5.2 Conceptual Experiment

We can use the model to characterize the potential effects of unemployment. Consider Figure 6b, which illustrates the effect for 49-year-olds alone. As discussed, a change in unemployment can affect both entry costs and health. We represent the impact of an increase in unemployment on entry cost as a downward shift in the cost function to the lower dashed red curve.[16] 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.

The second potential effect of an increase in unemployment is a worsening of health, which we conceptualize as a shock to health capital that increases the marginal value of future health care, in the manner of Grossman (1972). Since the height of the B function includes the value of health benefits received, a negative health shock increases the potential benefit from enrolling in DI. This impact is represented in Figure 6b by an upward shift of the benefits function from $B(d)$ to $B^U(d)$ (dashed orange curve). This shift need not be parallel. If the health shocks are larger for less-disabled individuals, the benefits function would become flatter, as shown in Figure 6b.[17] Because the entry-cost function is upward sloping where it crosses the benefit function, an upward shift in the benefits function would induce additional entry into DI compared to the cost shift alone. We denote the recession compliers induced by the change in costs and benefits as $\alpha^{U'}$; again, they are expected to have lower average medical spending than the inframarginal always-takers, as we saw in Section 4.2.

In Figure 6b, we have *scaled* the unemployment effect such that the number of individuals induced by the age discontinuity α^{50} is the same as $\alpha^{U'}$, the number of individuals induced by unemployment.[18] We do this to develop intuition about how the model identifies the relative roles of health shocks and entry costs in the effects of unemployment. Consider 49-year-olds when unemployment is low (denoted by x-axis value α). Either aging across

[16]For simplicity, we model the fall as independent of work capacity; the model's main 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.

[17]We characterize an increase in unemployment as *reducing* health because this is the direction most often discussed in the DI literature. However, in estimation we allow the benefit function to move in any direction to accommodate countercyclical health patterns as in Ruhm (2000).

[18]That is to say, the parameter α^U from equation (6) measures the increase in 49-year-old entry for a 1 percentage point increase in unemployment; in this figure, we model the percentage point change in unemployment ΔU such that $\alpha^U * \Delta U = \alpha^{50} = \alpha^{U'}$.

the discontinuity or an increase in unemployment admits individuals with the level of work capacity that lies between the gray vertical lines into DI. If they are admitted to DI because of the age discontinuity, there is no reason to think there is a concurrent discrete change in health: the additional entry is driven *only* by a change in entry cost. Thus their medical spending is given by the height of the original benefit curve B between α and $\alpha + \alpha^{50}$.

If these same individuals enter DI following a change in the unemployment rate, then there may be changes in their health (i.e., the benefit of entering DI). Their medical spending is thereby given by the area below the new benefit curve B^U. Thus, by comparing the medical spending of these compliers when they enter DI via a change in the unemployment rate to their expenditure when they enter due to aging, we can net out the entry-cost effect, allowing us to isolate any change in health that might occur. If medical spending is the same under these two mechanisms, then we can conclude that B and B^U overlap and thus that health shocks do not play a significant role in driving entry when the unemployment rate changes.

The full model, in Figure 6c, simply examines the effect of a 1 percentage point increase in the unemployment rate rather than the scaled effect we considered in Figure 6b. As can be inferred by dividing the entry coefficient for age 50 by the coefficient for the unemployment rate in column (1) of Panel B in Table 1, it would require a very large change—about 32 percentage points—in the unemployment rate to increase the entry of 49-year-olds by 253 per million per month (the increase associated with the age discontinuity).[19] Thus, we draw a smaller vertical shift in the cost function, indicating a smaller number of 49-year-old recession compliers.

The full model also depicts the effect of a 1 percentage point increase in the unemployment rate on 50-year-old entrants. Because 49- and 50-year-olds experience similar labor markets, we assume unemployment reduces $C(d)$ similarly for both 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

[19] Another limitation of the counterfactual depicted in Figure 6b is that the 49-year-old recession compliers are drawn from the region of the x-axis associated with a sedentary work capacity. But, under program rules, 49-year-old entrants with a sedentary work capacity are usually found not disabled. When unemployment is properly scaled, it is easy to see that 49-year-old recession compliers can be drawn from the x-axis range associated with a less-than-sedentary work capacity.

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.

5.3 Estimating Model Parameters

In this section, we use the data and estimates prepared in Section 4.4 to parameterize the model in Figure 6c.

5.3.1 Identifying the Parameters of the Benefits Functions

In Section 4.4 we estimated equation (6) to predict the entry rate for ages 49 and 50 at mean and higher unemployment, with the results reported in Panel B of Table 1.[20] At mean unemployment, α 49-year-olds, or 382 per million per month, enter DI, rising to 390 ($\alpha+\alpha^U$) at higher unemployment. The entry rate at mean unemployment for 50-year-olds is 635 per million per month ($\alpha + \alpha^{50}$) and 677 ($\alpha + \alpha^{50} + \alpha^U + \alpha^{50\times U}$) at higher unemployment.

The coefficients in the spending equation (e.g., equation (7)) provide estimates of the average spending of each group of entrants. That is, the average spending of 49-year-olds who enter at mean unemployment is given by β, and the average spending of 50-year-olds who enter at mean unemployment is given by $\beta + \beta^{50}$.

To proceed, we assume the benefits functions are linear in work capacity, an assumption we discuss in more detail in next section. Recall that we previously stated that individuals are ordered by their work capacity. Under that ordering, we can interpret our entry rate estimates as indicating the number of DI entrants with a work capacity at or below the x-axis value. If the benefit function is linear over this group, then the medical spending of the person located at the range midpoint is equal to the group's average medical spending.

We apply the midpoint formula to find the slope and intercept of the benefit function $B(d)$. 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 $n = \beta - \frac{\alpha\beta^{50}}{\alpha^{50}}$. Thus, the age discontinuity directly

[20] Specifically, α^U and $\alpha^{50\times U}$ represent the incremental effect of 1 percentage point of unemployment 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. Thus, defining "higher unemployment" to be, for example, 4 percentage points above mean would simply scale all effects proportionally, leaving the ratios in the analytical solutions for slope and intercept unchanged.

identifies the benefits function at mean unemployment by providing entry and spending estimates for two groups that applied during the same economic conditions.

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

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

Compare the slopes m and m^U. For the two to be equal, 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. If instead the spending of the group exposed to both sources of variation (50-year-olds in high unemployment) is higher than the spending of age discontinuity compliers, we would find a less negative (flatter) slope for the benefits function during high unemployment. Such a finding would suggest health differences between recession compliers and age discontinuity compliers.

To understand the identification of the difference in the intercept, assume for the moment that the slopes of the two curves are the same 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 is zero if $\frac{\beta^U}{\alpha^U}=\frac{\beta^{50}}{\alpha^{50}}$. Intuitively, in the scaled version of the model, we examined a setting in which α^U was equal to α^{50}, and we simply compared the spending changes β^U and β^{50}. Here, we simply normalize the spending changes by the number of compliers. If recession compliers and age discontinuity compliers change spending to a similar extent, there is no difference in the intercepts of the two benefits functions. If instead recession compliers appear more expensive than age discontinuity compliers, the model indicates a higher intercept for B^U. We would interpret such a finding as evidence of health shocks that affected recession compliers.

Panel A of Appendix Table A.3 reports the slopes and intercepts of the benefits functions. We obtain a bootstrapped standard error for each model parameter by estimating the αs and βs for resamplings of the data using county $\times$ entry-month clusters. The benefits function is more steeply downward sloped at mean unemployment than when unemployment is increased by 1 percentage point, although this difference is not distinguishable from zero. We actually find that the intercept is *higher* in mean unemployment than at higher unemployment, although again this effect is indistinguishable from zero.

Figure 7a depicts the benefits functions implied by the baseline specification. It is clear that the benefits functions are very close together and within the error with which the identifying points are known. Thus, the data suggest that recession compliers have the same spending levels as age discontinuity compliers, with no evidence of health shocks leading to higher spending among recession compliers.

5.3.2 Identifying the Parameters of the Cost Functions

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, by assumption, is movement along the benefits function. However, 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.

When positing the model, we assumed that the cost functions are linear and the reduction in entry costs during high unemployment was the same for 49- and 50-year-olds. With those assumptions, the sloped portion of the cost functions can be characterized with five parameters: m_{49} and n_{49} are the slope and the intercept for the cost function for 49-year-olds under mean unemployment, m_{50} and n_{50} are the slope and intercept for 50-year-olds under mean unemployment, and ΔC is the cost change associated with unemployment. Still, the five parameters of the cost functions are underidentified by the four points that they pass through.

However, we can calculate the slopes and intercepts of the cost functions given a value for ΔC. In Appendix Section A.3, 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 examine three scenarios: $\Delta C \in$ {-500, -5000, -50000}, which encompass a wide range of possible values for the recession-related reduction in the cost of DI entry.

For the middle value of $\Delta C = -\$5000$, we report the slope and intercept of the cost functions in Panel B of Appendix Table A.3 and draw them in Figure 7b (red and green curves). 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.[21] The flatter slope of the cost function for 50-year-olds means that the same vertical shift in the intercept generates a much larger entry response for 50-year-olds relative to the entry response for 49-year-olds. We find similar estimates for $\Delta C = -\$500$ (Appendix Figure A.4a) and $\Delta C = -\$50,000$ (Appendix Figure A.4b, suggesting that our cost function parameters are not very sensitive to the choice of ΔC.

5.4 Discussion

In this section, we discuss some of the assumptions underlying our analysis.

Ordering by Work Capacity. An important assumption embedded in our model is that 49- and 50-year-old "potential entrants" are continuously ordered by work capacity. To understand this assumption, consider the x-axis coordinate α that denotes entry among 49-year-olds at mean unemployment. We assume that *either type* of variation—1 percentage point of unemployment, or aging across the discontinuity—will result in the entry of the individuals arrayed to the right of α. At its root, our decomposition involves comparing the cost of these individuals when they enter DI via the age discontinuity to their cost when they enter via an increase in unemployment.

The descriptive findings in Section 4.4 indirectly support this assumption. First, Figure 5 shows that the two sources of variation interact to create greater entry than either source on

[21] In the figure, we have normalized all costs to be non-negative, which amounts to a vertical shift of about \$25,000.

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. Second, we find that increased entry from either source is driven in part by the same underlying mechanism—increased applications.

Treatment Effect Heterogeneity. Our graphical analysis compares two groups of compliers – recession compliers and age discontinuity compliers – to always takers (49-year-old entrants at mean unemployment). In principle, differences in medical spending could be driven either differences in the work capacity and underlying health of compliers, or by differences in the response of the compliers to the "treatment" of DI and Medicare (Kowalski, 2021). 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.5, 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.6, we demonstrate no relationship between these outcomes and national unemployment at enrollment (represented by the dashed blue curve) or age at entry.

Linearity of Functions. Linearity of the benefits functions in work capacity is a key assumption required for the analytic solutions for slopes and intercepts. Linearity could fail if, for example, individuals with differing work capacities have the same benefit from DI enrollment as this would generate flat regions or nonlinearities in the benefits functions. We cannot assess this assumption directly. However, we note that a relationship between work capacity and medical spending is supported both by Wolff et al. (2019) and Koroukian et al. (2017) and our own finding that age discontinuity compliers—individuals with a sedentary work capacity—spend less than other 49-year-old entrants who generally will have lower work capacities (Figure 3b).[22]

If the linearity assumption fails, our estimates represent the linear approximation to $B(d)$ that passes through the intersection of $B(d)$ and C^{49} and C^{50} and similarly for $B^U(d)$. The fact that these two linear approximations are similar would still represent evidence against a role for health shocks in countercyclical DI entry.

Nature of Health Shock. 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 recession-associated health shocks only temporarily reduce human capital, these effects may not be observable in our Medicare spending 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 either barriers to accessing medical care or because the nature of the health shock is not amenable to medical care.

[22] The other component of the benefits function, cash benefits, depends on the individual's earning history but is independent of current work capacity.

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 to adjust for known determinants of health.

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 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 in the year of 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.[23] We find that the cyclical pattern is still evident in the presence of those controls.

[23]When included with year-of-entry fixed effects as in Appendix Figure A.7, we require a second omitted year; we choose 2016.

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 Table A.4. 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. When we drop the county fixed effects, as in the fifth row of Appendix Table A.4, we indeed find a stronger correlation between unemployment and health status.

Finally, 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.4 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.

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 $\times$ 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 specifications used to estimate equations (6) and (7), which generate the parameters of the benefits functions at mean and high unemployment. For equation (6) predicting entry, we report specifications using within-county variation, all variation, or between-county variation by including a county fixed effect, no fixed effects, or entry-month fixed effects, respectively. For equation (7) predicting spending, we use the same fixed effects reported in Appendix Table A.4 (except for a fixed effect for age at entry, which is captured by the indicator for entering Medicare at age 50).

Appendix Figure A.9 demonstrates that, regardless of the specification, we consistently find no evidence for unemployment-associated health shocks. Each panel in the figure uses a single specification of equation (6) and reports benefits functions for varying specifications of equation (7). The benefits functions at mean (solid curves) and high (dashed curves) are always very similar, with the benefits function at high unemployment never lying above that for mean unemployment.

7 Conclusion

This paper examines the factors that drive increased enrollment in the federal Social Security Disability Insurance program during recessions. Using administrative data on health outcomes, we determine that individuals who enter the program when unemployment is high are in better health, as measured by lower spending and mortality, than individuals who enter when unemployment is low. Similarly, we find that a large increase in DI entry at age 50, the result of an age discontinuity in eligibility, is associated with sharp improvements in health. Using a graphical model, we compare changes in spending across the business cycle to changes in spending at the age discontinuity. Unemployment could increase DI entry by directly worsening health, which would mean that recession-induced individuals are in worse health than those who join because of the rule changes at age 50. However, we find that spending changes are similar for both types of induced entry.

Our results are inconsistent with the hypothesis that worsening health during recessions drives the take-up of disability insurance. Instead, our findings suggest that DI may be helping individuals to smooth consumption in response to temporary, medium-run shocks to employment conditions, a role that contrasts with the program's aim of protecting individuals from permanent shocks to their ability to work. These results suggest that offering other social programs like short-term disability insurance measures designed to cover medium-run shocks may better target the types of shocks that induce enrollment into the program during recessions.

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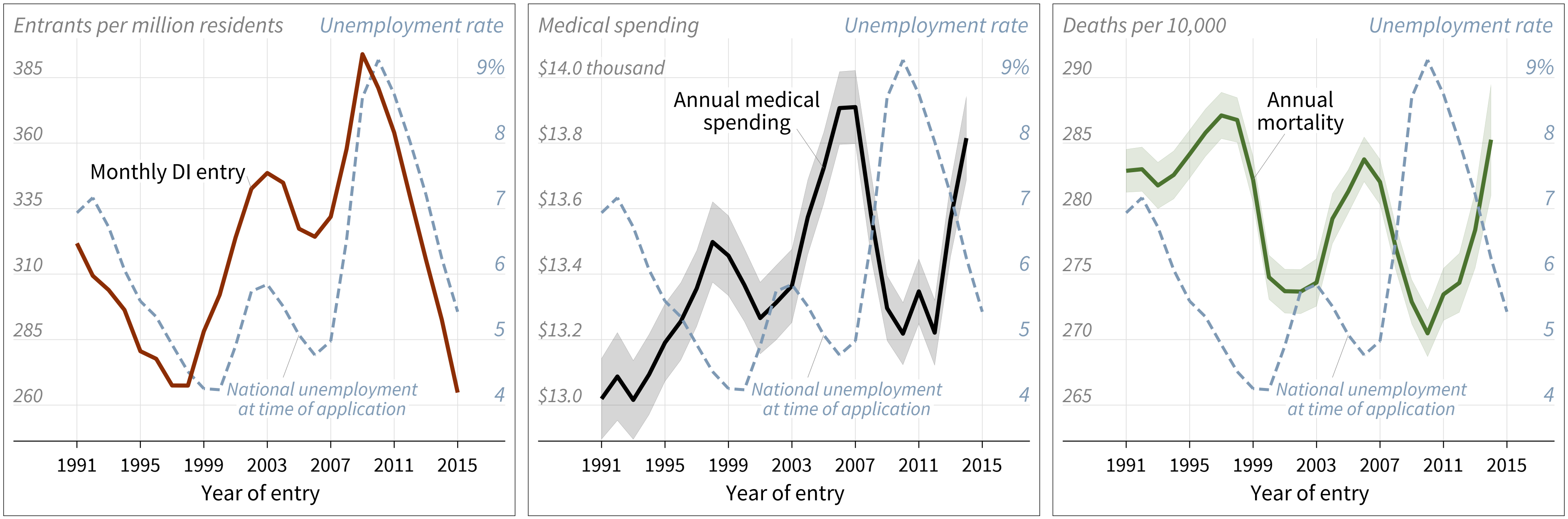
Figures and Tables

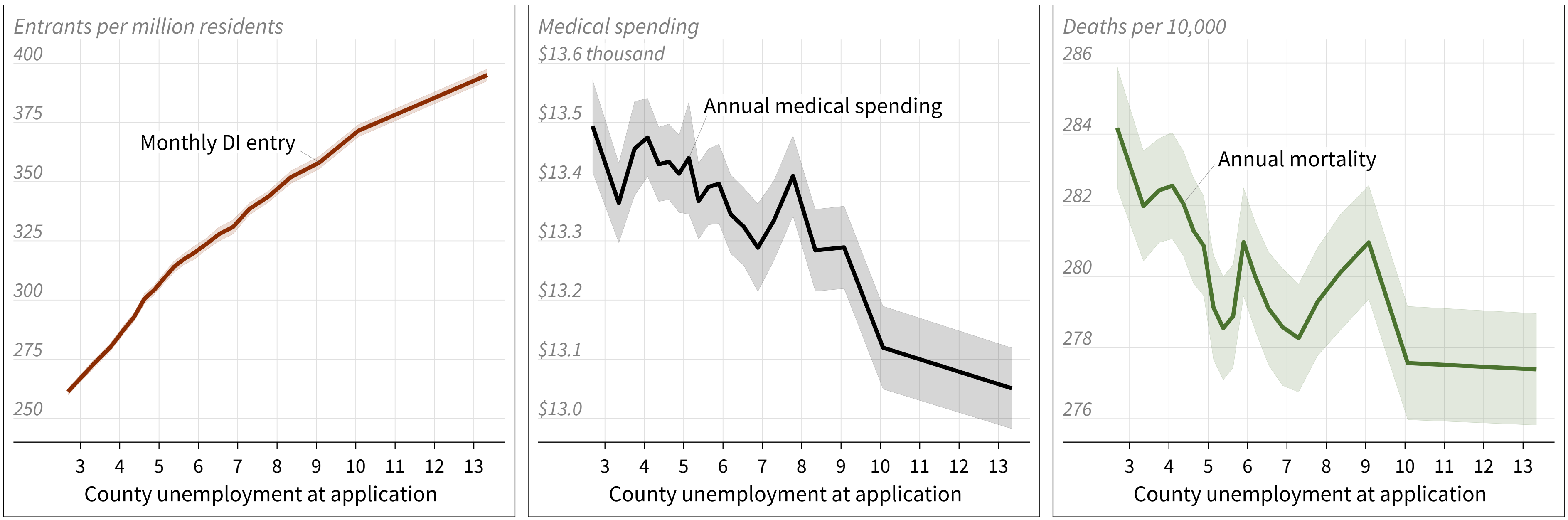
Figure 1: DI entry, medical spending, and mortality, by year of entry



(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.

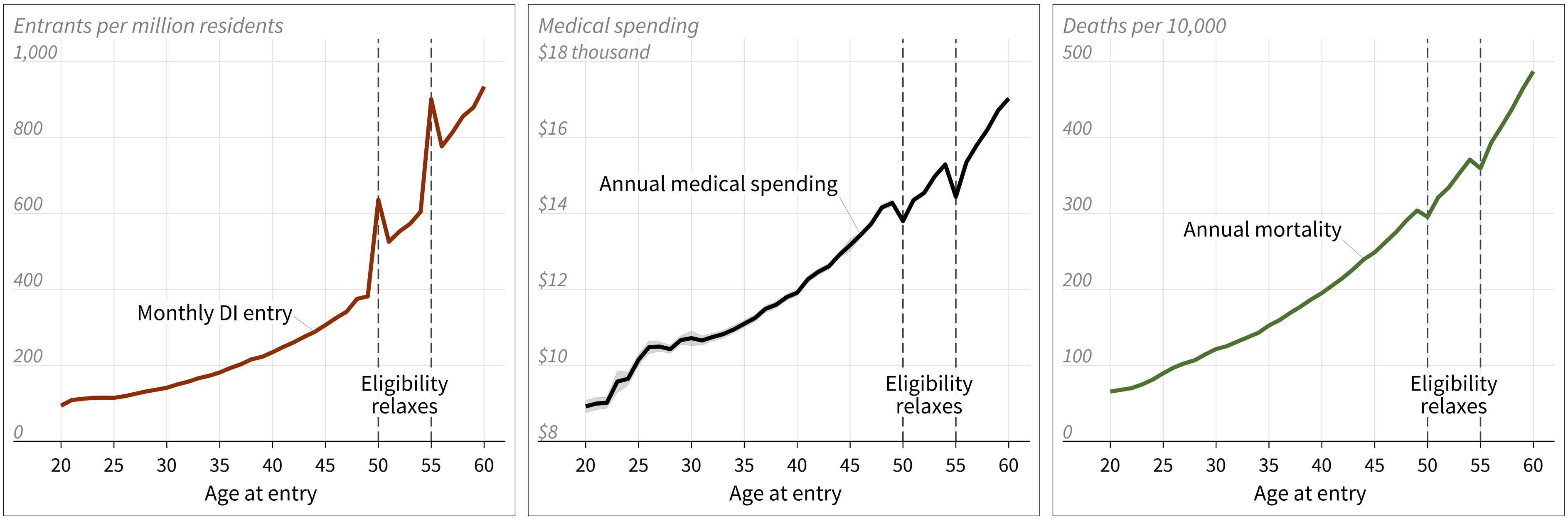
Figure 2: DI entry, medical spending, and mortality, by unemployment at application



(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.

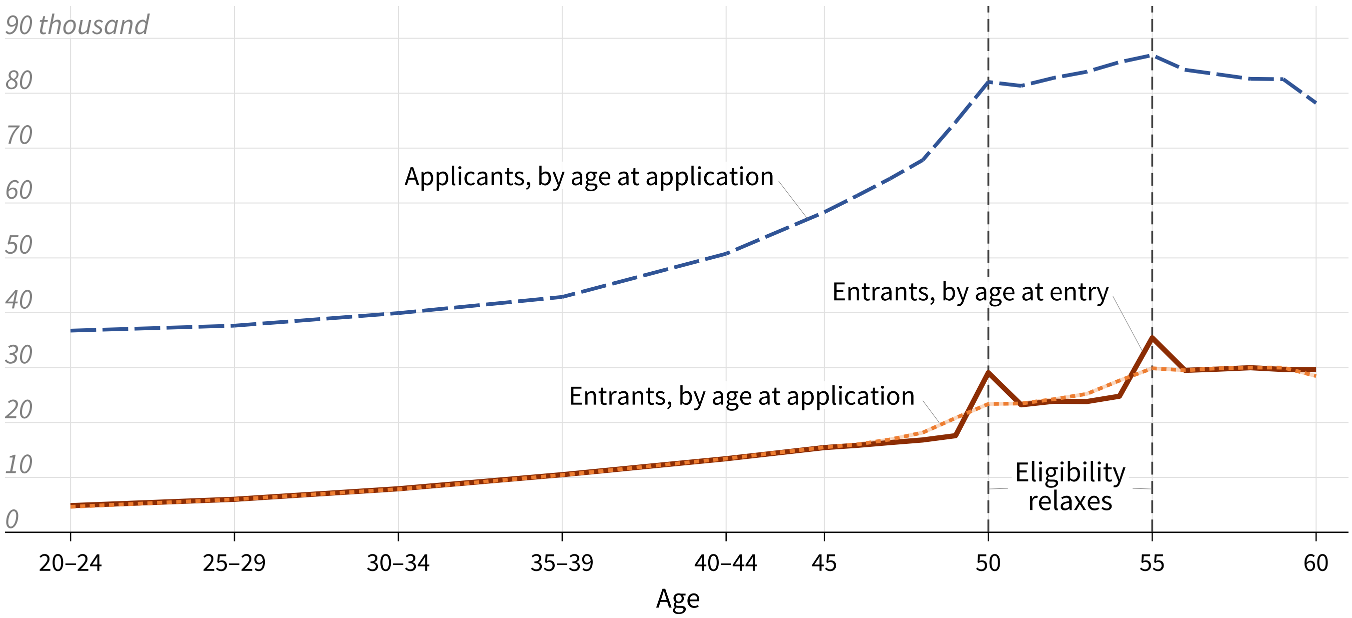
Figure 3: DI entry, medical spending, and mortality, by age at entry



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

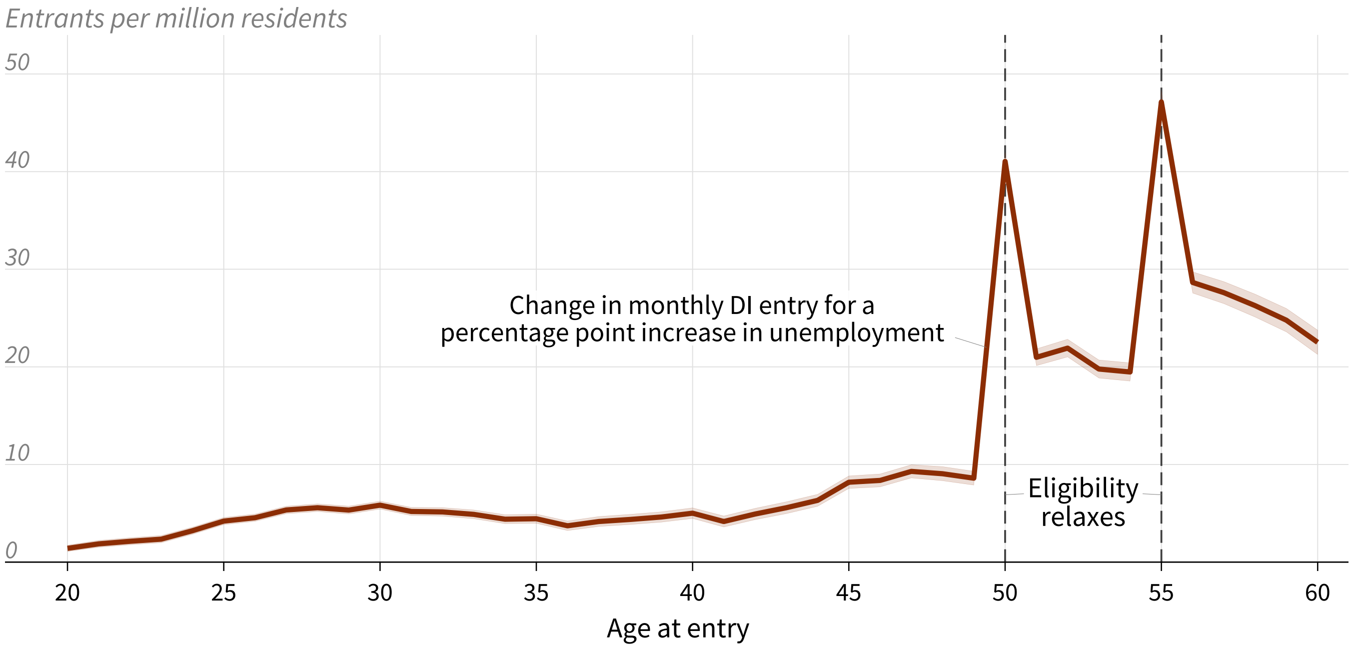
Notes: The figure reports DI entry, medical spending, and mortality in our primary sample, by age at DI entry. In panel (a), the solid brown curve reports the population-weighted average monthly DI entry for ages 20–60. Entry is measured for each county, month, and age as the number of entrants per million 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



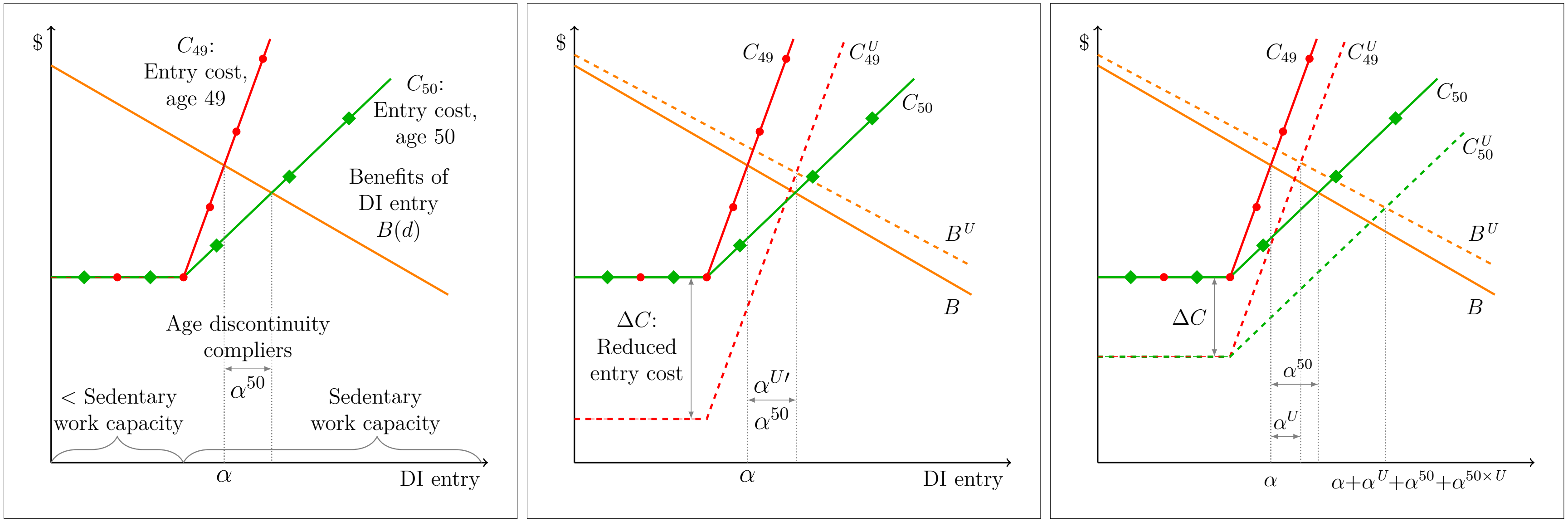
Notes: The figure reports the annual number of DI applicants and entrants per year of age. Data on the number of DI applicants come from a custom version of the Annual Statistical Report on the Social Security Disability Insurance Program (DI ASR) that covers applications filed in 2008–2017 and reports 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.

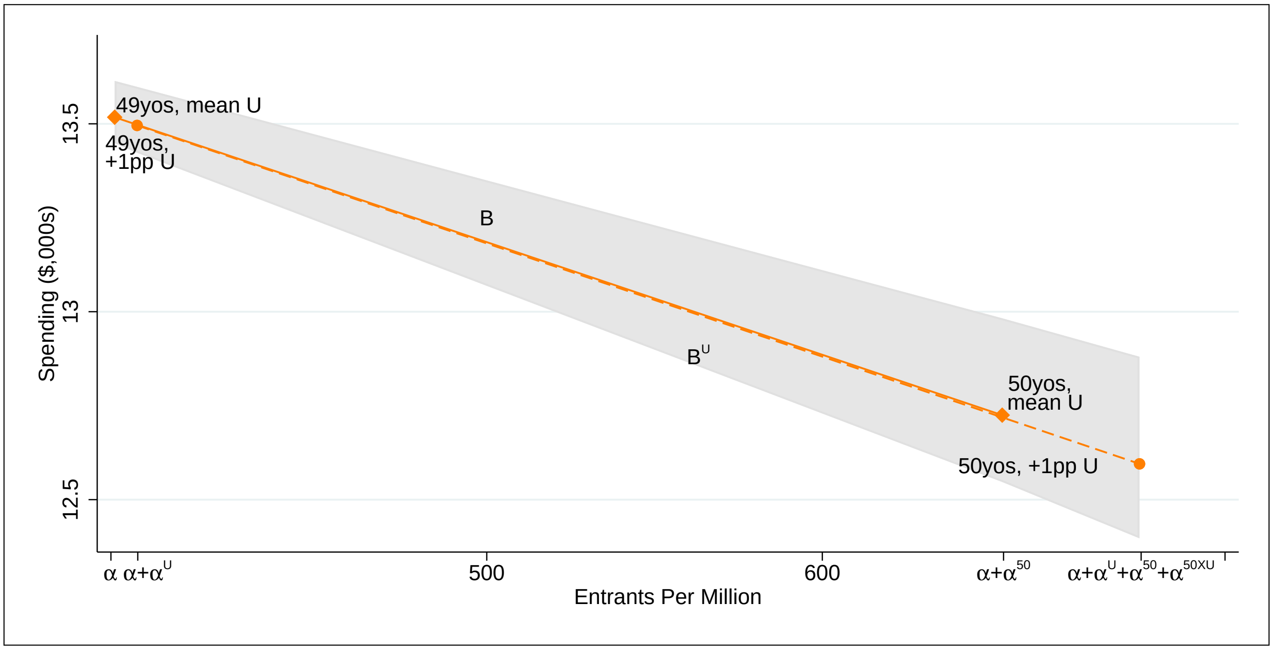
Figure 6: Conceptual model of DI entry



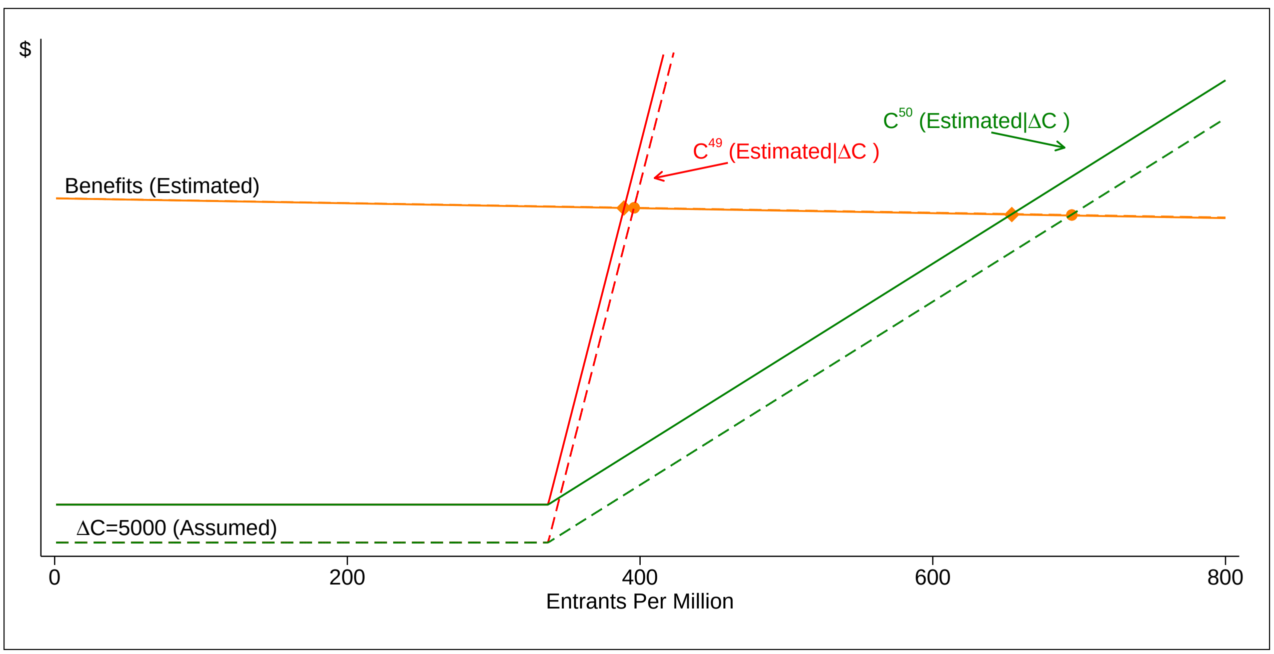
(a) Effect of age discontinuity in eligibility **(b)** Scaled effect of unemployment **(c)** Unscaled effect of unemployment

Note: The figure illustrates our conceptual model of DI entry. The vertical axis measures the costs and benefits of DI entry, in dollars, and the horizontal axis measures DI entry. Panel (a) represents separate cost functions for individuals aged 49 (red line with circle markers) and 50 (green line with square markers). Panels (b) and (c) illustrate how high unemployment reduces the opportunity cost of DI entry, represented by a downward shift of the cost functions (e.g., from the solid curve C_{49} to the dashed curve C_{49}^{U}) and potentially also shifts the benefits function upward and outward (from the solid curve B to the dashed curve B^{U}). See Section 5 for discussion.

Figure 7: Estimated model of DI entry



(a) Entry and benefits at mean (solid) and +1pp (dashed) unemployment for 49- and 50-year-olds



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

Notes: The figures depict our conceptual model as parameterized by equations (6) and (7). The solid curves represent model elements at average unemployment, and the dashed curves represent model elements at unemployment higher by 1 percentage point. The benefits functions B and B^U have the slopes and intercepts shown algebraically in Section 5.3.1. The cost functions C_{49}, C_{49}^U, C_{50}, and C_{50}^U have the slopes and intercepts shown in Appendix Section A.3, under an assumption that $\Delta C = -\$5000$. In Panel (b), we have normalized costs to be non-negative.

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	13.23***	–47.34***	–0.49***
	(0.13)	(4.08)	(0.09)
Fixed effects	County	County × Years enrolled	County × Years enrolled
Dependent variable mean	313.08	13,158.60	273.93
Observations	40,311,790	105,185,050	144,463,220
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)
$\tilde{U}$ (demeaned unemployment rate)	7.84***	17.18	–0.39
	(0.36)	(17.08)	(0.37)
$\tilde{U}$ × 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 age-specific DI entry, calculated as the number of individuals entering Medicare on the basis of disability at each age as a share of the population of that age in the county and month. The 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. Statistical significance at the 10%, 5%, and 1% levels are 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 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.10a 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.[1] 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.

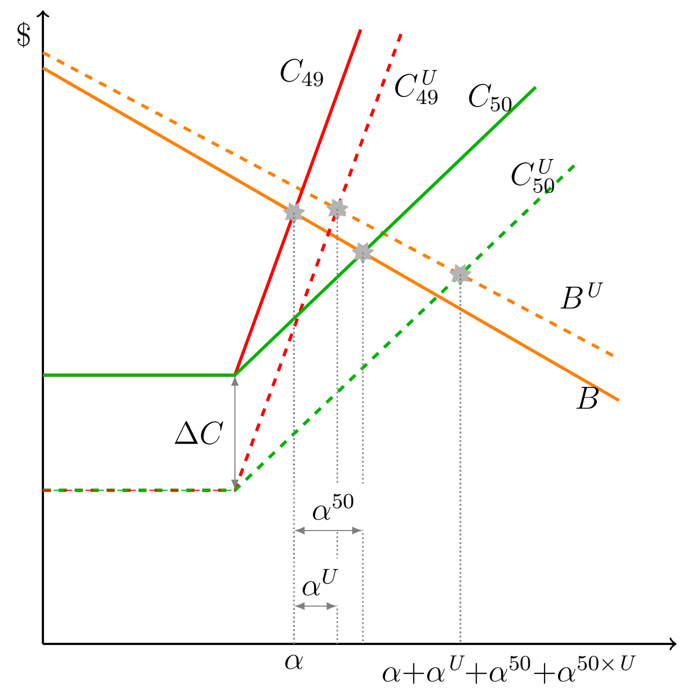
The precision of this spike suggests that the applications of individuals who applied before attaining the age of relaxed eligibility were eventually awarded with a disability onset date of the month they attained the higher age. For example, an individual who applied at 48 could be initially denied at age 49, then awarded benefits at the reconsideration or hearing

[1] 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.

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.10b reports 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.3 Parameters of Cost Curves



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^C_{49}. Thus, our first equation is

$$m^C_{49}\alpha + n^C_{49} = m\alpha + n$$

When unemployment is high, the benefits function B^U and cost function C^U_{49} intersect at x-axis value $\alpha + \alpha^U$. The slope m^U and intercept n^U of B^U were found in Section 5.3.1. By assumption, the intercept of C^U_{49} is $n^C_{49} + \Delta C$. Thus, we can write a second equation:

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

Subbing the first equation into the second

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

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

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

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

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 $\alpha + \alpha^{50}$.

$$m^C_{50}(\alpha + \alpha^{50}) + n^C_{50} = m(\alpha + \alpha^{50}) + n$$

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

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

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

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

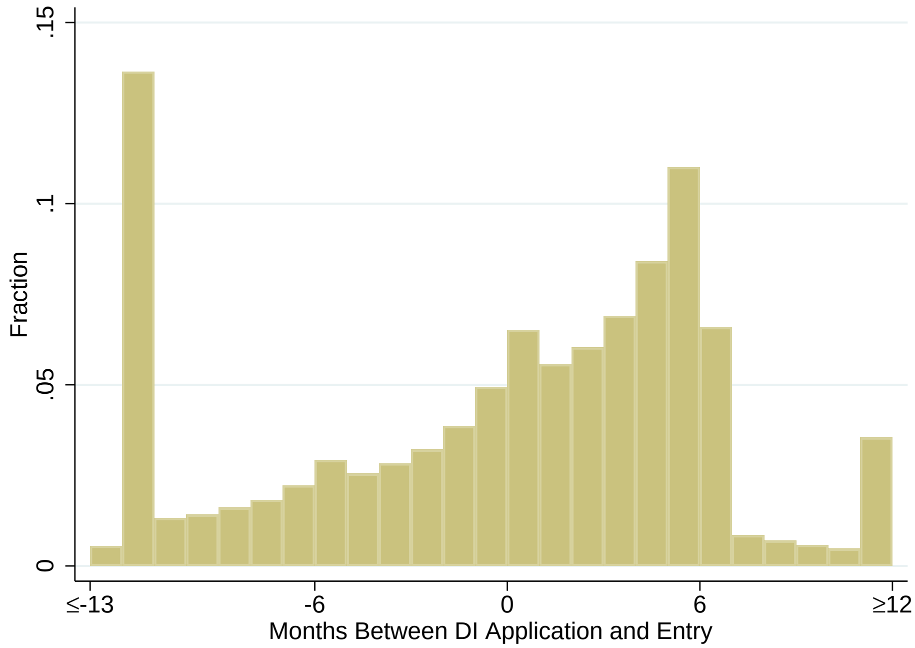
$$m^C_{50} = \frac{-\Delta C + m^U(\alpha + \alpha^U + \alpha^{50} + \alpha^{50\times U}) - m(\alpha + \alpha^{50}) + n^U - n}{\alpha^U + \alpha^{50\times U}}$$

And the intercept is expressed as

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

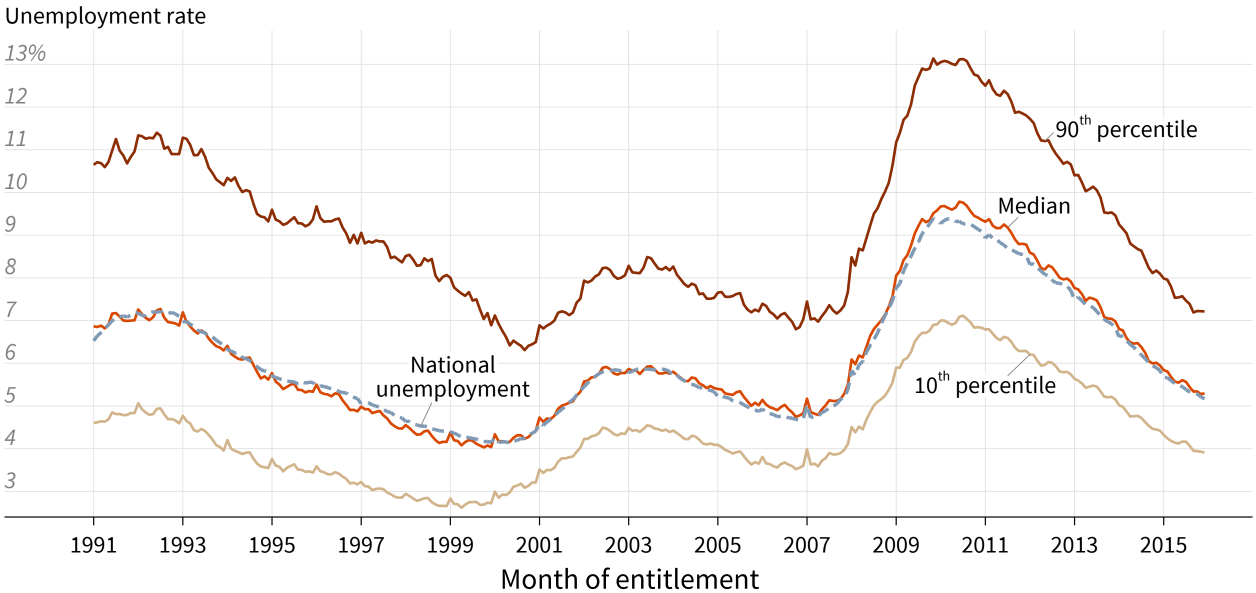
Appendix Figures and Tables

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



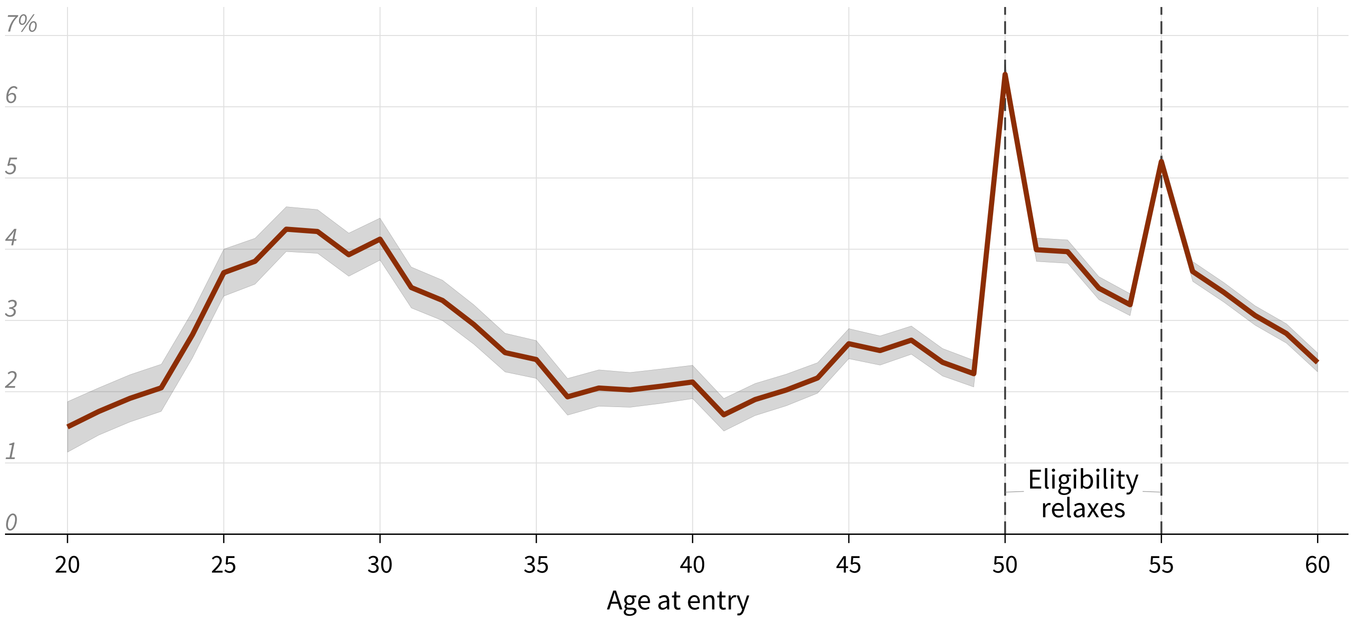
Notes: Figure represents the distribution of months between DI application and entry for individuals entering DI between 1991 and 2015, bottom- and top-coded at −13 months and 12 months, respectively. Source: Disability Analysis File Public Use File.

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



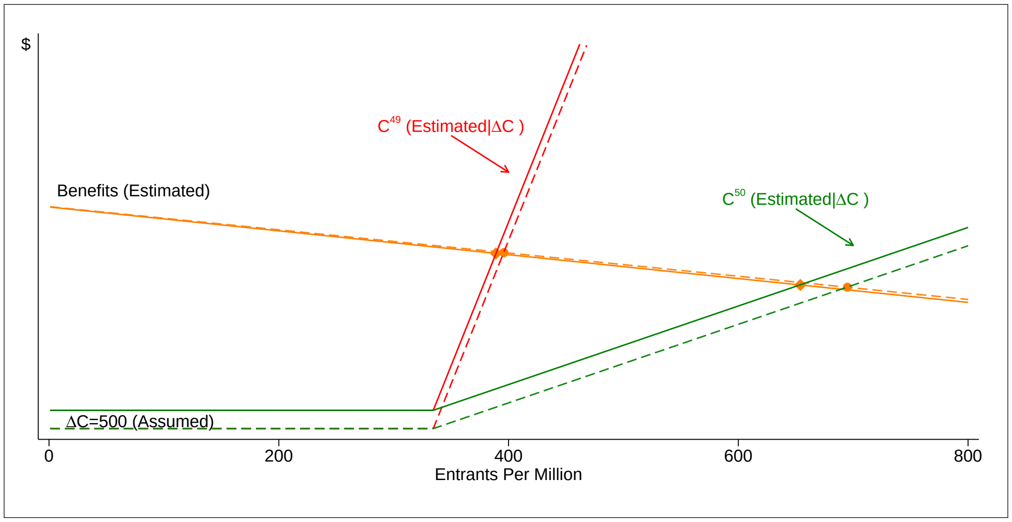
Notes: The figure summarizes county and national unemployment rates at the time of DI application among our primary sample of disability recipients ($N = 15,790,262$). Month of entitlement to DI benefits is taken to be two years prior to the month in which Medicare coverage began. Beneficiaries are assigned 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

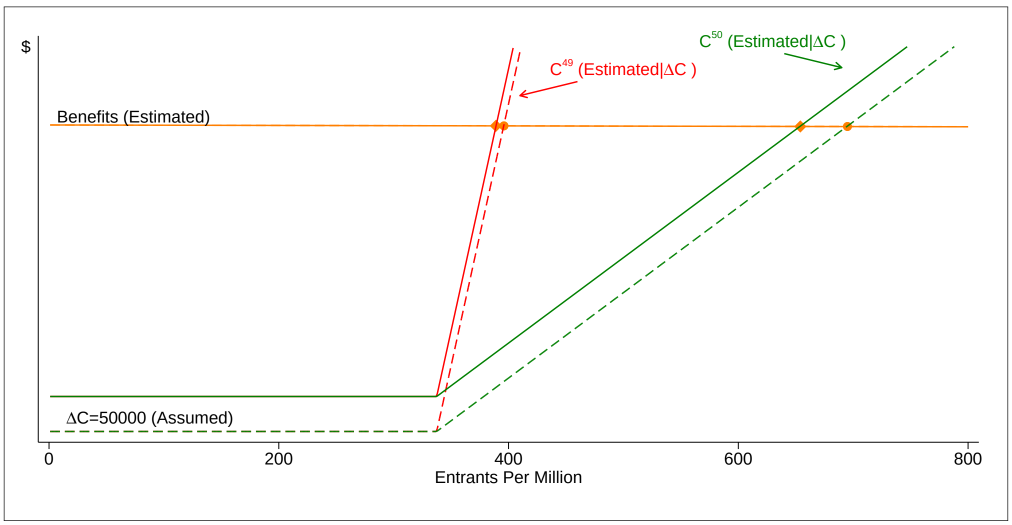


Notes: The figure shows the coefficients and confidence intervals from Figure 5 as a percentage of total DI incidence at each age of entry (reported in Figure 3a).

Figure A.4: Estimates of model parameters when $\Delta C = -\$500$ or $\Delta C = -\$50,000$



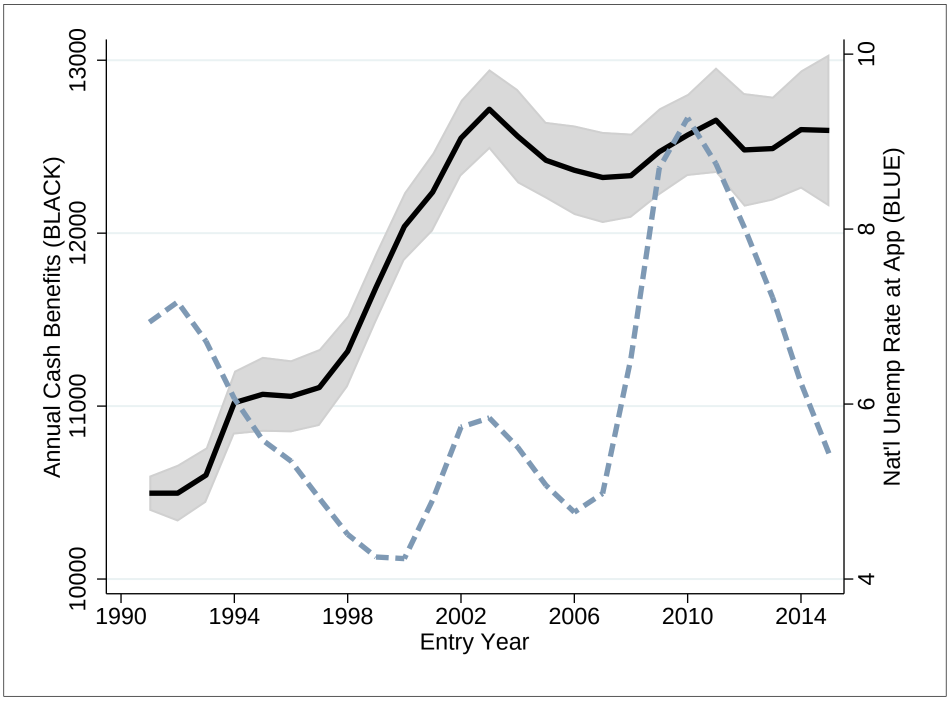
(a) $\Delta C = -\$500$



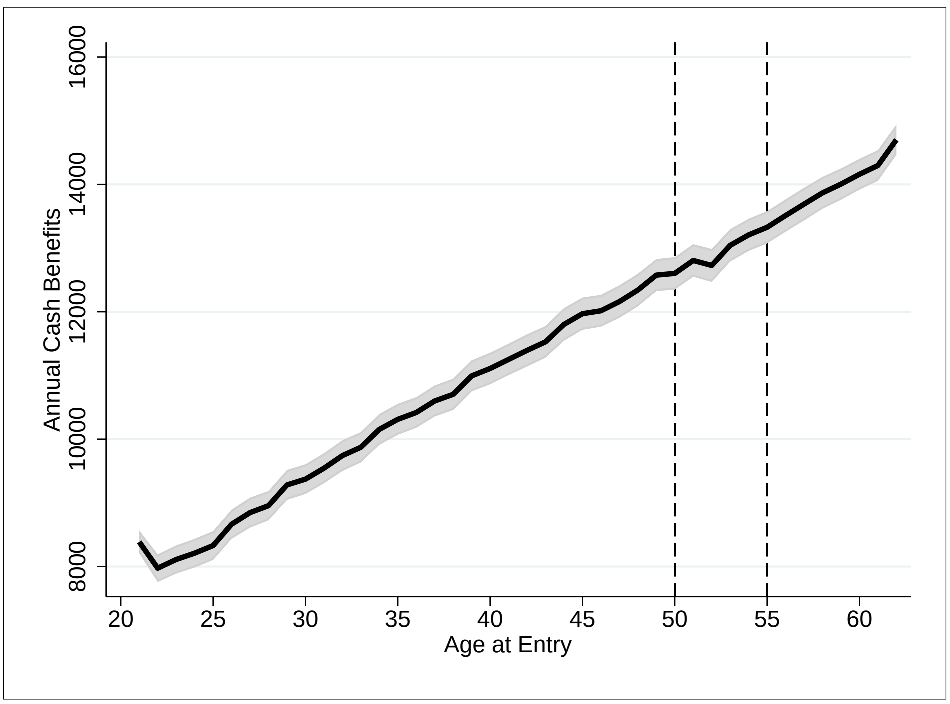
(b) $\Delta C = -\$50,000$

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.3. 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 5.3.1. The cost functions C_{49}, C_{49}^U, C_{50}, and C_{50}^U have the slopes and intercepts shown in Appendix Section A.3 when ΔC takes on the stated values.

Figure A.5: Annual cash benefits, by year of entry and age at entry



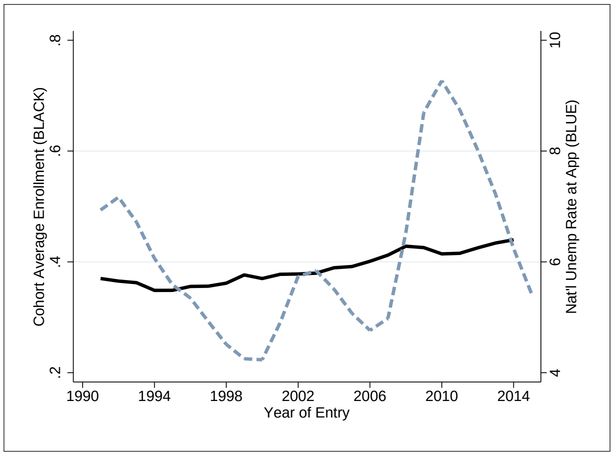
(a) Year of entry



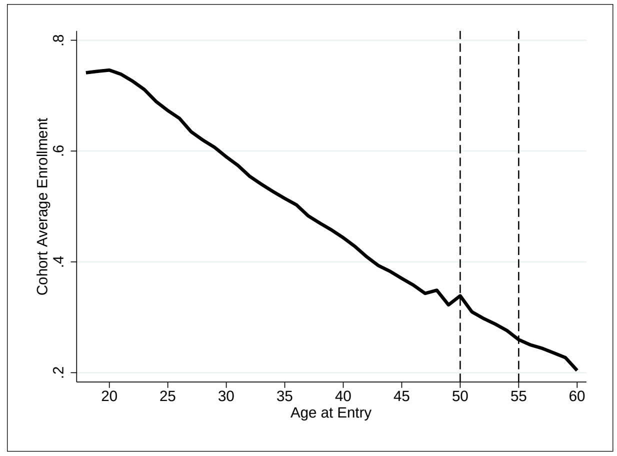
(b) Age at entry

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.

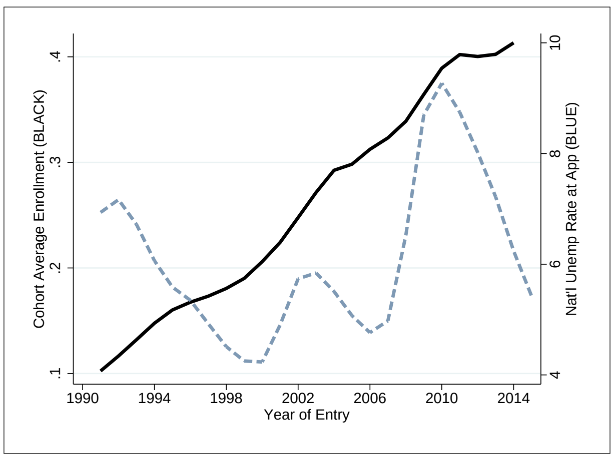
Figure A.6: Medicaid, Medicare Advantage, and Part B enrollment



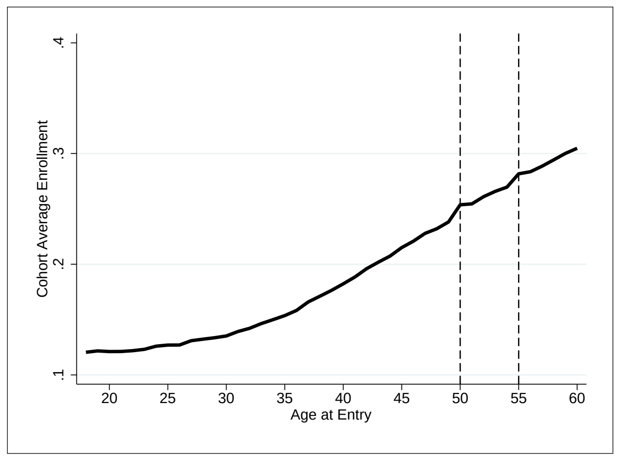
(a) Medicaid, by year of entry



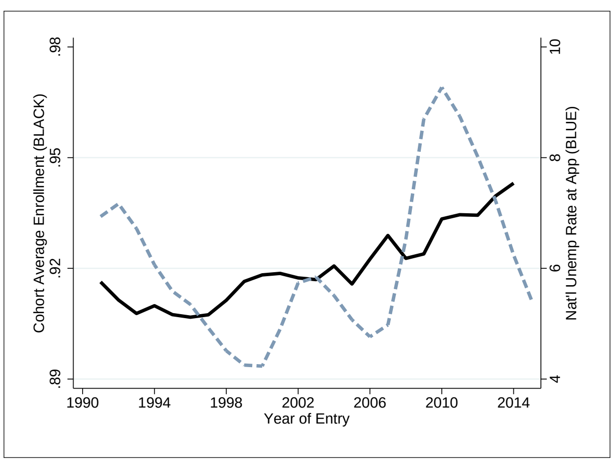
(b) Medicaid, by age at entry



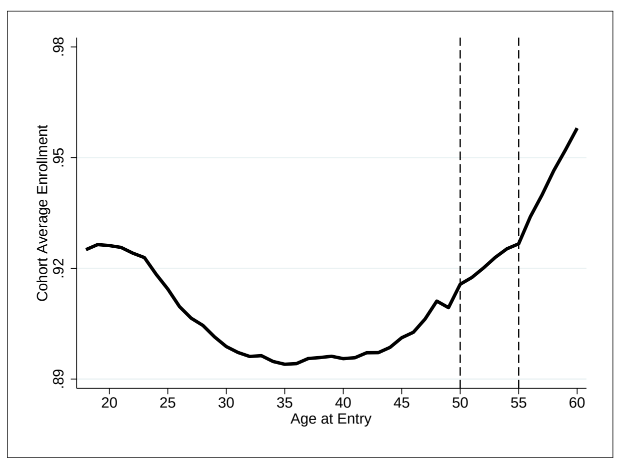
(c) Medicare Advantage, by year of entry



(d) Medicare Advantage, by age at entry



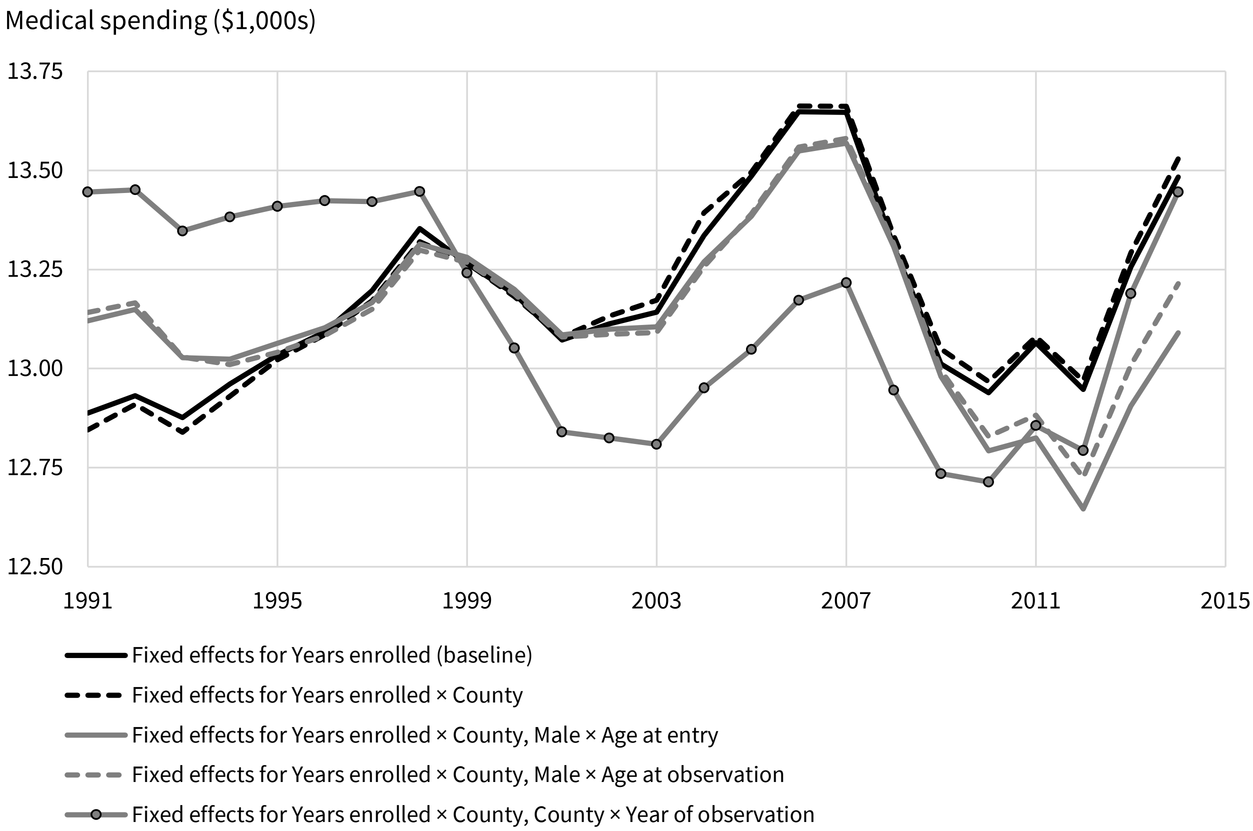
(e) Medicare Part B, by year of entry



(f) Medicare Part B, by age at entry

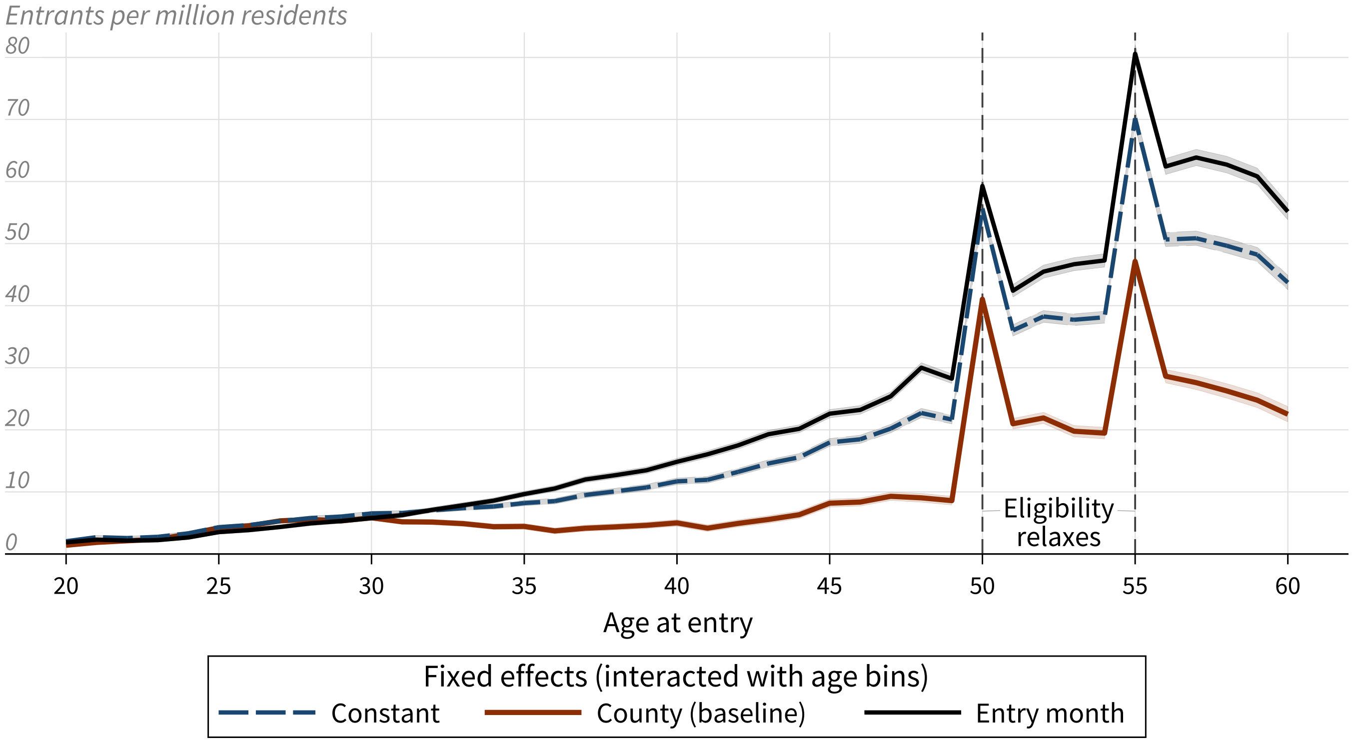
Notes: Panels (a), (c), and (e) report coefficients from estimation of Equation 2, where the dependent variable is an individual-year indicator of enrollment in Medicaid, Medicare Advantage, or Medicare Part B. The fixed effect associated with each year of entry is depicted in the black line (left axis) 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.7: DI medical spending, by year of entry: alternative specifications



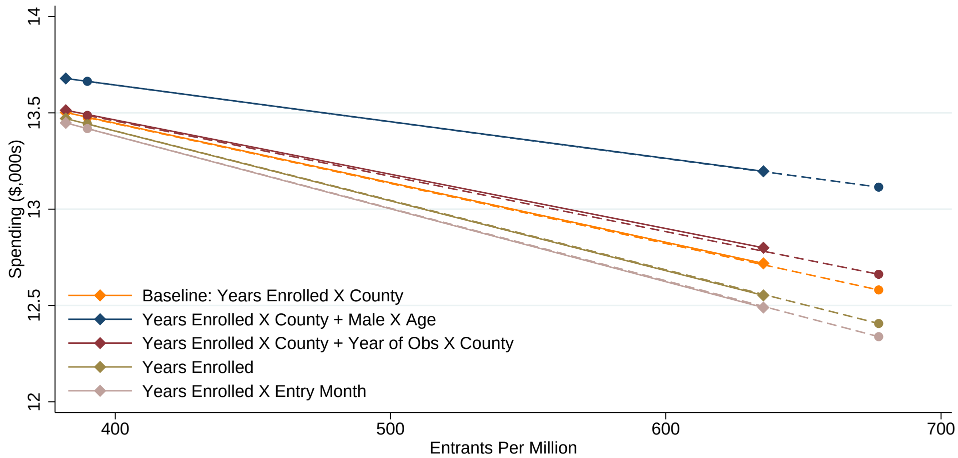
Notes: The figure reports results of estimating equation (2) under various controls specifications. The fixed effects included in each specification are defined in Appendix Table A.4. The solid black curve reports the baseline specification from Figure 1b.

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

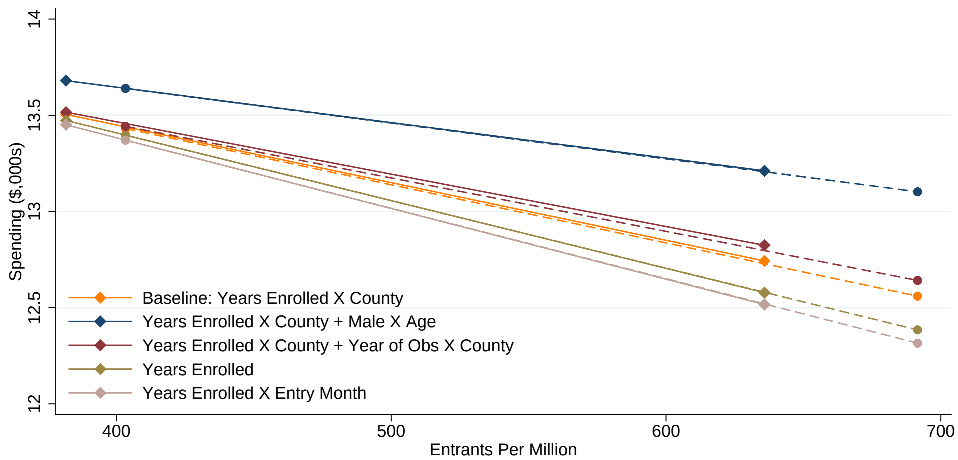


Notes: The figure shows the cyclicality of DI entry in our primary sample by age at entry, as estimated by equation (5) using three alternative sets of controls. Entry is measured for each county, month, and age as the number of entrants per million same-aged residents. The curve's height reflects the 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.

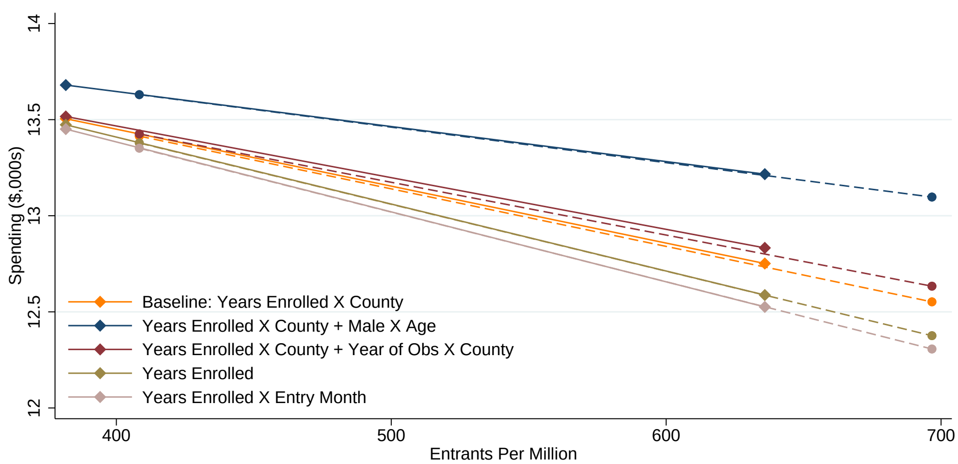
Figure A.9: Benefits function from model: alternative specifications



(a) County fixed effect in equation (6)



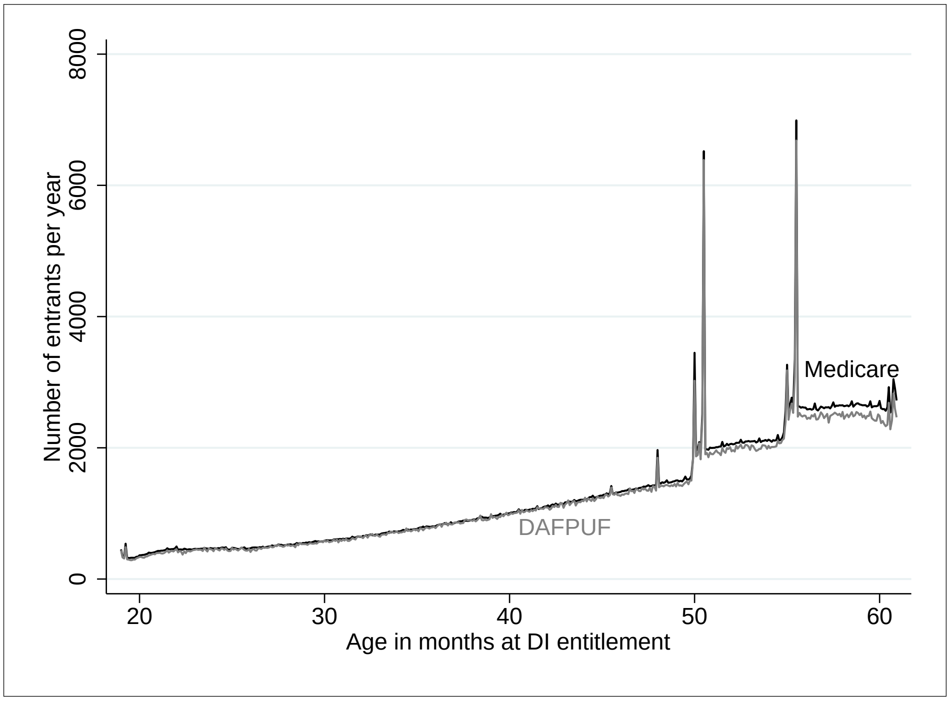
(b) No fixed effect in equation (6)



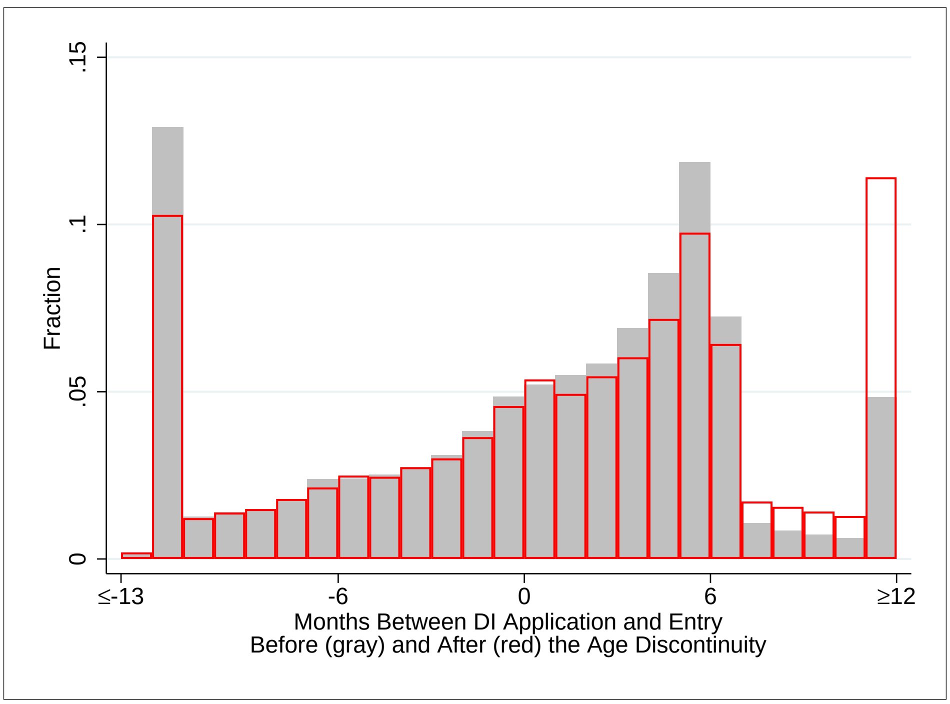
(c) Entry-month fixed effect in equation (6)

Notes: This model repeats Figure 7a under alternative specifications. The panels differ in the fixed effects included in Equation (6), predicting entry. Within each panel, each color reflects a different set of fixed effects included in Equation (7). The benefits function at mean unemployment is denoted by a solid line while the dashed line reflects high unemployment.

Figure A.10: 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).

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: Estimates of DI entry model parameters

	(1)
A. Parameters of Benefits Functions	
slope of B: m	–3.25 (0.39)
intercept of B: n	14,784 (114)
slope of B^{UR}: m^{UR}	–3.17 (0.35)
intercept of B^{UR}: n^{UR}	14,795 (110)
difference in slopes: $m^{UR} - m$	0.09 (0.12)
difference in intercepts: $n^{UR} - n$	11 (38)
B. Parameters of Cost Functions, Assuming $\Delta C = -\$5000$	
slope of C_{49} and C_{49}^{UR}: m_{49}	752 (35)
intercept of C_{49}: n_{49}	–278,993 (13,684)
slope of C_{50} and C_{50}^{UR}: m_{50}	121 (2)
intercept of C_{50}: n_{50}	–66,241 (1,047)
Entry fixed effects	County
Spending fixed effects	County × Years enrolled

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^{UR} using the equations in Section 5.3.1. Panel B reports the slopes and intercepts of cost functions using the equations in Appendix Section A.3 and an assumption on ΔC. To bootstrap standard errors, we resample county × entry-month units with replacement 100 times, estimating regression parameters (αs and βs) and calculating model parameters for each sample.

Table A.4: Cyclicality of DI medical spending and mortality: alternative specifications

	(1)	(2)
Specification	Annual medical spending ($)	Annual mortality (deaths per 10,000)
Years enrolled × County (baseline)	–47.34***	–0.49***
	(4.08)	(0.09)
Years enrolled × County, Male × Age (at entry)	–44.17***	–1.59***
	(4.06)	(0.09)
Years enrolled × County, Male × Age (at obs)	–37.94***	–1.20***
	(4.05)	(0.09)
Years enrolled × County, Year of obs × County	–22.10***	–0.43***
	(4.71)	(0.10)
Years enrolled	–71.22***	–4.63***
	(4.01)	(0.06)
Years enrolled × Entry month	–58.67***	–5.39***
	(4.55)	(0.06)

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.