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

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Abstract

Benefit awards for Social Security Disability Insurance (DI) increase during recessions and fall during expansions. We use Medicare administrative data for all DI recipients who entered Medicare between 1993 and 2017 to provide new evidence on the health of DI recipients who apply at different points in the business cycle. We find that each percentage point increase in the unemployment rate at the time of application corresponds to 4.1% 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 opportunity cost of applying for disability insurance, with reduced earning potential making the program more appealing. To separate these two channels, we leverage a feature of the DI eligibility process that relaxes the criteria at certain age thresholds. 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 the opportunity-cost channel accounts for nearly all recession-related DI entry.

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1 Introduction

Social Security Disability Insurance (DI) is the federal safety-net program for individuals who have work-limiting disabilities; admissions into the program increase during recessions and fall during expansions (Black, Daniel and Sanders, 2002; Autor and Duggan, 2003; Liebman, 2015; Maestas, Mullen and Strand, 2021; Charles, Li and Stephens Jr, 2018). This pattern arises even though federal regulations state that DI award decisions should be based on a claimant's functional capacity to work, not on cyclical economic conditions (20 C.F.R. §404.1566). Speculation about why awards respond to economic conditions has focused on two main channels (Cutler, Meara and Richards-Shubik, 2012). The first, the "health shock" channel, posits that individuals' health deteriorates during recessions, leading more people to become medically disabled. The second, the "opportunity cost" channel, posits that recessions make DI more attractive to those who might be medically qualified because their expected labor earnings fall in economically difficult times. Better understanding of the importance of each channel would illuminate the role of DI in the safety net and guide policy decisions on how best to meet the needs of individuals in a recession.

Two main challenges have hampered attempts to disentangle the roles of health shocks and opportunity costs in cyclical DI enrollment fluctuations. The first challenge is one of measurement: illuminating how medium- to long-run health outcomes vary with economic conditions requires detailed data on the health of individuals enrolled in DI. Such depth of detail goes beyond the information available through the Social Security Administration (SSA), which administers the DI program. The second is an identification challenge: separately identifying the effects of health shocks and opportunity costs requires isolating variation in one, but not the other, of these channels. However, distinguishing one from the other is difficult because recessions may simultaneously shift both.

In this paper, we overcome these challenges through a novel use of health-outcomes data and age-based discontinuities in eligibility rules. To obtain a direct measure of health, we leverage administrative data from Medicare, which provides health insurance to DI recipients beginning two years after they become eligible for cash benefits. Our study is the first to use Medicare data to explore the connections between DI and economic conditions. To overcome the identification challenge of economic conditions affecting both health and opportunity costs, we exploit age discontinuities in the DI eligibility rules that enable more individuals with low work capacity to join the program. Because individuals on either side of the age discontinuities have comparable health, the age discontinuities activate the opportunity-cost channel, but not the health-shocks channel. As a result, we can disentangle the effects of adverse economic conditions on these two potential drivers.

We begin by using the Medicare data to establish new, stylized evidence on the health of DI recipients who applied under different economic conditions. We link the universe of DI recipients entering Medicare between 1993 and 2017 to an estimate of the county unemployment rate at the time of their application to DI. We find that recipients who applied when unemployment rates were higher subsequently had lower Medicare spending. 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 variations in prices or other nominal spending patterns—by documenting a similar relationship between unemployment at application and subsequent mortality among DI entrants. Because economic conditions may affect both the composition and health of DI entrants, however, these findings alone are insufficient to distinguish the possible roles that health shocks and opportunity costs may play.

To identify the effects of these two channels, we turn to an age discontinuity in DI eligibility that plausibly affects the opportunity cost of DI entry but not the health of entrants. As a result of SSA using guidelines for disability determination that change as applicants age (i.e., the so-called "Medical-Vocational Grid Rules," described in Section 2.2), some individuals who are capable of only sedentary work and have low levels of education and transferable skills would be denied DI benefits at age 49, but awarded at age 50; a similar pattern emerges at ages 54 and 55. This change in eligibility criteria allows additional people who have just crossed these age thresholds to enter DI, even though their health has not changed. These applicants may have the same conditions as those applicants who are just under the age threshold but were denied awards under the stricter admissions criteria. We find a sharp increase in entry into DI at ages 50 and 55, when the eligibility criteria relax. Moreover, individuals who are just above these age thresholds have sharply lower spending and mortality than those who enter just below those points.[1] In addition, we find that the effect of the local unemployment rate on DI entry is especially large for individuals who enter above the age of 50. Individuals subject to the looser eligibility guidelines account for a disproportionate share of total DI countercyclicality.

After exploring how DI entrants' medical spending relates to local unemployment conditions and age discontinuities in DI eligibility, we proceed to combine these two sources of variation to shed light on role of opportunity costs and health shocks in countercyclical DI entry.

There are three types of individuals who are admitted to DI. Some individuals have impairments that are severe enough that they would apply for and be admitted to DI regardless of age or economic conditions; following the terminology of Angrist, Imbens and Rubin (1996), we refer to this group as "always-takers." DI recipients in a second group are more moderately impaired; while they would have qualified for DI on medical grounds, they only chose to enter DI when economic conditions deteriorated. Those in a third group only qualify for DI when they become subject to the looser eligibility requirements at ages 50 or 55. Once again following Angrist, Imbens and Rubin (1996), we refer to the second and third groups as "recession compliers" and "age discontinuity compliers," respectively.

Our decomposition strategy begins by noting that while recession compliers may differ from always-takers both due to the direct effect of recessions on health and the compositional effect of lower opportunity costs, age discontinuity compliers only differ from always-takers

[1] While the finding that spending falls sharply across the age discontinuity in eligibility is new to the literature, (Strand and Messel, 2019) report lower mortality for those entering at the higher ages.

at nearby ages because of the lower opportunity costs of applying at age 50. Thus, our strategy is to compare the observed differences between always-takers and the two complier groups in order to distinguish the opportunity-costs channel from the health-shocks channel.

To make this comparison between always-takers and compliers precise, we develop a graphical model of the costs and benefits of DI entry. The model reflects the patterns we observe across the business cycle and the age discontinuity in eligibility. The model posits that individuals obtain benefits from entering DI that are negatively correlated with their work capacity. That is, individuals with the lowest work capacity are assumed to have the highest medical needs; thus, they derive greater benefits from entry into the DI program, which entitles them to Medicare for health insurance. DI entry does entail costs, however. Individuals must forego earnings while applying for or receiving DI. There are also costs associated with documenting and proving disability, especially for marginally disabled individuals (Autor et al., 2015; Deshpande and Li, 2019; Kearney, Price and Wilson, 2021). We model these costs as increasing in work capacity because individuals with higher work capacity have higher potential earnings (Maestas, Mullen and Strand, 2013), and will likely have to incur greater costs to persuade the adjudicators that they qualify for DI. These costs rapidly become very large for individuals who are very unlikely to be declared disabled under SSA guidelines, such as individuals 49 or younger capable of sedentary work.

The model can be used to illustrate the effects of poor economic conditions on DI entry and medical spending. We model the opportunity-cost channel of poor economic conditions as a reduction in the cost of DI entry because unemployment temporarily and permanently reduces the cost of labor-market exit in favor of DI entry (Lindner, Burdick and Meseguer, 2017). If the health-shocks channel results in larger medical spending at any level of disability/work capacity, this appears in the model as an outward shift in the benefits function during high unemployment.

We use the model to compare always-takers to recession and age-discontinuity compliers. If a recession-complier entrant increases average spending by a larger amount than an age-discontinuity complier, the model implies that the kind of individual who joins due to a recession has higher spending than would otherwise would be expected. In the model, this would be evidence for a role for "health shocks" in DI countercyclicality.

Using reduced-form estimates from the data to parameterize the cost and benefit curves that govern DI entry, we find that the benefits curves implied by entry and spending patterns are exactly the same when unemployment is at its mean or when it is elevated. Equivalently, average spending is decreased by a similar amount by the addition of a recession complier or the addition of an age-discontinuity complier. Finding no evidence that "health shocks" worsen the health of recession compliers, we conclude that recession-associated decreases in opportunity cost fully explain DI countercyclicality.

This paper brings a novel and rich medical data source to bear on a key issue in labor and public economics: understanding the drivers of increased entry into DI during economic downturns. In doing so, we develop a new stylized fact: the health of DI entrants is procyclical, meaning that the larger cohorts induced into DI by high unemployment levels have lower average spending and mortality. The procyclicality of medical spending is itself useful for accounting for the budgetary impacts of periods of high unemployment. However, the procyclicality of medical spending could reflect either the compositional change of DI entry during recessions or a causal effect of recessions on health. Thus, a major contribution of our paper is our strategy for disentangling compositional changes from direct effects by combining two different factors—unemployment and the age discontinuity—that both have strong explanatory power for DI outcomes. These factors (and their interaction) increase DI entry, primarily among individuals with lower-than-expected medical spending. However, the effects of the age discontinuity cannot plausibly be driven by true changes in health. The novelty of our paper lies in using the age discontinuity to pin down the effects on DI entry and average medical spending that one would expect if unemployment had no direct effects on health.

Our paper joins a long literature examining the macroeconomic countercyclicality of DI entry. A number of papers find that poor economic conditions likely reduce the opportunity cost of DI entry, showing positive associations between DI entry and the unemployment rate (Autor and Duggan, 2003; Maestas, Mullen and Strand, 2021) or sector-specific shocks (Black, Daniel and Sanders, 2002; Charles, Li and Stephens Jr, 2018).[2] The microfoundations of the aggregate relationship are described by Deshpande, Gross and Su (2021), who examine the household finances of DI applicants. The authors find an "Ashenfelter's peak" in adverse financial outcomes (e.g., bankruptcy, foreclosure, or eviction) around the time of DI application, which could be driven by poor macroeconomic conditions causing poor household finances and subsequent DI applications. Lindner, Burdick and Meseguer (2017) characterize individuals induced to apply to DI due to recessions (analogous to our recession "compliers", but for DI applications rather than DI entry). They find that recession-induced applicants are more likely to be denied because their conditions are not severe or because they can previously do the work they could do, which complements our finding that recession-induced applicants who actually enter the program are healthier than awardees who apply under good economic conditions. In addition, they find that recession-induced applicants who are denied have lower earnings five years after application than denied applicants from good economic times, suggesting that the recession permanently lowered their earnings path.

A number of papers have found that the DI countercyclicality is strongest among older workers, among applicants entering via the Medical-Vocational Grid Rules, and among individuals with mild impairments, low skill, and low education (Maestas, Mullen and Strand, 2021; Lindner, 2016; Autor and Duggan, 2003; Duggan, Singleton and Song, 2007). The direct relationship that we draw to the age discontinuity, however, is new to the literature.[3] In our paper, the finding that the age discontinuity's effects on entry and spending are especially large in recessions helps explain the characteristics of the groups with the strongest DI

[2] Several papers have examined the role of unemployment insurance (UI) in the relationship between the unemployment rate and DI entry; Lindner (2016) finds that higher UI benefit levels reduce DI applications, while (Mueller, Rothstein and von Wachter, 2016) find, in contrast, that maximum UI duration has no effect.

[3] The fact that countercyclicality is disproportionately driven by older workers was noted by Cutler, Meara and Richards-Shubik (2012); however, they do not relate this finding to the age discontinuity in eligibility.

cyclicality—they are subject to the looser eligibility rules that begin at age 50. The fact that countercyclicality is strongest among individuals who are economically disadvantaged drives the finding of Deshpande and Lockwood (2021) that the countercyclicality of DI increases its aggregate insurance value—-i.e., that the DI program as currently operating insures against both health and non-health shocks. However, those authors note that the DI program has certain features, such as its permanence and strict limits on earnings, that make it a costly way to provide this type of insurance.

Our paper joins a shorter literature examining the age discontinuity in eligibility at age 50. Chen and Van der Klaauw (2008) use this discontinuity to examine how DI eligibility affects labor force participation, finding that individuals induced into DI by the age discontinuity would have had low labor force participation in its absence. The age discontinuity applies only to individuals without a high school degree (or a high school degree but no possibility of skilled work) who are found to have significant work limitations and an inability to perform past jobs; so it is not surprising that labor force participation among this group would be low. Strand and Messel (2019) find that the work-discouraging effect of DI, estimated by instrumenting with SSA examiner leniency, is similar for individuals in their 50s as for the full population, despite the looser guidelines. Finally, Deshpande, Gross and Su (2021) use the age discontinuity to establish that DI benefits generate substantial improvements in household finances.

Finally, our work contributes to a substantial literature on the relationship between recessions and health. Despite the folk wisdom that weakening of the economy should worsen health due to decreased income and access to health care, the empirical evidence has been mixed, with a number of papers showing a historical procyclical relationship between mortality and growth (Ruhm, 2000, 2003, 2005, 2012), but more recent work suggesting recessions may indeed harm health (Ruhm, 2015; McInerney and Mellor, 2012), especially for working-aged individuals Crost and Friedson (2017). Our work finds no evidence that recessions worsen (or improve) health among individuals with work-limiting disabilities.

Ruling out a significant role for health shocks in countercyclical DI entry has implications for policy and program design. If countercyclical DI entry were driven by worse health, then a logical recommendation would be to expand health insurance eligibility, or to provide direct means of support for the physical and mental health of the unemployed.[4] The fact that countercyclical DI is instead attributable to reductions in the opportunity cost of applying suggests a role for policies that maintain employment or income security for individuals with functional limitations.

2 Social Security Disability Insurance and Medicare

2.1 Social Security Disability Insurance Determination Process

DI is a Federal program that pays cash benefits to individuals with a work-limiting disability who have sufficient history of employment or self-employment.[5] Applicants to DI with sufficient work history are evaluated by SSA in five steps, where some applicants are awarded or denied benefits in each step, and the remainder continue to the next step.

Step 1. Is the individual working? Applicants who are working with average monthly earnings exceeding the substantial gainful activity (SGA) threshold ($1,310 in 2021 for non-blind people) are denied benefits.

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

Step 3. Is the individual's impairment "listed?" Applicants who have a "listed"

[4] The 2014 Medicaid expansion could conceivably have reduced DI enrollment, either by providing a new insurance option (thus reducing the relative benefit of DI enrollment) or by directly improving health (Miller, Johnson and Wherry, 2021). However, Schmidt, Shore-Sheppard and Watson (2020) find that the Medicaid expansion did not affect either applications or awards to DI.

[5] 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.

medical condition are awarded benefits (see the "Listing of Impairments," 20 C.F.R. §404 Subpart P, Appendix 1). Listed impairments include, for example, conditions of the musculoskeletal system that result in being unable to ambulate effectively, or certain respiratory or cardiovascular diseases. Each "listed" impairment is defined by particular elements of the medical evaluation (e.g., medical lab values). Individuals who do not meet these criteria may still be found to have disabilities that warrant their inclusion in the program, based on steps 4 and 5. It is not uncommon for individuals to have multiple impairments (e.g., respiratory disorders and obesity) that do not meet the criteria for disability according when considered individually, but do meet the criteria when considered in combination based on steps 4 and 5.

Step 4. Can the individual do the work they did previously? In this step, the SSA develops an assessment of the most work the individual can still do on a sustained basis, given their limitations. If the assessment suggests that the applicant can still perform the work associated with their previous occupation, they are denied benefits.

Step 5. Can the individual do any other type of work? Most applicants—70% over the years 2000 to 2014—are neither awarded nor denied benefits by the previous steps and are evaluated under Step 5 (Deshpande, Gross and Su, 2021). In Step 5, 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.[6] Together with the applicant's age, level of formal education, and the skills acquired in previous work experience, SSA determines whether the individual is able to transition to other work that is within their MSWC. The table that determines whether the applicant can do other work is known as the Medical-Vocational Grid Rules.[7] In recent years, around 40 percent of

[6]MSWC is intended to capture work capacity on the basis of the exertion involved. Individuals may also have other impairments (such as mental, postural, visual, or environmental conditions that affect their ability to work) that are not related 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, etc.) that prevent them from doing sustained work they are otherwise physically able to do.(Rule 204.00 of 20 C.F.R. §404 Subpart P, Appendix 2)

[7]See "Medical-Vocational Guidelines," 20 C.F.R. §404 Subpart P, Appendix 2.

denials were due to a finding that the worker 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 on the basis of MSWC, education, acquired skills, and age.[8] Applicants aged less than 50 who have an MSWC of "sedentary" are usually denied benefits,[9] but applicants with the same "sedentary" MSWC who are aged 50–54 may be awarded benefits. There is a similar age discontinuity in eligibility at age 55 for individuals with an MSWC of "light".

For an example of such a discontinuity, consider the grid rule recommendation for an applicant with an MSWC 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, SSA does not expect this individual 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 at 49. (Appendix Table A.1 summarizes the grid rule discontinuities.) The age discontinuities in eligibility are driven by educational background and work experience, not by the degree of impairment.

Deshpande, Gross and Su (2021) show that the rate of initial allowances for those being evaluated in Step 5 rises discontinuously from about 15% to 30% at age 50, and to above 50% at age 55.

[8] In 2020 the Trump administration considered a rule proposed by the Social Security Administration that would have reduced the role of age in the DI determination process, but the rule was not implemented (Davidson, 2020).

[9] For applicants assigned a "sedentary" MSWC, 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 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*).

2.3 Medicare Eligibility for Disabled 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.[10] Entitlement to Medicare begins 24 months after the month in which the individual enters the DI program and begins receiving DI cash benefits. The month of DI entry depends on the month of application as well as dates in the patient's medical record supporting disability, and is subject to various program rules. We describe three common scenarios below.

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 the individual's cash benefits would start five months after the end of employment. Medicare entitlement would begin 24 months later, 29 months after the month of application.

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

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 a number of months or even years. In the event of an eventual award, both DI and Medicare can be made retroactive. Suppose that 36 months after DI application, an individual is awarded DI with an entry date 5 months after applica-

[10]While DI also pays cash benefits to nondisabled dependents of a disabled worker, Medicare entitlement is limited to DI recipients with disabilities.

tion. Because the 24-month waiting period would have elapsed, the individual would gain 7 months of retroactive Medicare coverage, and he would thus enter Medicare 29 months after application.

There are a number of insurance situations among Medicare beneficiaries. All disabled DI recipients receive Medicare hospital insurance (Part A) at no charge. Because Part A does not have a premium, even those who have access to employer-sponsored insurance (via a spouse) enroll in Medicare as a secondary payer for hospitalizations. 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). We do not observe health care utilization for individuals in Medicare Advantage.

3 Data and Measures

3.1 Medicare

Our primary analysis sample is derived from Medicare administrative records on all Medicare beneficiaries from 1992 to 2017 (Centers for Medicare Medicaid Services, n.d.). We use these data to identify the 17 million individuals entering Medicare between ages 20 and 62 from 1993 to 2017. Once enrolled in Medicare, individuals remain in the dataset until death or certain kinds of DI exit;[11] individuals remain in the data when they transition to Medicare

[11] Non-elderly, disabled DI recipients stop receiving cash DI benefits either because of medical improvement (which may be established at a routine audit) or because they resume working above the substantial gainful activity (SGA) level. Those who stop receiving DI benefits due to work above the SGA level can maintain

eligibility due to elderly status.

For all DI beneficiaries, we record the calendar month in which Medicare coverage starts, the date of death (for decedents), and the indicators for the insurance situation in each year (enrollment in Medicare Advantage, Part B, and Medicaid). We find that 78% of person-years are enrolled in fee-for-service Medicare (not Medicare Advantage), 92% elect Part B, and 39% are dually eligible for Medicaid. In Section 6.1, we show that enrollment rates in Medicare Advantage, Medicaid and in Part B are insensitive to unemployment and the age discontinuity in eligibility, suggesting that they are not driving our results.

For the universe of fee-for-service Medicare beneficiaries, we observe health care use and spending from 1999 to 2017 (19 years, 105 million person-year observations). Thus, for the earliest cohorts of disabled Medicare beneficiaries, we do not observe any utilization data until their seventh year in Medicare. Our key metric is "medical spending," defined as the allowed amount (Medicare portion plus beneficiary cost sharing) for all covered services except outpatient prescription drugs. Outpatient prescription drugs were not covered by Medicare until 2006, so we exclude them for comparability across years. Our measure includes spending on physician visits, inpatient hospitalizations, outpatient services such as imaging or outpatient surgeries, stays in skilled nursing or hospice facilities, and durable medical equipment. We convert all spending values to 2017 dollars using the CPI-U for medical care.

3.2 Unemployment at DI Application

In our analysis, we relate the health status of Medicare beneficiaries to an estimate of the economic conditions at the time of application. However, our administrative Medicare data do not contain the date of DI application. Thus, we estimate the unemployment rate at the time of application by combining data from the Social Security Administration and the Bureau of Labor Statistics with our administrative Medicare dataset.

access to Medicare for nearly eight years, and they can participate in a state Medicaid buy-in program after that.

To determine when individuals entering Medicare in a given month may have applied to DI, we leverage the Social Security Administration's Disability Analysis File Public Use File (DAFPUF) (Social Security Administration, n.d.*a*). For a random 10% sample of DI recipients in years 1994–2018, the DAFPUF records include the Medicare entry month and month of DI application.[12] We use these data to determine the empirical probability that a Medicare entrant in month m applied to DI in month τ: $p_{m\tau}$, where $\sum_{\tau} p_{m\tau} = 1$.[13]

To create our estimate of local unemployment at application, we combine the empirical distribution of application months for each Medicare-entry month with county-month unemployment data from the Bureau of Labor Statistics beginning in 1990. Define $\text{unemp}_{c\tau}$ as the unemployment rate in each county c and candidate application month τ. We estimate unemployment at application for an entrant from county c in entry-month m as $\text{unemployment rate}_{cm} = \sum_{\tau} \text{unemp}_{c\tau} p_{m\tau}$, meaning unemployment in each county in each candidate-application month times the empirical probability of that application month. In a similar manner, we measure the national unemployment conditions at the time of application for each Medicare-entry month.

Basing our measure of unemployment at application on an individual's county captures the substantial variation in local economic conditions at any given time. Figure 1 records the distribution in the estimated unemployment rate at application for our sample of DI recipients entering Medicare between 1993m1 and 2017m12. The figure reports the 10th, 50th, and 90th percentile of county-level unemployment rates at application experienced by DI recipients entering Medicare in each month. As the figure shows, more than 10% of disabled Medicare entrants in January 1993 have an estimated unemployment rate at application exceeding 11%, and more than 10% applied when the county unemployment

[12] A small fraction of individuals enter DI but do not survive to the month of Medicare entry. These individuals do not appear in our Medicare administrative data. Using the DAFPUF, we find that 5% of the approximately 18 million individuals who join DI over the time period die prior to the month of Medicare entry.

[13] Appendix Figure A.1 shows the distribution of months between Medicare entry and DI application in the DAFPUF. The modes at 12 months and 29 months reflect the most common timelines, as discussed in Section 2.

rate was less than 4.5%. For any given entry month, the variation in the unemployment rate at application is driven by the different economic conditions in different counties in the candidate application months. The national unemployment rate at application tracks the median among Medicare entrants very closely, meaning that the unemployment conditions in counties with DI entrants are not dissimilar from national conditions.

Because we construct unemployment at application at the level of the county × month of Medicare entry, we cluster our standard errors at this level. This accounts for serial correlation both within individuals and across individuals joining Medicare at the same time and place.

4 Unemployment, DI Entry, and Health Outcomes

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.

4.1 Unemployment and DI Entry

We first show how national unemployment and DI entry vary over the 1993–2017 sample period. In Figure 2a, the solid red line reports the number of DI recipients entering Medicare in each year, and the dashed blue line reports the average national unemployment rate at the time of DI application for these entrants. This figure reveals a pattern of countercyclical DI entry that persists across the three business cycles covered by our sample period, and expands on 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).[14] Our analysis sample is a monthly panel of 3,210

[14]In Appendix Table A.2, we instead adapt the model of Maestas, Mullen and Strand (2021), and find similar results. However, the Liebman model is easier to adapt to characterize spending, as we do below.

counties observed from January 1993 to December 2017. For each county c and month m, the outcome $Entry_{cm}$ is calculated as the number of DI recipients aged 20-62 living in the county who become eligible for Medicare that month, divided by the Census county population aged 20-62 ("working-age") (Census Bureau Population Estimates Program, n.d.).[15] The entry outcome is regressed on $[unemployment\ rate]_{cm}$, calculated as in Section 4.1 as the average unemployment rate in county c over the distribution of DI application times for recipients who enter Medicare in month m. Specifically, we estimate

$$Entry_{cm} = \alpha[unemployment\ rate]_{cm} + [county\ FEs]_{cm} + \varepsilon_{cm}. \tag{1}$$

The primary controls in equation (1) are 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 county population, and cluster standard errors at the county by month level, which amounts to robust standard errors in this equation.

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 3a 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 13.1 additional DI entrants per million working-age residents per month. This amounts to a

[15] Liebman (2015) normalizes DI entry by the number of insured individuals (i.e., those with sufficient work history to quality for DI) who are not already receiving benefits, but there are no estimates of the number of qualifying individuals by county.

4.1 percent increase in DI entry, relative to the sample mean monthly DI entry rate of 318 monthly entrants per million working-age residents.

4.2 Unemployment and Health Outcomes 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 experienced at application.

We again begin with descriptive evidence, leveraging variation in the national unemployment rate using 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 include this fixed effect 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 sixth year since entry) appear artificially inexpensive. The coefficients on δ_{coh} represent the average Medicare spending associated with this cohort (net of fixed effects). 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 2b reports the average spending for each year-of-entry cohort (e.g., the cohort fixed effects δ_{coh} from equation (2)). Across the 24 cohorts entering between 1993 and 2016, average cohort net spending ranges from about \$13,300 to \$14,400 (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 cohorts that entered in 2009 experienced an unemployment rate of 5.0 percent, the lowest of the macroeconomic cycle, at the time of their applications (in approximately 2007), but had the highest spending of all entry cohorts. Conversely, the cohort that entered in 2012 experienced an unemployment rate of 9.5 percent, the highest of the cycle, at the time of their applications (in approximately 2010), but had the lowest spending of all cohorts.

Figure 2c 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. While mortality is an extreme (and binary) outcome, it can be measured in every year for every disabled Medicare enrollee, alleviating concerns about sample selection or confounding from the many other determinants of medical spending besides health status.

We can adapt equation (2) to examine the correlation of net medical spending and local unemployment at application by simply replacing the cohort fixed effects.

$$y_{it} = \beta[\text{unemp rate at application}]_i + X_{it} + \varepsilon_{it} \tag{3}$$

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 fixed effects for years enrolled account for the panel structure of our health outcomes data, while the county interaction accounts for persistent characteristics of each county.

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 3b reports the estimates of the relationship between unemployment ventiles and medical spending, and Figure 3c repeats the analysis for mortality outcomes. 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 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 $64 (0.5%) decrease in subsequent annual medical spending, and 0.55 fewer deaths per 10,000 person-years (a 0.2% reduction in mortality).

4.3 Age Heterogeneity in the Effects of Unemployment

As described in Section 2, DI eligibility increases discontinuously at ages 50 and 55. This discontinuity is evident in our data when we examine the age distribution of new Medicare entrants. Figure 4a demonstrates a sharp increase in the number of individuals entering DI at the specific ages when the vocational grid rules are relaxed, thus leading to a parallel surge of entrees into Medicare at ages 52 and 57. The number of 52-year-old disabled Medicare entrants over the sample period is nearly 50% greater than the number of 51-year-old entrants.

Figure 4b reports the average annual medical spending for individuals entering at each age. Specifically, the black solid line plots the fixed effects estimated for each age-at-entry e from the following equation:

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

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 individuals who enter at ages 52 and 57. For example, DI recipients who enter Medicare at age 51 have average annual net spending of about \$15,000; individuals who enter just above the first age discontinuity, at age 52, have average net spending of \$14,100, a 6% reduction. Using mortality as the dependent variable, we find a jump downwards right at the age discontinuities in eligibility. While the jump is smaller relative to the overall variance in mortality, the difference between individuals who enter at ages 51 and 52 is sizable: a 4% reduction.

Over our time period, 54% of all entry occurs at ages 52 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 e to estimate the effect of local unemployment at application across the age distribution.

$$\text{Entry}_{ecm} = \alpha_e[\text{unemp rate at application}]_{cm} + \delta_{ec} + \delta_{em} + \varepsilon_{ecm} \tag{5}$$

Figure 5 reports, for each age at Medicare entry, the effect of one percentage point of local unemployment at application on the age-specific DI incidence (i.e., number of entrants at age e from county c in month m divided by the estimate of the population at age $e-2$ from county c in month m, where we subtract 2 years to represent the average age at application). It is apparent that entry is more sensitive to unemployment above the age discontinuities in eligibility.[16] We find that a disproportionate share of total countercyclicality in DI incidence is attributable to individuals who enter Medicare after 52 (and, thus, enter DI after age 50).

We are particularly interested in the first age discontinuity in the DI vocational grid, at

[16] The high sensitivity of individuals who enter at age 20 may be a consequence of the process for the transition of disabled children from SSI to DI, which involves a determination of whether the individual could work.

Medicare-entry age 52. Our comparisons between those entering at age 51 and age 52 show substantial differences—increased entry into DI, decreased health, and increased sensitivity to unemployment. To examine this transition more closely, we repeat the analyses reported in Panel A of Table 1, but we restrict the sample to individuals who entered at ages $e \in \{51, 52\}$ and interact the (demeaned) unemployment rate with each entry age.

$$\begin{aligned} \text{Entry}_{ecm} &= \alpha + \alpha^{UR}\text{UR}_{cm} + \alpha^{52}1(e=52) + \alpha^{52\times UR}1(e=52)\text{UR}_{cm} + X_{ecm} + \varepsilon_{ecm} \\ y_{it} &= \beta + \beta^{UR}\text{UR}_{cm} + \beta^{52}1(e=52) + \beta^{52\times UR}1(e=52)\text{UR}_{cm} + X_{it} + \varepsilon_{it}, \end{aligned} \tag{6}$$

In this equation, we simplify interpretation by defining UR_{cm} as the demeaned local unemployment rate at application. We include a parameter for the regression constants α and β to represent entry and spending for those entering at age 51 under conditions of mean unemployment. Finally, X_{ecm} is a single set of county fixed effects, since individuals in these ages are subject to the same county factors such as labor markets. As in Equation 3, X_{it} 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 estimation for entry. Consistent with the jump in entry at age 52 visible in Figure 4a, we find that entry jumps from 390 new 51-year-old entrants per million resident 51 year-olds (α), to nearly 643 per million at age 52 ($390 + 253$). A one percentage point increase in the local unemployment rate at application from its mean (6 percent) increases entry for 51 year olds by 7.6 per million (approximately 1.9%, note this result differs slightly from Figure 5 because the county fixed effect is not interacted with age at entry). However, that same increase has a larger effect on 52 year olds, increasing their entry rate by 41.7 per million (7.6+34.1, 6.5% increase relative to entry at mean unemployment). We consistently find that the unemployment sensitivity is greater for 52 year olds than for individuals entering DI at ages slightly below the threshold.

Panel B, Column 2 of Table 1 reports the impact of unemployment on medical spending for entry-ages 51 and 52. The constant term (β) represents average net medical spending for

51 year olds who apply for DI under mean unemployment. The downward shift in spending for 52 year olds that was clear in Figure 4b is represented by the negative estimate for β^{52}, which constitutes a drop in spending relative to entry-age 51 of 4.1%. We see that an increase in unemployment has no effect for 51 year olds (β^{UR}), but reduces spending for 52 year olds by 0.4% ($= (4-54)/(14776-602)$). The third column of panel B shows that mortality falls for individuals who entered at age 52 relative to age 51, and for each percentage point of unemployment.

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 health of the larger group. Together, these results suggest that compliers—responsive to either higher levels of unemployment, or to the more lenient age admission rules—are somewhat healthier than always-takers who would have joined the disability insurance program regardless of either economic conditions or the shift in eligibility requirements. In the next section, we describe a graphical model for explicitly comparing compliers induced by unemployment or the age discontinuity.

5 Health Shocks versus Opportunity 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 opportunity costs of applying for DI, by decreasing expected future earnings from remaining in the workforce (the "opportunity costs" channel).[17] In this section, we explain our

[17] A third possible mechanism is that 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.

strategy for separately identifying the impact of health shocks and opportunity costs shifts by comparing the medical spending of two groups of people: those who enroll in DI due to a change in unemployment (i.e., recession compliers), and those who enter DI only due to the looser eligibility applying at older ages (i.e., age discontinuity compliers).

5.1 Conceptual Framework

Consider the simple model depicted in Figure 6a. Individuals are characterized by their level of work capacity and sorted along the x-axis, with individuals with lower work capacity (i.e., those whose disabilities limit their ability to work to a greater degree) farther on the left, and those with greater work capacity farther on the right. Although DI cash benefits do not depend on an individual's level of disability, individuals with lower work capacity have higher valuation for disability benefits due to higher expected medical needs and spending.[18] Thus, we draw a declining function B representing the expected benefit of entering DI.

There are costs to obtaining DI benefits in the form of foregone paid work and expenses incurred during the application process (e.g., hiring disability lawyers, documenting health status, etc.). Applicants who have high levels of work-limiting disabilities that leave them incapable of undertaking even sedentary work on a sustained basis are very likely to be admitted to DI regardless of age. Consequently, the cost of applying for DI is low and flat over a range of severe levels of work-limiting disabilities (solid flat line with circles and squares). However, this changes once an individual's work-limiting disabilities decrease to the point at which the SSA process finds them capable of sustained sedentary work. This change potentially occurs for two reasons: The first is that as individuals' work capacity increases, new jobs become available to them, causing their wage expectations to rise. The second is that SSA guidelines direct that individuals designated as capable of sedentary work should not be awarded benefits below age 50, making establishing disability more difficult

The criteria explicitly prohibit evaluation of cases based on the availability of jobs (20 C.F.R. §404.1566).

[18] Research supports a strong positive correlation between level of disability (measured by limitations in activities of daily living) and medical spending (Wolff et al., 2019; Koroukian et al., 2017).

for people below the age cut-off. It is possible that younger individuals capable of sedentary work could be determined to be disabled under the criteria, but only by documenting their health conditions and appealing an initial denial—both of which entail additional costs. The less disabled the person is, the larger is this cost. Consequently, the cost curve for 51 year olds is steeply increasing over this range of sustained work capacity (solid red line with circles).[19] Our cost curve is consistent with the evidence developed in Deshpande and Li (2019) in their analysis of the closure of proximate 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.

For 52 year olds, however, the same level of disability corresponding to a sedentary MSWC can now result in a DI award, depending on the individual's education and work history. While there are costs associated with successfully arguing for a declaration of disability, these are somewhat smaller for this older group than they are for younger workers for whom the same conditions collide with more stringent grid rules. Thus, the cost function for 52 year olds (in green with squares) rises throughout that region, although somewhat less steeply than it does for the 51 year olds.

For levels of work-limiting disability such that benefits exceed costs, individuals will apply to and be awarded DI benefits.[20] Thus, the x-axis also measures DI entry, with points of intersection between the benefit and cost curves corresponding to greater DI entry. Age-discontinuity compliers are represented by the increase in entry from α to $\alpha + \alpha_{52}$.

Figure 6b depicts the effect of high unemployment in this framework. We represent the "opportunity cost" effect of an increase in unemployment as a downward shift in the cost

[19]If the SSA's determination is final and absolute, the cost curve would be vertical. If, instead, individuals judged to have a sedentary MSWC can obtain eventual approval via redetermination and appeal, but need to remain unemployed in order to do so, a steep cost curve is more realistic.

[20]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.

curve, to the lower red-green dashed line, arising from reduced earnings prospects in the near future. The reduction in the opportunity cost of DI moves the intersection of the cost and benefit curves to the right. Thus, benefits exceed costs for a slightly larger group, and DI entry increases. The recession compliers who enter due to this shift are likely to have lower average medical spending than the inframarginal always-takers. Due to the flatter slope of the cost curve among 52 year olds, the same unemployment-induced reduction in opportunity costs means this recession-induced entry route admits more 52 year olds than by 51 year olds.

Figure 6b illustrates the second potential effect of an increase in unemployment, a worsening of health. Since the height of the B curve includes the value of health benefits received, a negative health shock increases the potential benefit from enrolling in DI. This is is represented in Figure 6b by an upward shift of the benefits function from B to B^{UR} (dashed orange line). This shift need not be parallel. If the health shocks are larger for less-disabled individuals, the benefits curve would become flatter, as in Figure 6b.[21] We find that, when holding the cost curve fixed, the upward shift in the benefits curve also induces additional entry into DI.

In reality, an increase in unemployment could induce entry into DI through both of these channels. The x-axis in Figure 6b depicts the entry increase associated with high unemployment. Entry among 51 year olds at high unemployment is represented by $\alpha + \alpha^{UR}$, entry among 52 year olds experiencing high unemployment is expressed as $\alpha + \alpha^{UR} + \alpha^{52} + \alpha^{52 \times UR}$, with the final term capturing the possibility that 52-year-old entrants are more sensitive to high unemployment.

[21] We characterize an increase in unemployment as *reducing* health because this is the direction most often discussed in the DI literature. However, there is also reason to believe that increasing unemployment may actually *improve* health, in which case the benefit curve would shift down.

5.2 Estimating Model Primitives

In this section, we use the data and estimates prepared in Section 4.3 to parameterize the model in Figure 6b.

5.2.1 Identifying the Parameters of the Benefits Curves

In Section 4.3 we estimated two models of DI entry and medical spending for individuals entering at ages 51 and 52. The coefficients in the entry equation are direct estimates of α and the incremental effects α^{51}, α^{52} and $\alpha^{52\times UR}$ and are reported in Panel B of Table 1.

The coefficients of the spending model provide estimates of average spending among those entering DI under various conditions. We can express the total medical spending of any group as the integral of the benefits curve for that group. Thus, for the four groups of entrants we consider, we have four equations:

$$\alpha\beta = \int_0^{\alpha} B(d)df(d)$$
$$(\alpha+\alpha^{UR})(\beta+\beta^{UR}) = \int_0^{\alpha+\alpha^{UR}} B^{UR}(d)df(d)$$
$$(\alpha+\alpha^{52})(\beta+\beta^{52}) = \int_0^{\alpha+\alpha^{52}} B(d)df(d)$$
$$(\alpha+\alpha^{UR}+\alpha^{52}+\alpha^{52\times UR})(\beta+\beta^{UR}+\beta^{52}+\beta^{52\times UR}) = \int_0^{\alpha+\alpha^{UR}+\alpha^{52}+\alpha^{52\times UR}} B^{UR}(d)df(d)$$

To proceed, we make two strong assumptions: the $B(d)$ and $B^{UR}(d)$ are both linear functions (as drawn in the figures), and the underlying distribution of work-limiting disability $f(d)$ is uniform.

Under the assumptions of linearity and uniformity, the four integrals reduce to four equations in four unknowns, and it is possible to explicitly solve for the parameters of the two linear functions. We focus first on the slope m and intercept n of the benefits function during mean unemployment B.

$$m = 2\frac{\beta^{52}}{\alpha^{52}} \qquad n = \beta - \frac{\alpha\beta^{52}}{\alpha^{52}}$$

The identification of the benefits function is achieved by exploiting the age discontinuity in eligibility. Since we know that individuals entering at ages 51 and 52 are *not* experiencing different health, we simply examine the change in average spending β^{52} that results from increasing the entry rate by α^{52}.

The slope and intercept of B^{UR} follow a similar logic.

$$m^{UR} = 2\frac{\beta^{52} + \beta^{52\times UR}}{\alpha^{52} + \alpha^{52\times UR}} \qquad n^{UR} = \beta + \beta^{UR} - \frac{(\alpha + \alpha^{UR})(\beta^{52} + \beta^{52\times UR})}{\alpha^{52} + \alpha^{52\times UR}}$$

Compare the slopes m and m^{UR}. For the two slopes to be equal, the incremental entrants induced by the combined effect of the age discontinuity and unemployment, $\alpha^{52\times UR}$, must alter spending in the same proportion as the incremental entrants induced by the age discontinuity alone. If instead the spending of unemployment-induced DI entrants is higher than the spending of those induced by the age discontinuity, we would find a less negative (flatter) slope for the benefits function during high unemployment. Such a finding would suggest that unemployment-induced entrants are in worse health than individuals induced by the age discontinuity.

To understand the identification of the difference in the intercept, assume for the moment that the slopes of the two lines are the same, such that we can substitute $\frac{\beta^{52}}{\alpha^{52}}$ for $\frac{\beta^{52}+\beta^{52\times UR}}{\alpha^{52}+\alpha^{52\times UR}}$. Then we can difference the two intercepts:

$$n^{UR} - n\Big|_{m=m^{UR}} = \beta + \beta^{UR} - \frac{(\alpha + \alpha^{UR})\beta^{52}}{\alpha^{52}} - (\beta - \frac{\alpha\beta^{52}}{\alpha^{52}}) = \beta^{UR} - \frac{\alpha^{UR}\beta^{52}}{\alpha^{52}}$$

The difference in intercepts is zero if $\frac{\beta^{UR}}{\alpha^{UR}} = \frac{\beta^{52}}{\alpha^{52}}$. Intuitively, if the ratio of spending changes to entry changes is the same for unemployment marginals and age-discontinuity marginals, there is no difference in the intercepts of the two benefits lines. If instead the ratio of spending change to entry change for unemployment $(\frac{\beta^{UR}}{\alpha^{UR}})$ is larger than the same ratio for the age discontinuity $\frac{\beta^{52}}{\alpha^{52}}$, that suggests that the benefits curve is higher in the case of high unemployment; hence, unemployment causally worsens the health of individuals with disabilities.

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 one percentage point, although the difference in slopes is small. We actually find that the intercept is *higher* in mean unemployment than at higher unemployment, although this effect is indistinguishable from zero.

Figure 7 depicts the benefits curves 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 individuals who enter DI due to high unemployment have the exact same spending as individuals who enter DI due to the age discontinuity.

5.2.2 Identifying the Parameters of the Cost Curves

In the previous section, we showed that our data suggest a small rotation of the benefits function associated with a small increase in unemployment. To determine the economic importance of the shift, we calculate the effect of unemployment under the counterfactual of a completely fixed benefits function. To do so, we now turn to the cost functions.

There are four cost curves depicted in Figure 6b: C_{51}, C_{51}^{UR}, C_{52}, and C_{52}^{UR}. In the previous section we identified the benefits curves by exploiting the age discontinuity in eligibility, which, by assumption, is movement along the benefits curve. However, we do not have a similar source of variation identifying the slope of the cost curves; instead, each of the four points that we characterize in the data are associated with different cost curves.

To reduce the number of parameters associated with the cost curves, we assume they are linear. We also assume that unemployment induces a simple downward shift in the cost curve that is the same for both 51 and 52 year olds. With that assumption, the sloped portion of the cost curves can be characterized with five parameters: m_{51} and n_{51} are the slope and the intercept for the cost curve for 51 year olds under mean unemployment, m_{52} and n_{52} are the slope and intercept for 52 year olds under mean unemployment, and ΔC is the cost change associated with unemployment. Still, the five parameters of the cost curves 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.1, we present equations for the slope and intercepts of the two cost curves as a function of ΔC and the slopes and intercepts of the benefit curves. We examine three scenarios: $\Delta C \in$ (-500, -5000, -50000), which we view as encompassing a wide range of possible values for the recession-related reduction in the opportunity cost of DI application. For the middle value of ΔC =-\$5000, we report the slope and intercept of the cost curves in Panel B of Table A.3 and draw them in Figure 7 (upward sloping red and green line segments).

The dashed red and green line segments represent the reduced opportunity costs in a recession, with the intercept for these segments at \$5,000 less than the intercept for the solid segments. The flatter slope of the cost curve for 52 year olds means that the same vertical shift in the intercept generates a much larger entry response for 52 year olds relative to the entry response for 51 year olds. We find similar estimates for ΔC=-\$500 (Appendix Figure A.2a) and ΔC=-\$50000 (Appendix Figure A.2b), suggesting that our cost curve parameters are not very sensitive to the choice of ΔC.

6 Potential Confounders or Alternative Interpretations

In this section, we explore potential confounders affecting our estimates, or alternative interpretations of our findings.

6.1 Enrollment in Medicaid, Medicare Advantage, and Medicare Part B

Our analysis relies on comparing spending levels of individuals entering in different economic conditions or at different ages. However, Medicare spending as measured in our claims data can be affected by a number of institutional features of Medicare. In this section, we show that these institutional features do not covary with economic conditions, or with age at entry, and, thus, they are unlikely to explain our findings.

Many disabled Medicare beneficiaries are "dually eligible" for Medicaid. While Medicare remains the primary insurance for dually eligible individuals, Medicaid-eligible individuals are not subject to typical Medicare cost sharing. If individuals were to consume more care in the absence of cost sharing, and if Medicaid eligibility were more common among individuals who enter during poor economic conditions or after the age discontinuity, our findings of differential spending could instead be an artifact of higher Medicaid eligibility.

To examine this possibility, we replicate Figures 2b and 4b using Medicaid eligibility for individual i in year t as the dependent variable of equations (2) and (4), respectively. The alternative figures are reported in Panels (a) and (b) of Appendix Figure A.3. Rather than the countercyclical pattern we saw in Figure 2b, we simply see a gently rising line. In comparison to the jumps at age 52 and 57 visible in Figure 4b, we see that individuals who join DI at younger ages are more likely to be dually eligible.

We do not observe spending data for individuals enrolled in Medicare Advantage. If data censoring were correlated with unemployment at application or age at entry, then part of the changes in spending we analyze could instead be due to Medicare Advantage enrollment. To determine whether Medicare Advantage enrollment varies with economic conditions at application or age at entry, we again estimate equations (2) and (4), using Medicare Advantage enrollment as the dependent variable. Panel (c) of Appendix Figure A.3 shows that Medicare Advantage enrollment is higher for more recent cohorts, without a clear relationship with unemployment. Panel (d) suggests that Medicare Advantage enrollment increases with age at entry, but without jumps at the age 50 and 55 thresholds.

Finally, we observe incomplete spending data for individuals who enroll in Medicare Part A (for hospital services) but do not elect Medicare Part B (for physician services). About 8% of our sample chose not to enroll in Medicare Part B, usually because the individual is eligible for commercial insurance via spousal or retiree benefits. However, there is no particular relationship between Medicare Part B enrollment and unemployment (Panel (e)) or age at entry (Panel (f)).

7 Conclusion

This paper examines the factors that drive increased enrollment in the federal Social Security Disability Insurance program during recessions. We document that entry into the program increases when unemployment is high, and that individuals who enter at such times have lower average spending levels than those who apply during periods of low unemployment. We compare health spending of those admitted to DI by using detailed health data from Medicare, the health insurance program to which they gain access. We are thus able to compare changes in spending across the business cycle to changes in cohort spending that occur after age 50, when DI eligibility thresholds exogenously relax. 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 fluctuations in enrollment into the program during recessions.

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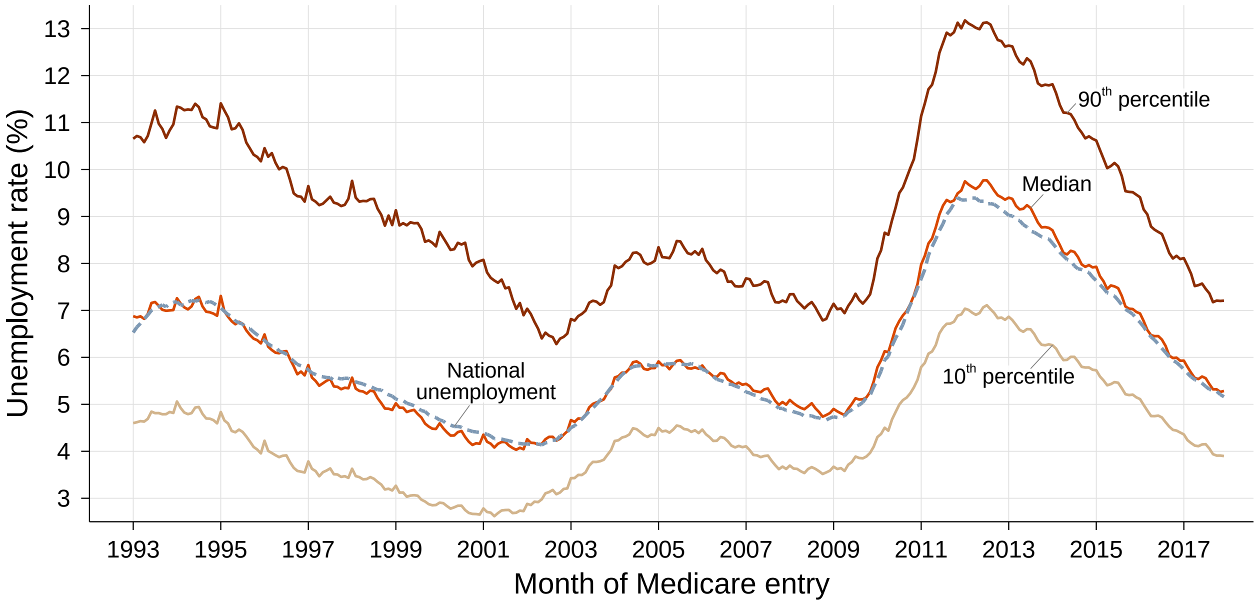
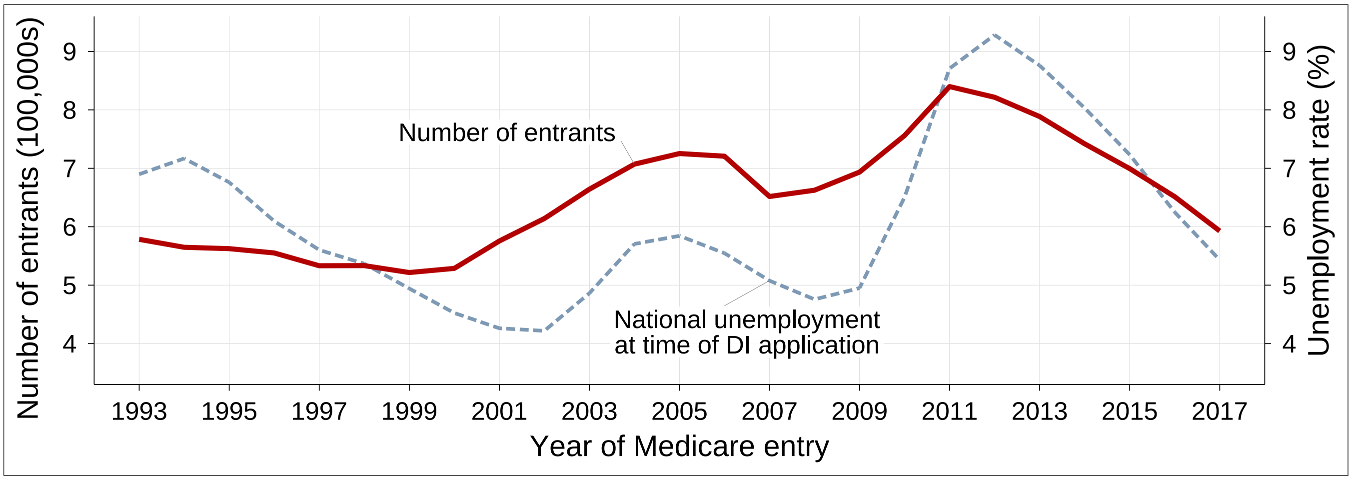
Figures

Figure 1: County unemployment at application, by month of Medicare entry

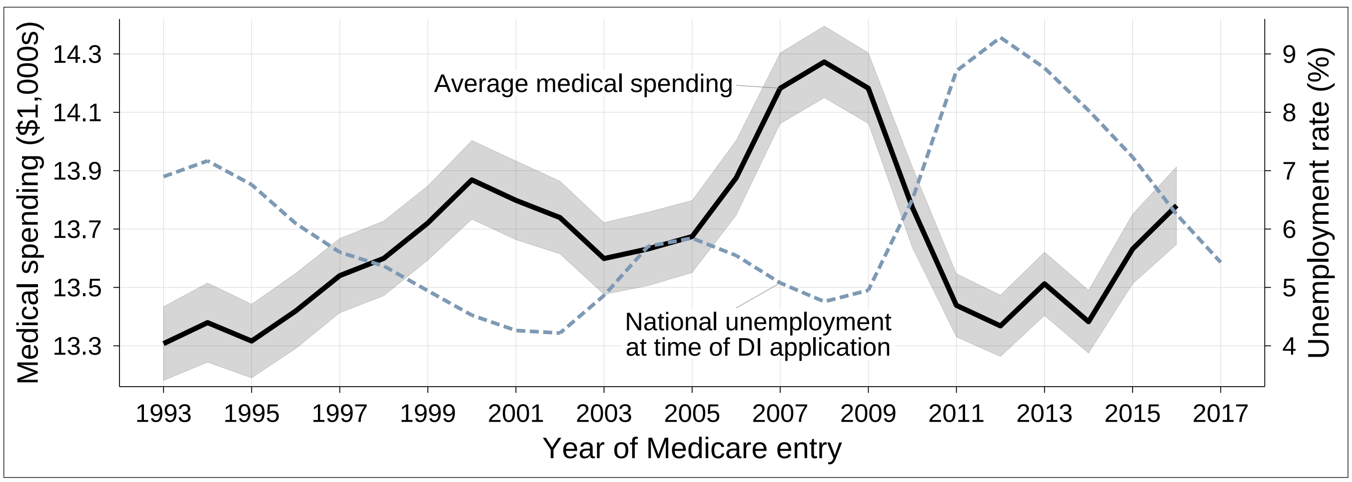


Note: The figure summarizes unemployment rates in the initial county of residence among DI recipients at the time (month) of their application for DI, by the month of Medicare entry. Section 3.2 describes the calculation of county unemployment at the time of application. The brown, orange, and tan lines indicate the 90^{th}, 50^{th}, and 10^{th} percentiles, respectively, of county unemployment rates at the time of DI application. The average national unemployment rate at the time of application is depicted by the dashed blue line.

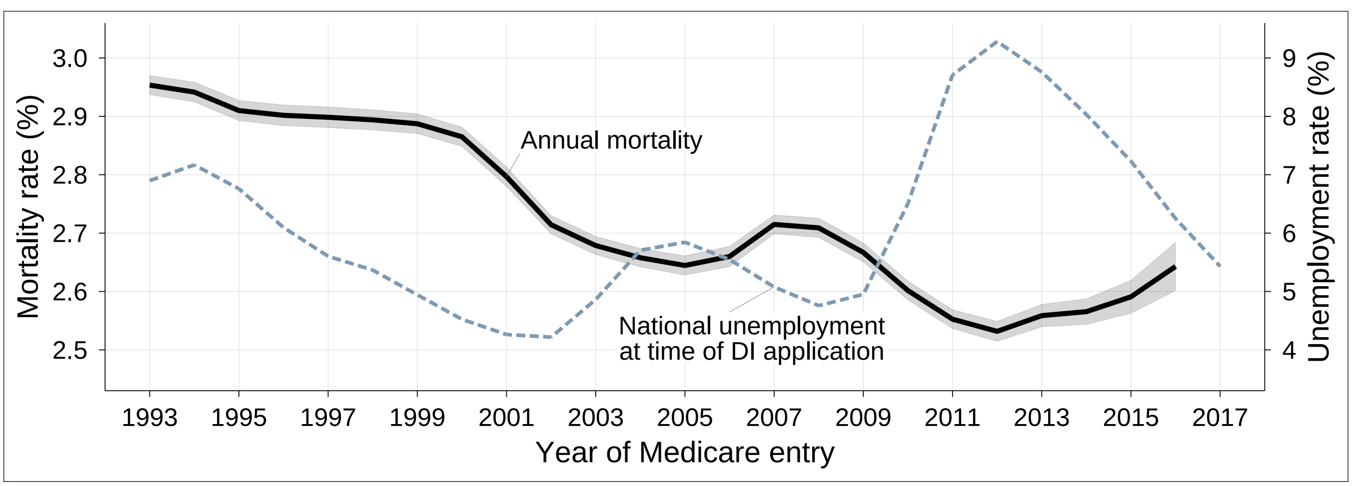
Figure 2: Number of entrants, medical spending, and unemployment at application, by entry year



(a) Number of entrants



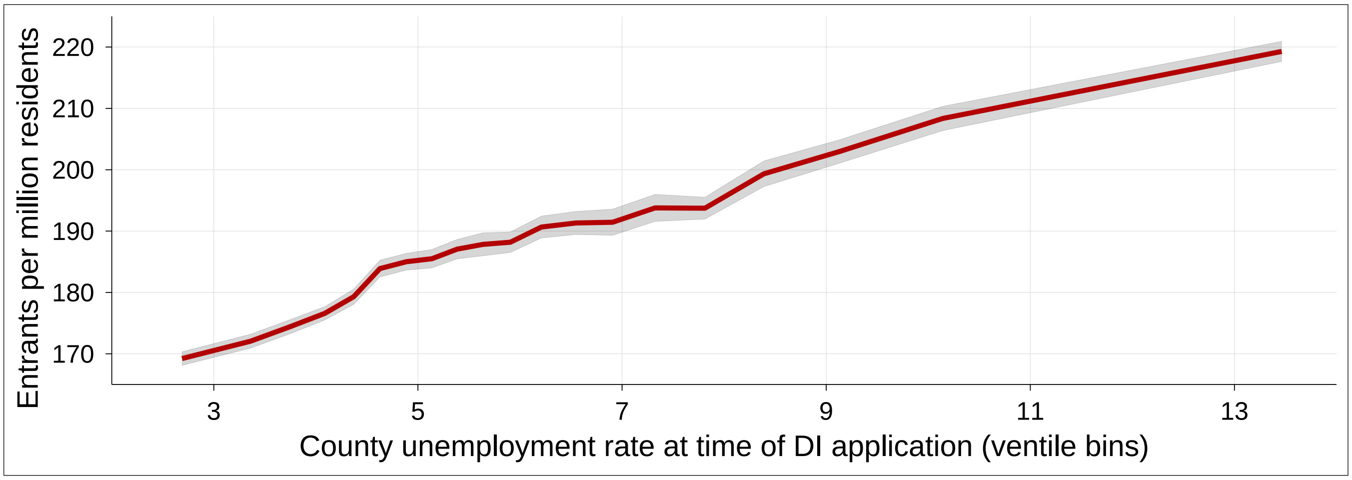
(b) Average medical spending



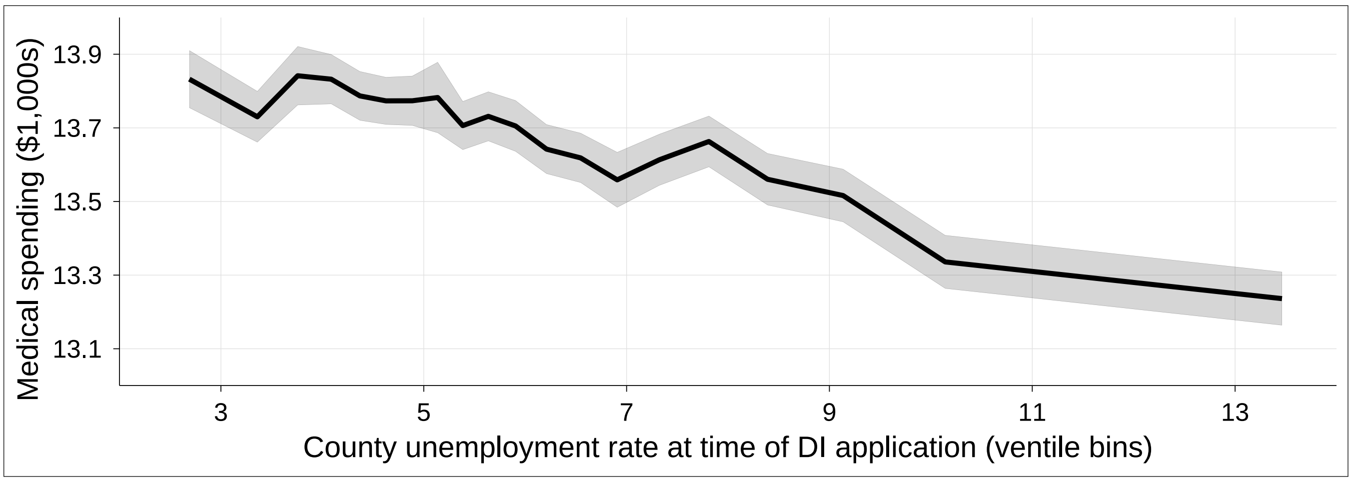
(c) Annual mortality

Note: In Panel (a), the solid red line (left axis) counts the number of DI recipients entering Medicare in each year. In Panels (b) and (c), the solid black lines (left axes) represent the average subsequent medical spending and annual mortality rates, respectively, for individuals entering in each year, as estimated in equation (2). In all panels, the blue dashed line (right axis) represents the average national unemployment rate at the time of DI application, as calculated in Section 3.2, for entrants in each year. Entry is measured at the county X month level 1993m1-2016m12. Annual medical spending is measured at the person-year level for the FFS universe 1999-2016. Mortality is measured for the person-year level for the Medicare universe 1993-2016. The 95% confidence interval on those estimates, calculated from standard errors clustered on the county by month of entry, are represented in gray.

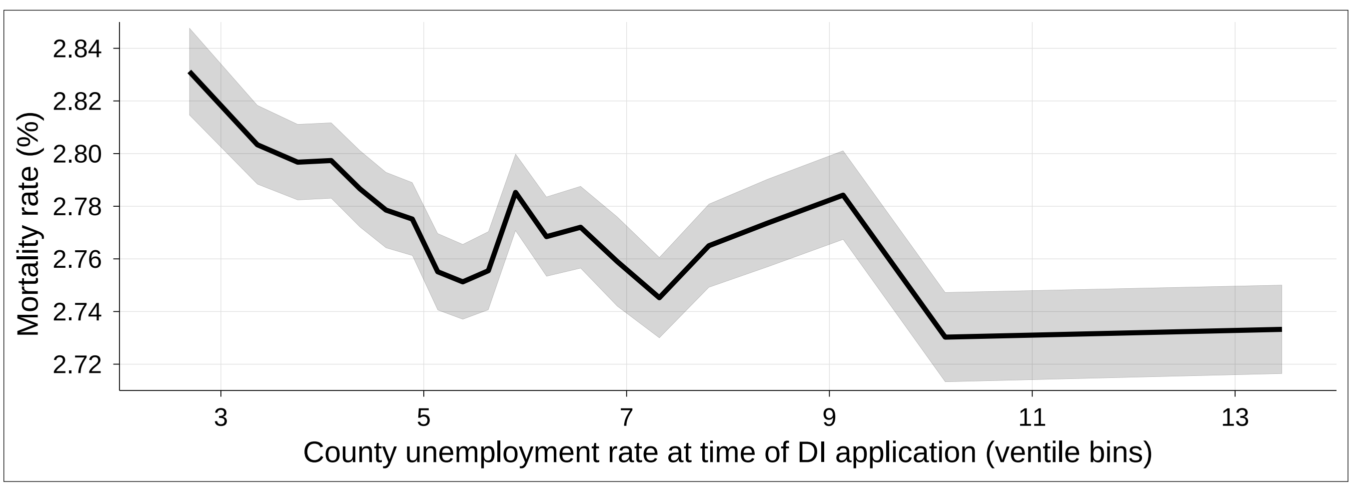
Figure 3: DI Entry, Medical Spending, and Mortality, by Unemployment at Application



(a) Entry



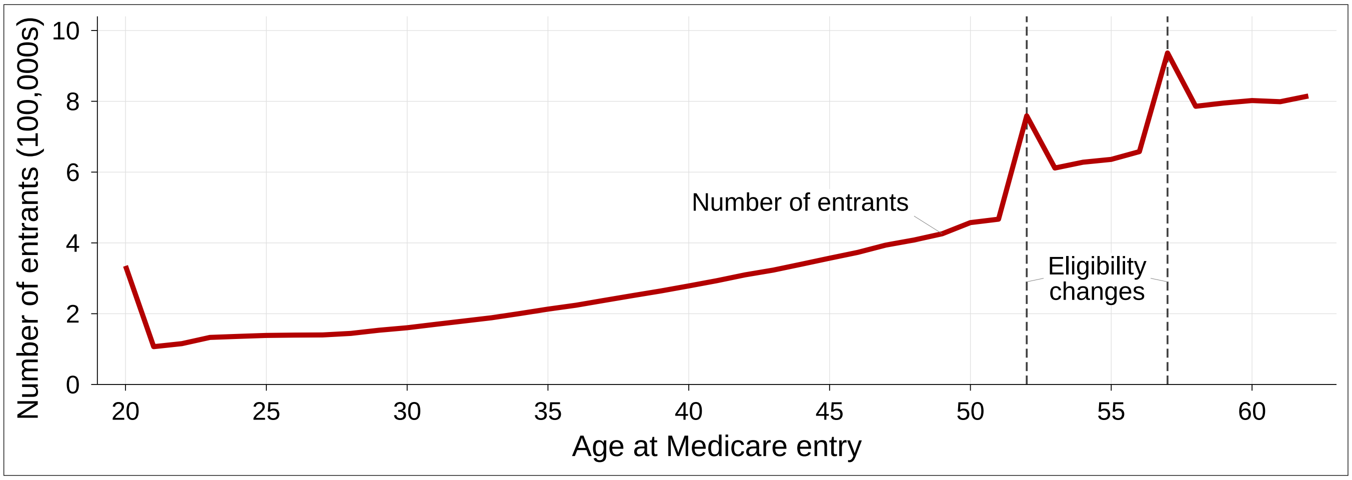
(b) Average medical spending



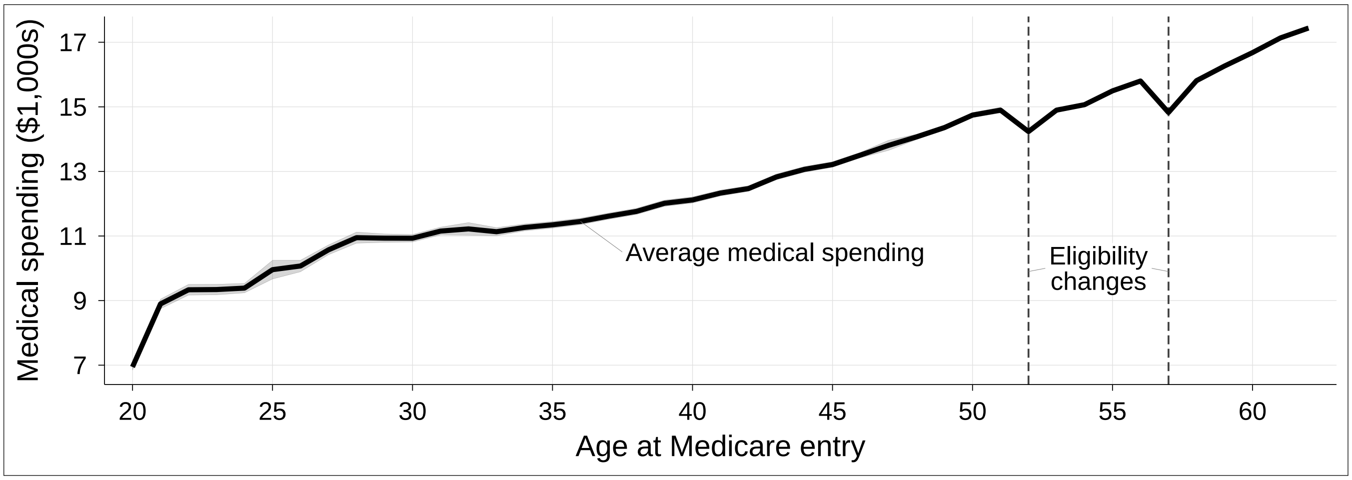
(c) Annual mortality

Note: In Panel (a), the solid red line reports how the number of DI entrants who become eligible for Medicare in a given county and month varies according to the county unemployment rate (in ventile bins) at the time of DI application. The entry regression uses monthly county observations and includes county fixed effects. Panels (b) and (c) report similar estimates, but where the outcomes are annual observations of subsequent medical spending and mortality, respectively, of DI entrants. These regressions use annual individual observations and include fixed effects for initial county by years enrolled. The 95% confidence interval on those estimates, calculated from standard errors clustered on the county by month of entry, are represented in gray.

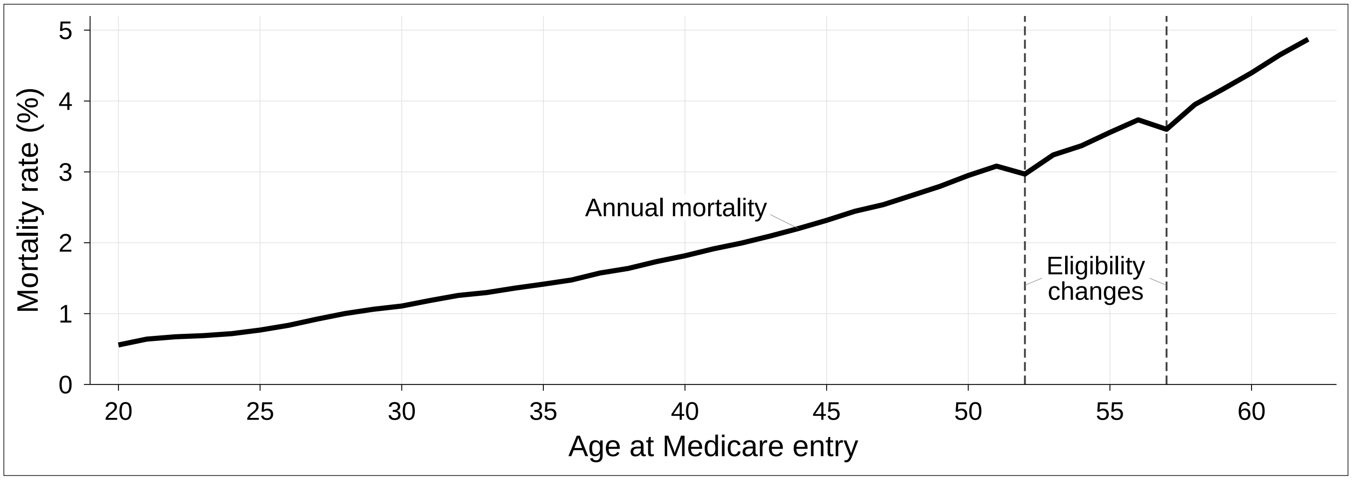
Figure 4: Number of entrants and medical spending, by age at entry



(a) Number of entrants



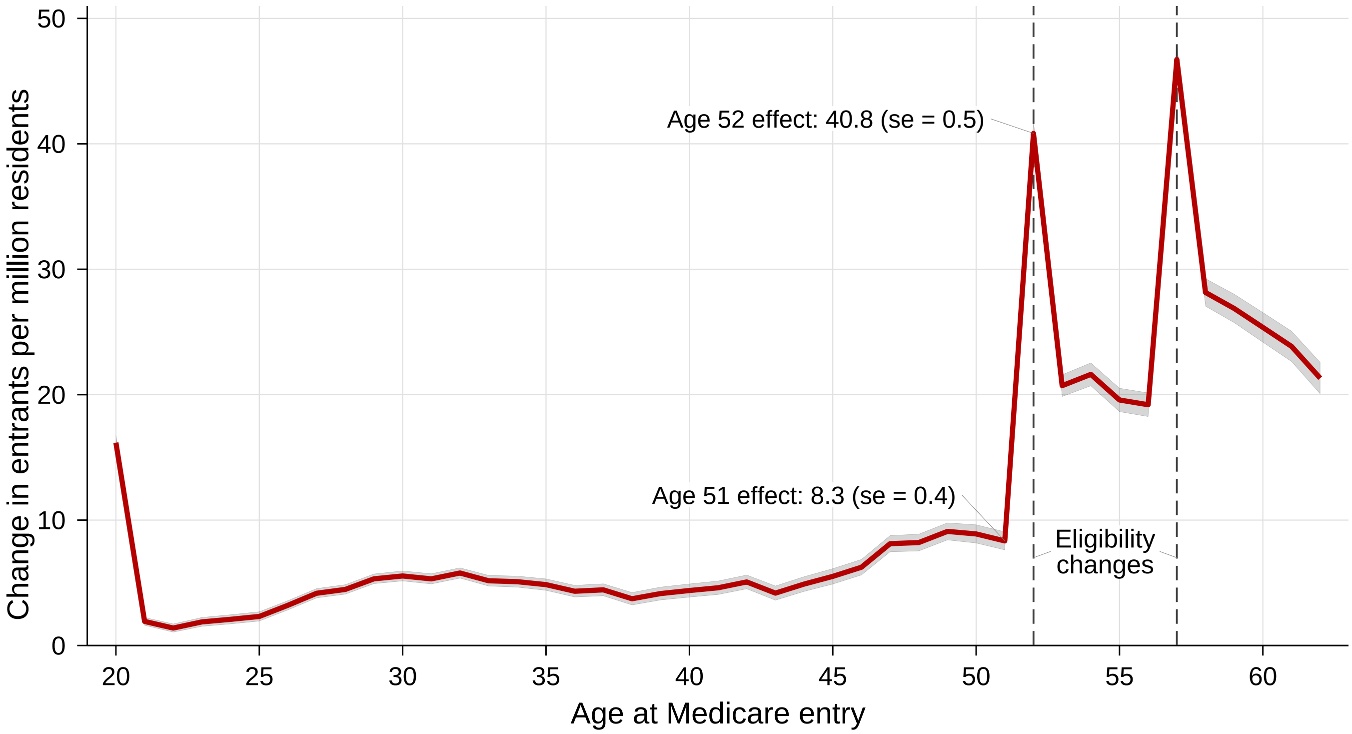
(b) Average medical spending



(c) Annual mortality

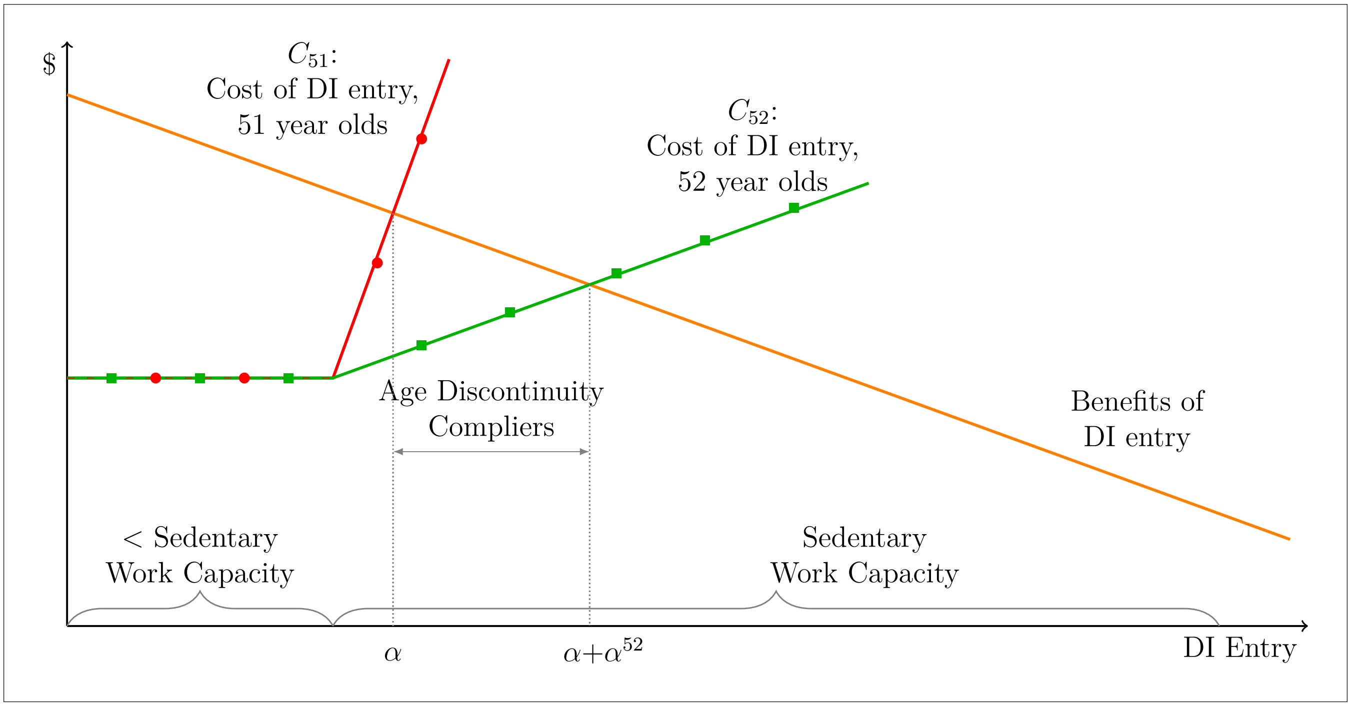
Note: In Panel (a), the solid red line counts the number of DI recipients entering Medicare at each age over the time period 1993–2017. In Panels (b) and (c), the solid black lines represent the average subsequent medical spending and annual mortality rates, respectively, for individuals entering at each age, as estimated in equation (4). The 95% confidence interval on those estimates, calculated from standard errors clustered on the county by month of entry, are represented in gray.

Figure 5: DI entry versus county unemployment at application, by age at Medicare entry

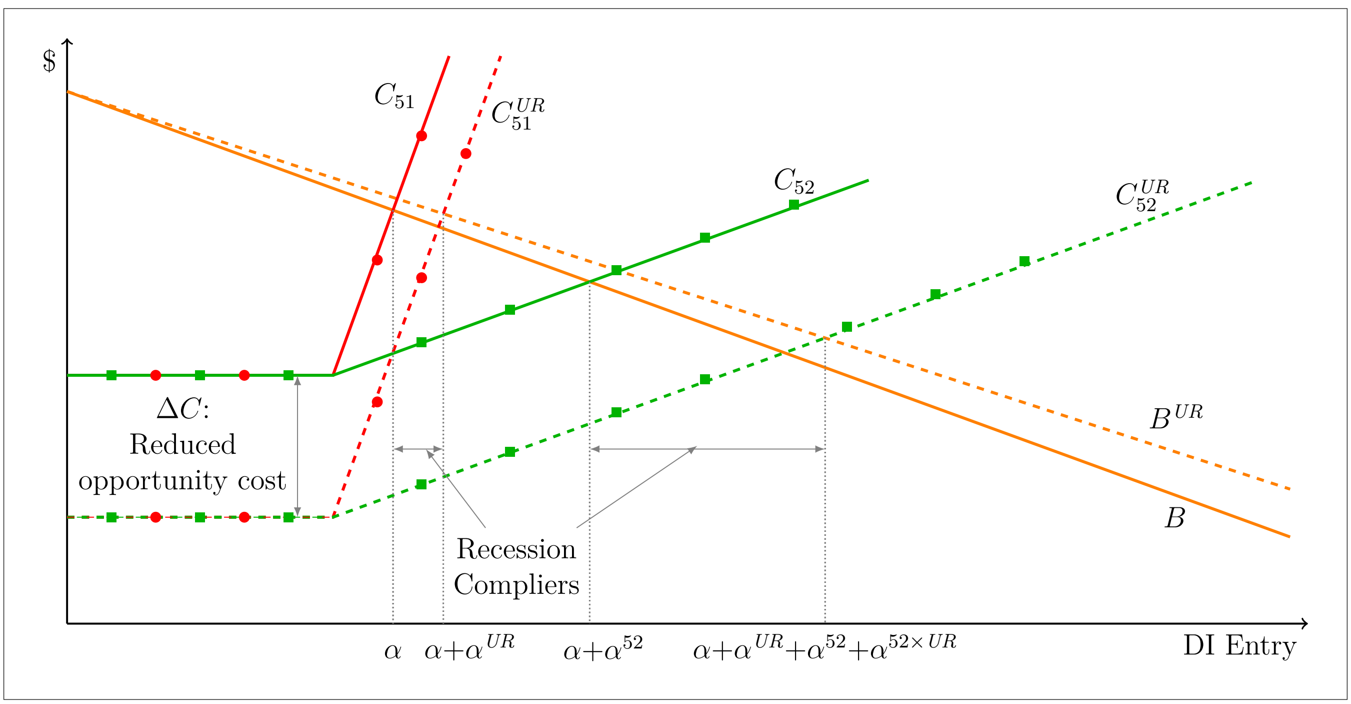


Note: The figure shows the coefficients from estimating equation (5). The height of the line represents the change in monthly DI entrants of a given age (at the time of Medicare entry) per million county residents associated with a one percentage point increase in the county unemployment rate at the time of DI application. The 95% confidence interval on those estimates, calculated from standard errors clustered on the county by month of entry, are represented in gray.

Figure 6: Conceptual Framework



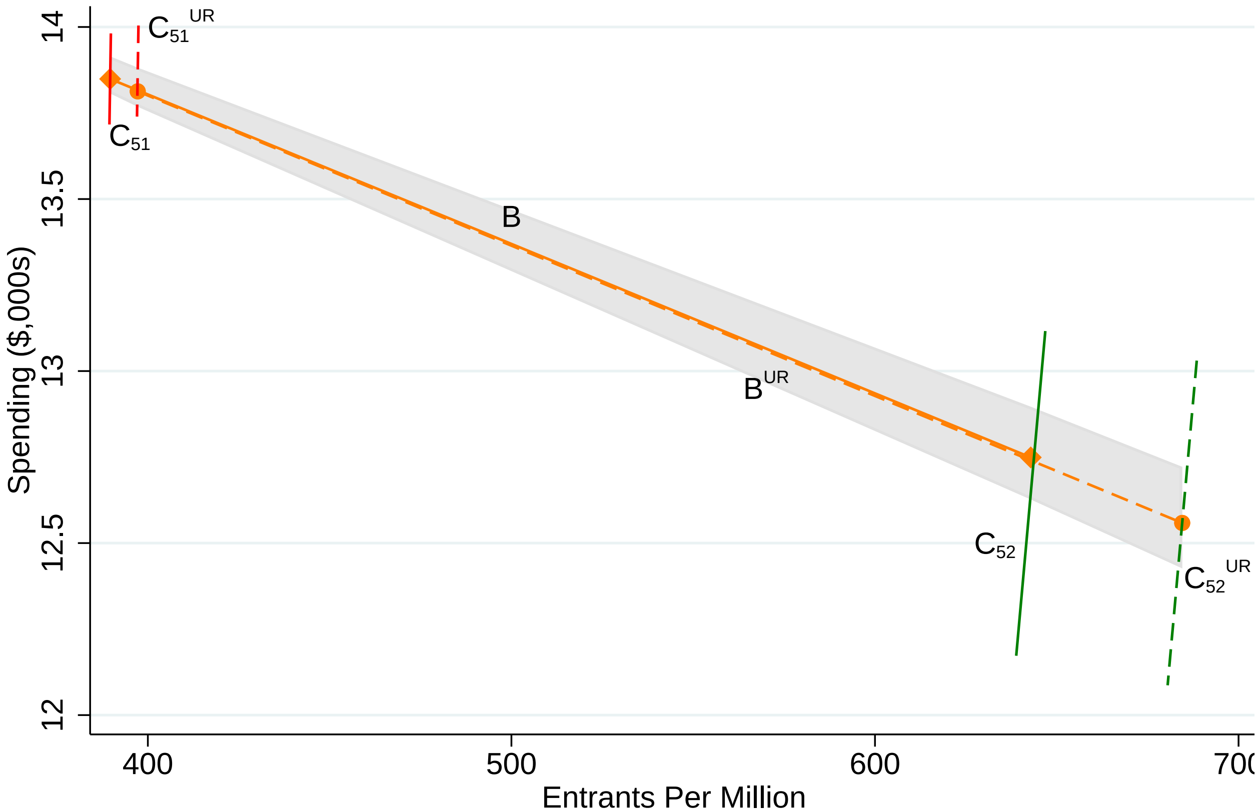
(a) Effect of Age Discontinuity in Eligibility at 52



(b) Effect of Unemployment: Reduced Opportunity Cost and Shift in Benefits Curve

Note: This figure represents our conceptual model of DI entry. The y-axis measures the costs and benefits of DI entry, measured in dollars, and the x-axis measures DI entry. Panel (a) represents separate cost functions for individuals aged 51 (red circles) and 52 (green squares). High unemployment reduces the opportunity cost of DI entry, represented by the downward shift of the cost functions in Panel (b) to the dashed lines. High unemployment potentially also shifts the benefits function upward and outward to B^{UR} (dashed). See Section 5 for discussion.

Figure 7: Estimates of Model Parameters When ΔC=-\$5000



Note: Figure represents elements of the conceptual model, using parameters estimated from the data using the specification in the first column of 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^{UR} have the slopes and intercepts shown algebraically in Section 5.2.1. The cost functions C_{51}, C_{51}^{UR}, C_{52}, and C_{52}^{UR} have the slopes and intercepts shown in Appendix Section A.1, under an assumption that ΔC=-\$5000.

Tables

Table 1: Cyclicality of Disability Insurance (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	13.10***	–64.34***	–0.55***
	(0.13)	(4.27)	(0.09)
Fixed effects	County	County × Years enrolled	County × Years enrolled
Dependent variable mean	317.88	13,662.88	277.14
Observations	935,820	105,277,494	144,405,012
B. Cyclicality of DI entry and cohort outcomes, by age at entry (51–52)			
Intercept	389.63***	14,775.91***	305.25***
	(0.70)	(42.96)	(0.85)
Age 52 at entry	253.22***	–602.34***	–10.63***
	(1.04)	(52.72)	(1.09)
UR (demeaned unemployment rate)	7.59***	4.09	–0.53
	(0.36)	(17.77)	(0.37)
UR × Age 52 at entry	34.07***	–54.38***	–0.78**
	(0.48)	(17.65)	(0.35)
Fixed effects	County	County × Years enrolled	County × Years enrolled
Dependent variable mean	515.48	14,419.08	298.84
Observations	1,871,640	7,473,987	10,495,164

Notes: The table reports how the number of DI entrants who become eligible for Medicare in a county and month and their subsequent health outcomes relate to unemployment conditions in the county at the time their application for DI. Each column reports coefficients and their standard errors (in parentheses) from a separate regression. Outcomes are indicated by the column label. Panel A reports results from equation (1) (column (1)) and equation (3) (columns (2)–(3)) using the main sample, comprising DI entrants who become eligible for Medicare at ages 20–62. Panel B reports results from estimating equations (6) based on the subset of DI entrants who become eligible for Medicare at ages 51-52. Statistical significance at the 10, 5, and 1 percent levels indicated by *, **, and *** respectively.

Appendix A: For Online Publication Only

A.1 Model: Slopes and Intercepts for Cost Curves in terms of ΔC

To identify the slopes and intercepts of the cost curves, we first begin with our identifying equations. The benefit curve for normal economic conditions has slope m and intercept n. It intersects the cost curve for 51 year olds at x-axis value α. Define the slope for the cost function for 51 year olds as m^C_{51} and its intercept n^C_{51}. Thus, our first equation is

$$m^C_{51}\alpha + n^C_{51} = m\alpha + n$$

When unemployment is high, the benefits function B^{UR} and cost function C^{UR}_{51} intersect at x-axis value $\alpha + \alpha^{UR}$. The slope m^{UR} and intercept n^{UR} of B^{UR} were found in Section 5.2.1. By assumption, the intercept of C^{UR}_{51} is $n^C_{51} + \Delta C$. Thus, we can write a second equation:

$$m^C_{51}(\alpha + \alpha^{UR}) + n^C_{51} + \Delta C = m^{UR}(\alpha + \alpha^{UR}) + n^{UR}$$

Subbing the first equation into the second

$$m^C_{51}(\alpha + \alpha^{UR}) + m\alpha + n - m^C_{51}\alpha + \Delta C = m^{UR}(\alpha + \alpha^{UR}) + n^{UR}$$

$$m^C_{51} = (-\Delta C - m\alpha - n + m^{UR}(\alpha + \alpha^{UR}) + n^{UR})/\alpha^{UR}$$

And similarly, we can find n^C_{51} in terms of known parameters:

$$n^C_{51} = m\alpha + n - (-\Delta C - m\alpha - n + m^{UR}(\alpha + \alpha^{UR}) + n^{UR})\frac{\alpha}{\alpha^{UR}}$$

A similar exercise can be done for the cost curves for 52 year olds. The cost curve for 52 year olds in good economic times intersects B at $\alpha + \alpha^{52}$.

$$m^C_{52}(\alpha + \alpha^{52}) + n^C_{52} = m(\alpha + \alpha^{52}) + n$$

And in times of high unemployment, the dashed lines intersect at $\alpha + \alpha^{UR} + \alpha^{52} + \alpha^{52\times UR}$.

$$m^C_{52}(\alpha + \alpha^{UR} + \alpha^{52} + \alpha^{52\times UR}) + n^C_{52} + \Delta C = m^{UR}(\alpha + \alpha^{UR} + \alpha^{52} + \alpha^{52\times UR}) + n^{UR}$$

We can again combine the equations to solve for m^C_{52} and n^C_{52} in terms of ΔC. Subbing the first equation into the second:

$$m^C_{52}(\alpha+\alpha^{UR}+\alpha^{52}+\alpha^{52\times UR})+(m-m^C_{52})(\alpha+\alpha^{52})+n+\Delta C = m^{UR}(\alpha+\alpha^{UR}+\alpha^{52}+\alpha^{52\times UR})+n^{UR}$$

$$m^C_{52} = \frac{-\Delta C + m^{UR}(\alpha + \alpha^{UR} + \alpha^{52} + \alpha^{52\times UR}) - m(\alpha + \alpha^{52}) + n^{UR} - n}{\alpha^{UR} + \alpha^{52\times UR}}$$

And the intercept is expressed as

$$n^C_{52} = m(\alpha+\alpha^{52})+n-\frac{(-\Delta C + m^{UR}(\alpha + \alpha^{UR} + \alpha^{52} + \alpha^{52\times UR}) - m(\alpha + \alpha^{52}) + n^{UR} - n)(\alpha + \alpha^{52})}{\alpha^{UR} + \alpha^{52\times UR}}$$

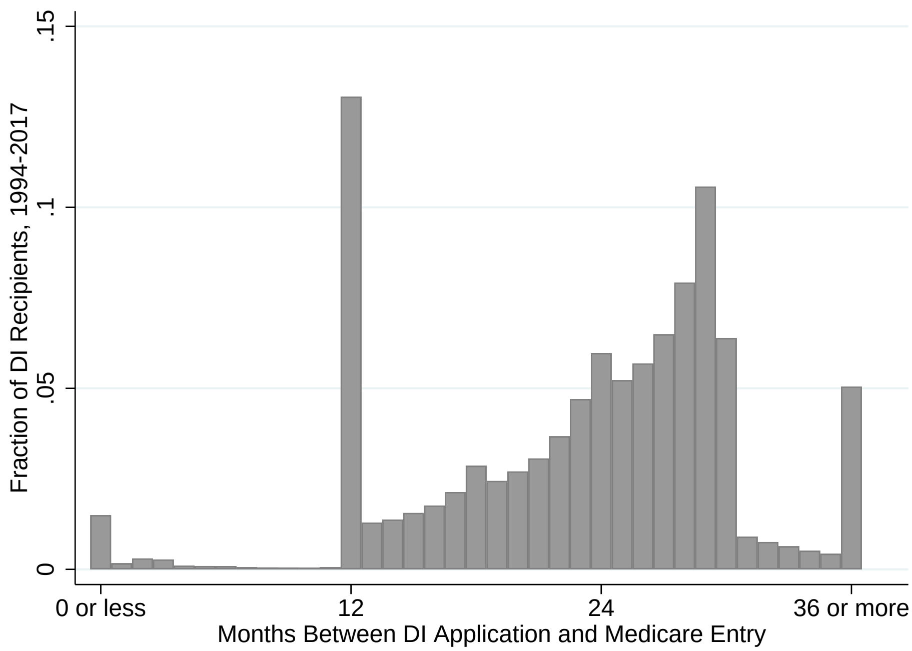
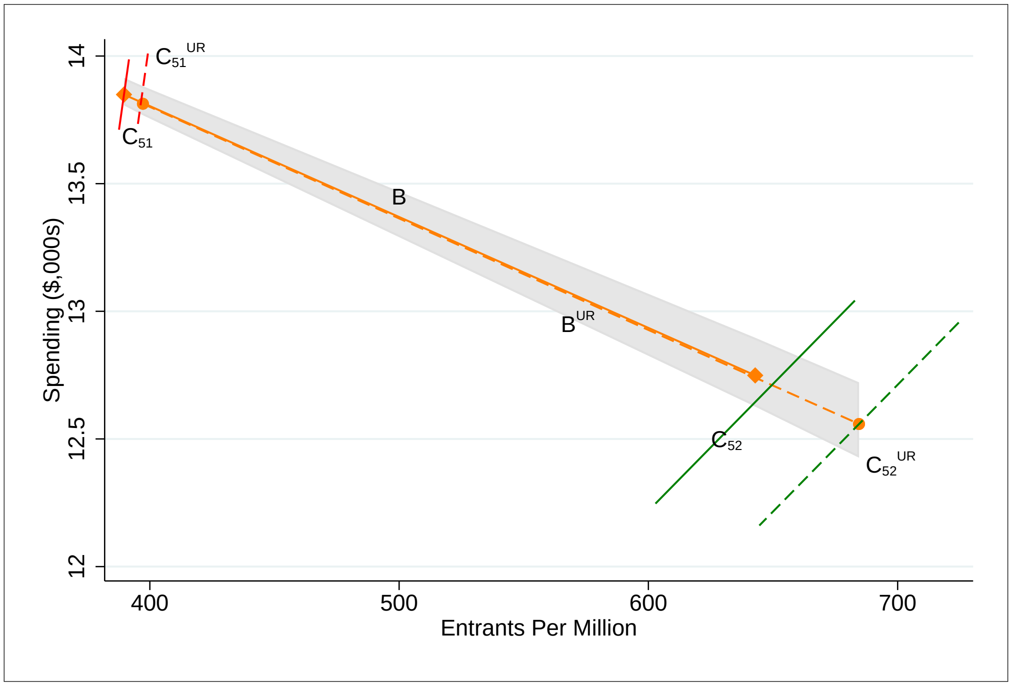


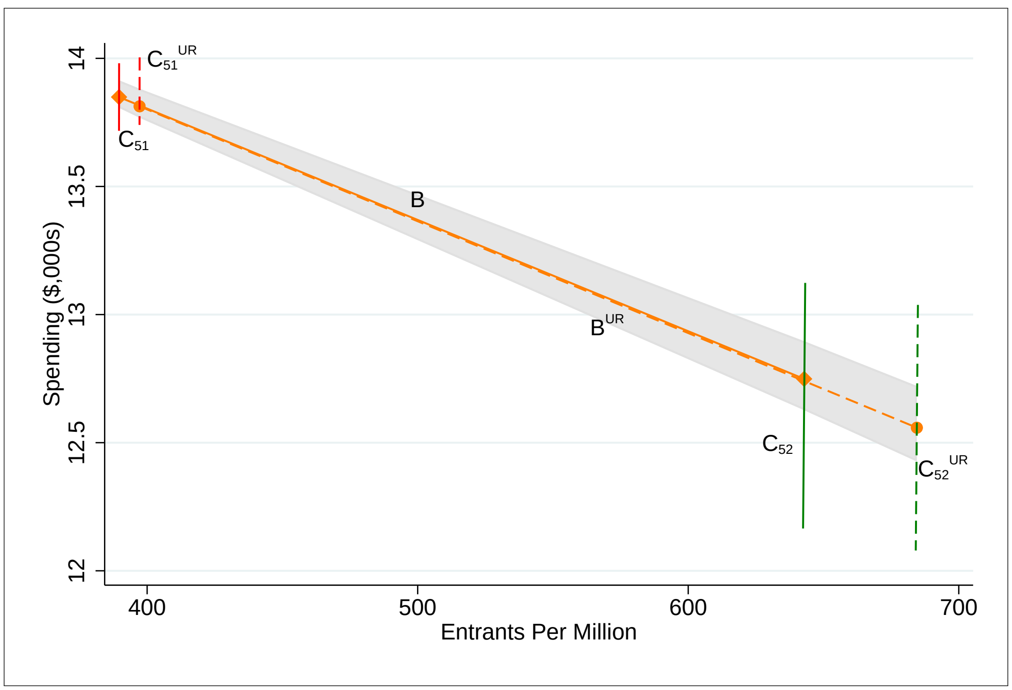
Figure A.1: Distribution of Months Between Medicare Entry and DI Application

Note: Figure represents the distribution of months between DI application and Medicare entry for individuals entering DI between 1994 and 2017, top- and bottom-coded at 36 months and 0 months, respectively. Source: Disability Analysis File Public Use File.

Figure A.2: Estimates of Model Parameters When ΔC=-\$500 or ΔC=-\$50,000



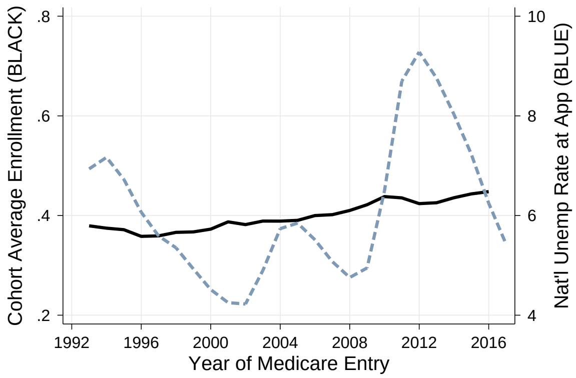
(a) ΔC=-\$500



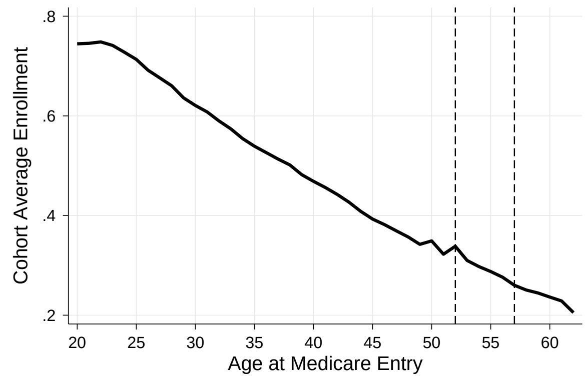
(b) ΔC=-\$50000

Note: Figure represents elements of the conceptual model, using parameters estimated from the data using the specification in the first column of 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^{UR} have the slopes and intercepts shown algebraically in Section 5.2.1. The cost functions C_{51}, C_{51}^{UR}, C_{52}, and C_{52}^{UR} have the slopes and intercepts shown in Appendix Section A.1 when ΔC takes on the stated values.

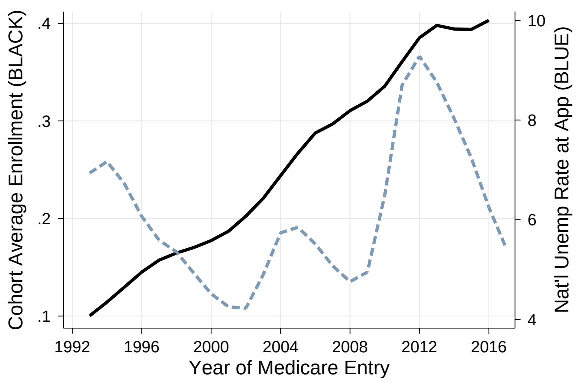
Figure A.3: Enrollment in Medicaid, Medicare Advantage, and Medicare Part B by Calendar Year of Medicare Entry or Age at Entry



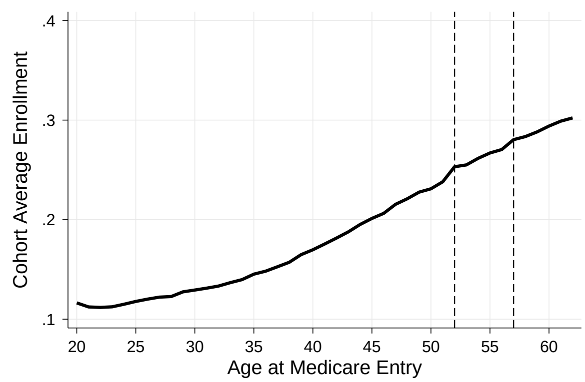
(a) Medicaid and Unemployment



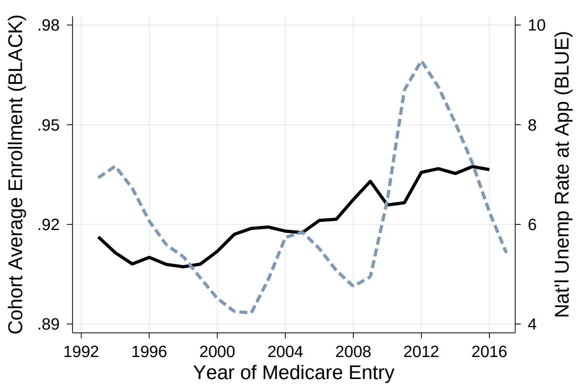
(b) Medicaid and Age at Entry



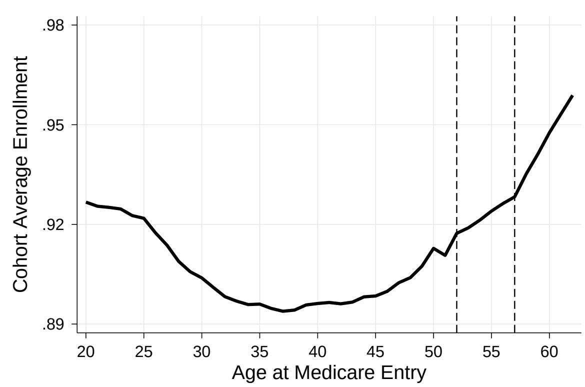
(c) Medicare Advantage and Unemployment



(d) Medicare Advantage and Age at Entry



(e) Medicare Part B and Unemployment



(f) Medicare Part B and Age at Entry

Note: Panels (a), (c), and (e) represent 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 diamonds. 95% CIs estimated from standard errors clustered on the county by entry month are reported in gray.

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: Impact of Number of Unemployment: Maestas, Mullen, and Strand Model

Dep. Var.: DI Entrants, County × Entry-Month			
Number Unemployed at Application	0.0040427** (0.0004359)	0.0015694** (0.0002595)	0.0014903** (0.0002473)
Fixed Effects		County	County Entry Month
Implied Effect of 1pp on Number of Entrants	5557 (599)	2157 (357)	2048 (340)
Implied Effect of 1pp on Incidence	18.9 (2.0)	7.3 (1.2)	7.0 (1.2)
N		937,500	

This 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. 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 3.2. Standard errors are clustered on the county. We follow the authors in converting the coefficient estimates into 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. To facilitate comparisons with Table 1, we subsequently convert those numbers to incidence by dividing by the average population over the time period.

Table A.3: Estimates of Model Parameters

	(1)
A. Parameters of Benefits Functions	
slope of B: m	-4.76 (0.16)
intercept of B: n	15,703 (49)
slope of B^{UR}: m^{UR}	-4.57 (0.13)
intercept of B^{UR}: n^{UR}	15,688 (41)
difference in slopes: $m^{UR} - m$	0.19 (0.06)
difference in intercepts: $n^{UR} - n$	-15 (17)
B. Parameters of Cost Functions, Assuming ΔC=-$5000	
slope of C_{51} and C_{51}^{UR}: m_{51}	662 (22)
intercept of C_{51}: n_{51}	-244,002 (8,355)
slope of C_{52} and C_{52}^{UR}: m_{52}	118 (1)
intercept of C_{52}: n_{52}	-63,191 (841)
Entry fixed effects	County
Spending fixed effects	County $\times$ Years enrolled

Notes: 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 5.2.1. Panel B reports the slopes and intercepts of cost functions using the equations in Appendix Section A.1 and an assumption on ΔC. To bootstrap standard errors, we resample county $\times$ entry-month units with replacement 100 times, estimating regression parameters (αs and βs) and calculating model parameters for each sample.