PRELIMINARY

Disability Insurance Income Saves Lives[*]

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Abstract

We show that higher payments from U.S. Social Security Disability Insurance (DI) reduce mortality. Using administrative data on all new DI beneficiaries from 1997 to 2009, we exploit discontinuities in the benefit formula through a regression kink design. We estimate that $1,000 in annual DI payments decreases the annual mortality rate of lower-income beneficiaries by around 0.1 to 0.25 percentage points, implying that the elasticity of annual mortality with respect to annual DI income is around -0.6. These mortality effects imply large benefits that have not been taken into account in the welfare analysis of DI and other social income insurance programs.

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I. Introduction

According to classic public finance theory, the welfare effects of social income insurance programs like Social Security, disability insurance, unemployment insurance and workers' compensation are judged by trading off the protections they provide through reducing consumption risk against the moral hazard costs from the resulting reductions in labor supply (Baily 1978, Chetty 2006, Chetty and Finkelstein 2013). In evaluating this tradeoff empirically, consumption has been measured in a way that excludes health consumption (Gruber 1997, Chetty 2008, Meyer and Mok 2013). If such programs affect life expectancy or health more broadly, then this could have important additional consequences for evaluating their benefits relative to their costs. This could be particularly important for programs that focus on populations in poor health.

The primary goal of this paper is to examine how disability insurance income affects beneficiaries' mortality. Disability insurance is a key part of the safety net provided by social insurance programs, as it protects workers and their families from the major economic risks associated with a permanent disability that prevents or limits work. U.S. Social Security Disability Insurance (DI) currently insures over 150 million American adults against these risks, and in 2016 paid approximately $147 billion to 11 million disabled workers and their families (Social Security Administration (SSA) 2016). Beneficiaries are heavily dependent on such payments: 80 percent are in households that receive more than half of their income from DI, and 31 percent are in households that had no income other than from DI (Bailey and Hemmeter 2014). DI beneficiaries are also in poor health: approximately 14 percent of those who entered DI between 2006 and 2010 died within four years, a mortality rate that is roughly ten times the rate for working-age adults in the general population (Arias 2014, Zayatz 2015).

Given these characteristics, a fundamental policy question is whether DI income improves the health of those who receive it. There is a surprising lack of evidence on this question, apart from a study using Dutch disability reforms that found opposite-signed effects of DI income on health for men and women (Garcia-Gomez and Gielen 2014). One reason may be the difficulty in identifying causal effects of income on health for a program that specifically targets people whose health is poor, leading to potential reverse causality concerns (Smith 1999).

Other evidence is limited to the larger literature on how income affects health in non-DI contexts.[2] That larger literature provides little guidance for evaluations of DI in particular, however: DI beneficiaries' high mortality rates and low average income suggest they could exhibit a different-sized effect of income on health than other populations. Direct estimates of the impact of DI income on health promise to shed light on the benefits of DI, as well as illustrate the broader importance of incorporating health-related benefits in the evaluation of social income insurance programs. They are also relevant to current policy, as changes to DI benefit levels were considered in the President's Fiscal Year 2014 Budget (Office of Management and Budget 2013) and discussions preceding the Bipartisan Budget Act of 2015.[3]

To the best of our knowledge, none of the existing literature has studied the causal effects of DI payments on health outcomes in the U.S. or considered the implications of such health effects for benefit-cost analysis of social income insurance programs in general, or DI in particular.[4] Chetty and Finkelstein (2013) note the limited attention given to the potential benefits of DI: "One particularly important program that has received relatively little attention in terms of measuring benefits and welfare consequences is disability insurance" (*p*. 189). In considering the potential benefits of DI, studies of the welfare effects of DI largely focus on its value for smoothing consumption or reducing income volatility, without considering direct measures of health outcomes (*e.g.*, Bound, Cullen, Nichols, and Schmidt 2004, Chandra and Samwick 2005, Ball and Low 2009, Meyer and Mok 2013, Low and Pistaferri 2015, Autor, Kostøl, Mogstad, and Setzler 2017).[5] The scant evidence on the causal health effects of DI contrasts with the large

[2] A large literature spanning many disciplines has established that there is a strong positive correlation between income and good health, including reduced mortality and morbidity (*e.g.* Kitigawa and Hauser 1973). However, in some cases it has been difficult to establish whether these observed correlations are due to a causal relationship of income being protective of health (Smith 1999, Deaton 2003). For examples of studies that examine the health effects of income from social insurance or transfer programs other than DI, see Duflo (2003), Case (2004), Jensen and Richter (2004), Snyder and Evans (2006), Salm (2011), Barham and Rowberry (2013), Evans and Garthwaite (2014), Aizer *et al.* (2016), and Hoynes, Schanzenbach, and Almond (2016). For examples of studies that use other types of income, see Preston (1975), Preston and Taubman (1994), Ruhm (2000), Deaton and Paxson (2001), Case, Lubotsky, and Paxson (2002), Akee *et al.* (2013), and Cesarini *et al*. (2016). A related question is how employment or job displacement affects health (Sullivan and von Wachter 2009).

[3] See https://www.washingtonpost.com/news/wonk/wp/2015/10/27/big-changes-to-disability-benefits-could-be-possible-with-this-budget-deal/?utm_term=.25979bae29ef

[4] Other literature has investigated the effect of health insurance on health and its value, *e.g.* Card, Dobkin, and Maestas (2009), Almond, Doyle, Kowalski, and Williams (2010), Finkelstein *et al.* (2012), or Finkelstein, Hendren, and Luttmer (2015).

[5] Deshpande (2016) also examines how Supplemental Security Income for low-income youth affects income volatility. See Diamond and Sheshinski (1995) for a theoretical exploration of optimal DI.

and growing literature quantifying the costs associated with the reduction in work due to disability insurance.[6]

We estimate the causal effect of income on mortality by using a Regression Kink Design (RKD) applied at three "bend points" in the formula that determines DI benefit amounts. The monthly DI payment – known as the Primary Insurance Amount (PIA) – is a progressive function of a beneficiary's Average Indexed Monthly Earnings (AIME), which are the average of past earnings in Social Security-covered employment over the individual's highest-earning years. As shown in Figure 1, the marginal rate at which PIA replaces AIME discontinuously changes at two "bend points": it changes from 90 percent to 32 percent at the "lower bend point" and from 32 percent to 15 percent at the "upper bend point." In addition to these two bend points, family payment rules create a third bend point where the marginal replacement rate for a family's combined benefits to the primary beneficiary and dependents changes from 85 percent to 48 percent of AIME. We refer to this as the "family maximum bend point." We use SSA microdata on all new DI beneficiaries from 1997 to 2009, covering 3,648,988 beneficiaries in the full sample. Our primary outcome is the average annual mortality rate during the first four years on DI. It is important to note that Medicare eligibility and other program rules do not vary around the bend points, which implies we will estimate the impact of DI income rather than DI eligibility *per se*.[7] Our RKD estimates will therefore reflect treatment-on-the-treated effects at each of these bend points (Card *et al.* 2015). Intuitively, the RKD allows us to assess whether there are sharp changes in the slope of the relationship between mortality and our assignment variable that correspond to the sharp changes in DI payments as a function of AIME at these bend points.[8]

We find that DI payments reduce mortality, particularly among lower-income beneficiaries. At the lower bend point, corresponding to the fourth percentile of AIME among DI

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[6] For example, see Bound (1989), Gruber and Kubik (1997), Gruber (2000), Black, Daniel, and Sanders (2002), Autor and Duggan (2003), Chen and van der Klaauw (2008), von Wachter, Song, and Manchester (2011), Weathers and Hemmeter (2011), Campolieti and Riddell (2012), Maestas, Mullen, and Strand (2013), Borghans, Gielen, and Luttmer (2014), French and Song (2014), Gubits, Lin, Bell, and Judkins (2014), Kostøl and Mogstad (2014), Autor, Maestas, Mullen, and Strand (2015), Moore (2015), Coile (2016), and Gelber, Moore, and Strand (forthcoming). For a review of earlier work, see Bound and Burkhauser (1999).

[7] Weathers and Stegman (2012) study the health effects of accelerating Medicare eligibility for new DI beneficiaries.

[8] We have previously used this identification strategy and context to examine the effect of DI income on beneficiary earnings (Gelber, Moore, and Strand forthcoming). For more background on the RKD, see Card *et al.* (2015).

recipients where annual DI income is \$8,543,[9] we estimate that an increase of \$1,000 in annual DI payments decreases beneficiaries' annual mortality rate by 0.26 percentage points. At the family maximum bend point, corresponding to the 30th percentile of AIME for the primary beneficiary where annual DI income for the primary beneficiary is \$12,648 and a further \$6,324 is paid for the beneficiary's dependent(s), we estimate that an increase of \$1,000 in annual DI payments decreases beneficiaries' annual mortality rate by 0.09 percentage points. These estimates correspond to elasticities of mortality with respect to DI income of -0.56 and -0.57, respectively. Around the upper bend point, corresponding to the 84th percentile of AIME where the primary beneficiary receives \$20,777 per year, we find no robust evidence of an effect, though our confidence intervals cannot rule out substantial effects. We perform several robustness and placebo tests to verify that our estimates at the lower and family maximum bend points represent true causal policy effects, as opposed to an underlying non-linearity in the relationship between mortality and AIME.

Our baseline point estimates show that it costs around \$59,000 to save an additional life year at the lower bend point, and about \$237,000 at the family maximum bend point. \$50,000 is considered the "lower boundary" on the value of a statistical life year (VSLY) measure recommended by the latest major expert panel (Neumann, Cohen, and Weinstein 2014, Neumann *et al.* 2017). Therefore, our results suggest that the gains in life expectancy we document represent an important benefit of DI not recognized in previous estimates of optimal disability insurance benefit levels.

By identifying a group of Americans for whom income strongly affects life expectancy, our findings also inform the literature on the economic determinants of health in general. Relative to ours, other estimates of the effect of income on health in developed countries in modern times are generally much smaller (Cutler, Deaton, and Lleras-Muney 2006). However, our estimates of the elasticity of mortality to income of around -0.56 are near the middle of the range found in previous literature for high-mortality, low-income groups in other contexts, including old-age pensioners in Russia (-0.94 in Jensen and Richter 2004), U.S. Union Army veterans receiving pensions in the early 1900s (-0.57 in Salm 2011), and elderly recipients of conditional cash transfers in Mexico (-0.18 in Barham and Rowberry 2013). Our results show

[9] All dollar amounts are expressed in 2013 dollars.

that the lifespan of individuals in the U.S. with disabilities and low lifetime income can benefit from additional income in ways that are similar to individuals in less developed economies or from earlier time periods. Going beyond previous literature on social income insurance and mortality in developed or developing countries, we calculate the gross welfare benefits of these transfers' effects on mortality. Our results on DI highlight the more general lesson that these benefits can be large in income insurance programs that transfer income to vulnerable populations in the modern, developed country context.

The remainder of the paper is structured as follows. Section II describes the policy environment. Section III explains our identification strategy. Section IV describes the data. Section V shows our graphical analysis and RKD estimates of the effects. Section VI discusses implications for the welfare analysis of DI. Section VII concludes. The online appendix contains additional material.

II. Policy environment

DI insures workers for disabilities that limit their ability to work.[10] The rules determining DI payments form the basis for our identification strategy. A DI primary beneficiary's PIA, which is the monthly payment the beneficiary will receive, is calculated using their AIME. AIME depends on annual earnings from the age of 21 to a disabled worker's date of eligibility for DI. Earnings are converted to current values using the National Average Wage Index (NAWI), and then the lowest one-fifth of earnings years – up to five years – are dropped.[11] Earnings in the remaining years are averaged and converted to monthly values to establish the AIME.

[10] Beneficiaries qualify for DI because they are judged to have disabilities that prevent them from earning above the "Substantial Gainful Activity" limit. The Social Security Act, Section 223(d), defines disability as the "inability to engage in any substantial gainful activity by reason of any medically determinable physical or mental impairment which can be expected to result in death or which has lasted or can be expected to last for a continuous period of not less than 12 months." In Gelber, Moore, and Strand (forthcoming) we used an RKD based on bend points in the PIA-AIME relationship, in combination with SSA administrative data, to identify the effect of DI benefit payments on earnings. Thus, some of the background discussion in this paper, particularly in the Policy Environment, Empirical Strategy, and Data sections, overlaps and draws on Gelber, Moore, and Strand (forthcoming). However, the results in this paper are entirely new as they address a different outcome, mortality.

[11] Earnings are converted to the year of eligibility using the NAWI with a two-year lag (*e.g.*, 2007 earnings are scaled by NAWI values for 2005). At least two years must be used in the AIME computation. Disabled workers who have fewer than three years discarded from the AIME calculation (under the rule dropping one-fifth of low earnings years), may have up to three additional years removed based on child care if they had no earnings and a child aged under three years. See SSA (2015) for more information.

AIME is converted to PIA using a formula designed to provide higher replacement rates for individuals with relatively poor earnings histories. For DI beneficiaries who became eligible in 2013, PIA was equal to 90 percent of the first $791 of AIME, plus 32 percent of the next $3,977 of AIME, plus 15 percent of AIME over $4,768; see the solid line in Figure 1. The formula creates kinks in the graph at $792, where the marginal replacement rate declines from 90 percent to 32 percent, and at $4,769, where the marginal replacement rate declines from 32 percent to 15 percent.[12] We follow SSA terminology by referring to these as "bend points": the initial change in the marginal replacement rate is the "lower bend point," and the second change is the "upper bend point."[13] The bend points were set through the 1977 Social Security Act Amendments and are adjusted annually based on the NAWI. Policy-makers crafting this law set the bend points in order to achieve Social Security benefit levels that were both progressive and financially sustainable, but not with the direct aim of achieving particular effects on outcomes such as mortality (Kelley and Humphreys 1994).

Another kink in the relationship between AIME and DI payments is created by the "family maximum" rules, which determine the benefits that can be paid to the disabled worker and their spouse and children (Romig and Shoffner 2015). Dependent payments are made for family members who are expected to have relied on the primary beneficiary financially; these are typically children under 18 or a spouse caring for children under 16.[14] Dependents receive 50 percent of a primary beneficiary's PIA, subject to the cap created by the family maximum rules.[15] This cap specifies that the total DI benefits a family receives from a worker's earnings record cannot be greater than 85 percent of AIME or 150 percent of PIA. (It also cannot be less than PIA.) For DI beneficiaries with dependents, what we will call the "family maximum bend point" occurs at the AIME level at which the binding rule changes from the 85-percent-of-AIME

[12] For clarity, note that "kink" is used both to describe the change in the PIA-AIME schedule at the bend points, and the change in slope in the outcome variable around the bend points.

[13] In practice, the PIA is capped both by the maximum tax paid annually on covered earnings, and also maximum family benefit rules that we discuss below. See SSA (2013) for more information.

[14] A (former) spouse can receive benefits at any age if he or she is caring for children under age 16. The majority of dependents are minors: among DI awards made in 2013, 76 percent of dependents were children under 18. A further 11 percent were spouses caring for children aged under 16, eight percent were students aged 18 or 19, and five percent were disabled adult children (SSA 2015).

[15] If an auxiliary DI beneficiary designates the "representative payee" as the primary beneficiary, the auxiliary's DI payments are paid as one payment to the primary beneficiary. For auxiliary beneficiaries who do not designate a representative payee or who designate another individual as the representative payee, the primary beneficiary does not physically receive this payment.

rule below the bend point, to the 150-percent-of-PIA rule above the bend point.[16] As shown in Figure 1, in 2013 this bend point occurs where AIME is $1,860. The primary beneficiary's marginal replacement rate is 32 percent at that point. Thus, when considering the determination of total family benefits, at the bend point the marginal replacement rate for each dollar of AIME changes from 85 percent (under the 85-percent-of-AIME rule) to 48 percent (*i.e.*, 150 percent of the 32 percent replacement rate). The family maximum rules imply that the total payments to dependents are the same regardless of whether there are one or multiple dependents.

We therefore have three bend points at which the marginal relationship between DI benefits and AIME changes: the lower and upper bend points that affect the DI payments to the primary beneficiary, and the family maximum bend point that affects the total family DI payments to primary beneficiaries plus their dependents.

Two policy issues affect how we interpret the policy variation around the lower bend point. The first relates to how family maximum rules affect DI payments near the lower bend point. Dependent benefits are not paid at low levels of AIME, because the initial 90 percent marginal replacement rate exceeds the 85-percent-of-AIME cap on total family payments. As a result, the marginal replacement rate at which AIME is converted to total family payments in this range is 90 percent. As illustrated in Figure 1, once AIME reaches a sufficient level that PIA is equal to 85 percent of AIME, which occurs at an AIME that is $75 higher than the AIME at the lower bend point, the family-level marginal replacement rate becomes 85 percent (due to the 85-percent-of-AIME cap). Thus, for beneficiaries with dependents, there is little change in this marginal replacement rate around the lower bend point. This attenuates the marginal change in DI income at the lower bend point for all beneficiaries (*i.e.*, combining both those with dependents and without), relative to the change we would observe only for beneficiaries without dependents. However, due to data limitations we cannot confidently identify whether a beneficiary near the lower bend point has dependents.[17]

[16] The term "family maximum bend point" could also refer to the rules for the maximum family payments for Old Age and Survivors Insurance (OASI), which are different. We use the term as it applies to DI.

[17] We cannot confidently identify whether a beneficiary has dependents near the lower bend point because the family maximum differentially affects the incentive to report dependents below *vs.* above the lower bend point: additional dependents lead to additional benefits above, but not below, the lower bend point. Appendix Figure A1 shows that the number of beneficiaries with reported dependents indeed increases sharply above the lower bend point (even though the number of beneficiaries does not rise sharply, as shown in Figure 2). Appendix Table A1 confirms that the fraction of the sample with dependents rises discontinuously at the lower bend point.

The second issue is how Supplemental Security Income (SSI) interacts with DI for "dual-eligible" beneficiaries, *i.e.* beneficiaries who are eligible for both programs. SSI provides cash and Medicaid to disabled individuals who, apart from a home and a car, have only a few thousand dollars in assets. The monthly SSI federal benefit rate for individuals in 2013 was \$710.[18] Most individuals who are eligible for both SSI and DI receive only DI, with two exceptions. First, some newly awarded DI beneficiaries are eligible for SSI but have DI benefits that are greater than their SSI benefits; these beneficiaries still can claim SSI benefits during the DI waiting period, which is at most five months (there is no waiting period for SSI), after which they receive only DI. Second, some DI beneficiaries have a PIA that is less than the SSI federal benefit rate. These individuals receive both DI and SSI benefits on an ongoing basis (as well as SSI during the DI waiting period). These beneficiaries' total benefits, summing DI and SSI, are equal to the SSI federal benefit rate (with the SSI program paying the difference between their DI benefit and the SSI federal benefit rate).

For dual-eligible beneficiaries whose AIME puts them under the lower bend point, SSI eligibility therefore implies that total disability payments (summing over DI and SSI) do not change as a function of AIME. The SSI monthly payment amount of \$710 is nearly identical to \$712, the PIA they would receive if they had an AIME that put them at the lower bend point. In effect, this implies that for dual-eligibles the slope of total disability benefits as a function of AIME increases from zero to 32 percent near the lower bend point (as opposed to the change from 90 to 32 percent among non-dual-eligibles). However, it is difficult to exploit this change, as other policy variation also affects dual-eligibles around the bend point. Those with a PIA below the SSI monthly Federal Benefit Rate and who meet SSI's other qualifications including its asset test are eligible for Medicaid through SSI, whereas those above are only eligible for Medicare through DI after a waiting period. Those below are subject to SSI's 50 percent benefit reduction rate for current earnings greater than \$65 a month, whereas those above are not. SSI eligibility also weakens the role of the family maximum rules, as DI benefits replace SSI payments one-for-one, and this applies to DI dependent benefits and SSI benefits for children.

[18] Most states supplement this with additional cash payments. SSI recipients also generally receive Medicaid coverage and food stamp (Supplemental Nutrition Assistance Program, SNAP) eligibility; in California, SSI recipients receive a supplement in lieu of SNAP. They are subject to more restrictive work rules that include benefit reductions for earnings above \$65 per month.

To address these issues with the dual-eligible sample, we remove DI beneficiaries from our sample who also receive SSI during the waiting period and/or concurrent with DI receipt.[19] By removing dual-eligibles we remove those who are eligible for Medicaid through SSI, and the population we study is therefore solely on Medicare, not Medicaid, during the period we study. Medicaid eligibility – which depends on current income, assets, and family structure – therefore does not systematically vary around the bend points, which are determined by lifetime earnings as reflected in AIME. We verify that the probability of being dually eligible for DI and SSI is smooth around the bend points, consistent with the supposition that SSI receipt is not a margin on which there is sorting in relation to the bend points.

III. Empirical strategy and interpretation of estimates

A. Identification strategy

We exploit this policy variation using an RKD, which uses a change in the slope of treatment intensity to identify local treatment effects by comparing the relative magnitudes of the kink in the treatment variable and the induced kink in the outcome of interest. Estimates can be interpreted as a "treatment-on-the-treated" parameter (Card *et al.* 2015).[20] In our context, the treatment intensity is the size of DI benefits (*i.e.*, the PIA or the family maximum), the assignment variable is the AIME observed when the individual first applies for DI, and our primary outcome variable is the mortality rate of beneficiaries after entering DI.

Mathematically, we want to estimate the marginal effect of DI benefits (B) on the probability of mortality (Y). Benefits depend on AIME (A). Using the RKD, we can estimate the marginal effect around a given bend point A_0 as:

$$E\left[\frac{\partial Y}{\partial B}\middle|A = A_0\right] = \frac{lim_{A\to A_0^+}\frac{\partial E[Y|A = A_0]}{\partial A} - lim_{A\to A_0^-}\frac{\partial E[Y|A = A_0]}{\partial A}}{lim_{A\to A_0^+}\frac{\partial E[B|A = A_0]}{\partial A} - lim_{A\to A_0^-}\frac{\partial E[B|A = A_0]}{\partial A}} \quad (1)$$

That is, the marginal effect we estimate is the change at the bend point in the slope of mortality as a function of AIME, divided by the change in the slope of DI benefits. Mortality is often analyzed with a hazard model (*e.g.* Cox 1972); however, the econometrics of RKD have not been established for hazard models (*cf.* Calonico, Cattaneo and Titiunik 2014, Card *et al.* 2015).

[19] It is not feasible to use our identification strategy on the combined population of dual-eligibles and non-dual-eligibles around the lower bend point, because the change at the lower bend point in the mean marginal replacement rate averaged over dual-eligibles and non-dual-eligibles is close to zero.
[20] Recent work applying the RKD includes Manoli and Turner (2014) and Landais (2015).

Identification of the effect of DI benefits on mortality through this RKD relies on two key assumptions (Card *et al.* 2015). First, in the neighborhood of a bend point, the direct marginal effect of the assignment variable on the outcome of interest must be smooth (*i.e.*, continuously differentiable). Second, conditional on unobservables, the density of the assignment variable is continuously differentiable in this neighborhood. These assumptions may not hold if we observe sorting in relation to the bend points, as indicated by a change at a bend point in the slope or level of the density of the assignment variable, or in the distribution of predetermined covariates.

Such sorting appears implausible in our context and would be surprising to find in the data. Our assignment variable is AIME from the year of applying for DI ("initial AIME"). Because this is measured before individuals go on DI, it cannot be affected by earnings while on DI. Because calculating PIA on the basis of an individual's earnings history is complex, it is difficult for individuals to estimate precisely where their earnings history will put them in relation to the bend points. Typically, the AIME calculation takes account of many years of earnings history: in 2012, 66 percent of DI entrants were aged 50 years or older and thus had a relevant earnings history lasting 28 or more years (SSA 2013). This, together with the use of lagged values from the NAWI to adjust both earnings and bend points and the dropping of the lowest-earnings years, makes it hard for DI applicants to generate a particular AIME. Moreover, individuals are often unaware of relevant Social Security rules (Liebman and Luttmer 2015). Even if individuals were aware of these rules, they would typically have to change their earnings over long periods of time to change their AIME substantially. This is especially difficult for disabled workers, who typically experience decreasing earnings trajectories in the years before applying for DI (von Wachter, Song, and Manchester 2011). A year just prior to applying for DI would typically be among the lowest-earning years and would therefore be excluded from the AIME calculation.

B. RKD implementation

The identification results for RKD are relatively new (Nielsen, Sørensen, and Taber 2010, Calonico, Cattaneo, and Titiunik 2014, Card *et al.* 2015), and many issues related to its empirical implementation are unsettled. We follow available guidance for the RKD and – where none is available for the RKD – guidance for the regression discontinuity design (RDD), while also assessing the robustness of the results to alternative choices.

We use a "sharp" RKD as our main specification. When B is a deterministic function of A, the denominator of (1) is known and only the numerator needs to be estimated. The determination of PIA and family maximum on the basis of AIME is determined by law. Moreover, we show that the observed DI benefits are nearly identical to the Social Security formulas.[21] Accordingly, in our main specification we assume that the PIA depends deterministically on the AIME as shown in Figure 1, and we estimate only the numerator of (1), the change in the slope of the conditional expectation of the mortality rate at the bend point. If the relationship between the mortality rate Y and AIME is linear, then we can estimate:

$$Y_i = \beta_0 + \beta_1(A_i - A_0) + \beta_2(A_i - A_0)D_i + \varepsilon_i \qquad (2)$$

where i indexes observations and $D_i = 1[A \geq A_0]$ is a dummy for being above the bend point. We limit the analysis to observations for which $|A\text{-}A_0| \leq h$, where h is the bandwidth size. The slope of the mortality rate as a function of AIME below the bend point is captured by β_1, and we test for a change in slope in that relationship at the bend point by examining whether β_2 is significantly different from zero. Our primary coefficient of interest is therefore β_2. ε_i is an error term. Following Card *et al.* (2015, 2017) we use White robust standard errors. For small changes in income, we postulate that the relationship between DI income and mortality can be characterized as linear and use a linear probability model as our baseline, but we verify in the Appendix that our results are materially unchanged under a grouped logit specification.

Our main outcome of interest is the mean annual mortality rate averaged over the first four years that individuals receive DI, which we calculate as the probability of dying within four years of initially receiving DI divided by four to put this in annual terms. We calculate mortality rates using data aggregated to bins that span \$50 of AIME, which is the largest size at which all of our dependent variables pass the two tests of excess smoothing for RDD recommended by Lee and Lemieux (2010). In other words, in each of these bins, we compute the mortality rate in each year, and then we take the mean of the annual mortality rate across these four years in each bin. Thus, i indexes bins in equation (2). By averaging data within each bin, we estimate standard errors that we view as conservative, following another of Lee and Lemieux's (2010) suggestions

[21] We show that the average difference between actual and estimated PIA is \$1.80 around the lower bend point, \$2.18 around the family maximum bend point, and \$2.62 around the upper bend point. We also verify that a "fuzzy" RKD that uses actual DI payments to estimate the denominator in (1) produces similar results.

in the RDD context.[22] We also show results when estimating our regressions at the individual level and using other bin sizes.

A key issue is the choice of bandwidth. Several bandwidth selection algorithms have been proposed for RKD, including a MSE-optimal "data-driven" procedure (Calonico, Cattaneo, and Titiunik 2014) and a "rule-of-thumb" procedure (Card *et al.* 2015). Card *et al.* (2017) caution researchers against assuming there is a default procedure, and show that different approaches may perform better or worse depending on the empirical application. We adopt the following approach. We implement the bandwidth selection procedures recommended by Calonico, Cattaneo, and Titiunik (2014), and choose the symmetric bandwidth that minimizes MSE (rounded to $50 to match our use of bin-level data). For the average four-year mortality rate – our main outcome of interest – our bandwidths are $400 at the lower bend point, $700 at the family maximum bend point and $650 at the upper bend point.[23] We use these respective bandwidths throughout the analysis wherever possible, as doing so allows a direct comparison of different results for the same bend point. We also report estimates using our main specification for a wide range of bandwidths to assess the robustness of the results to this choice.

Another issue is how to control for the underlying relationship between the assignment variable and our outcomes. A variety of approaches have been adopted.[24] Our initial specification (2) controls for the linear term (A-A_0). A linear specification should be appropriate if there is a constant marginal relationship between income and mortality, as might be expected when using a narrow range for income. However, we also wish to address the possibility that the baseline relationship between the mortality rate and AIME is better captured through the addition of higher-order terms to (2), such as quadratic or cubic terms. Our approach therefore is to estimate versions of equation (2) with (a) linear, (b) linear and quadratic, or (c) linear, quadratic, and cubic terms in AIME, demonstrating robustness to all three choices.

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[22] This choice also implies that we use a continuous dependent variable instead of a binary one. Our approach therefore avoids issues related to estimation and inference when a binary outcome is relatively uncommon, which is relevant here as the probability of death for any one individual can be relatively low.
[23] At the lower bend point, the AIME of $791 constrains the bandwidth to a value less than that (given that we seek to use a symmetric bandwidth). In practice, there are almost no observations below an AIME of $200, as beneficiaries with such low earnings are unlikely to have sufficient quarters of coverage to qualify for DI.
[24] Card *et al.* (2015) use linear and quadratic specifications. Calonico, Cattaneo and Titiunik (2014) propose an RKD estimator where a quadratic term in the assignment variable can be used to correct the bias in the linear estimator. Ganong and Jäger (2014) argue that cubic splines perform better than other estimators.

Two final issues are whether to allow for a discontinuity in the level of the mortality rate at the bend points and whether to control for covariates. When treatment effects are heterogeneous, the imposition of continuity is necessary for change in slope at the bend point to be considered a causal parameter (Card *et al.* 2015). However, Ando (forthcoming) suggests that there are concerns that imposing continuity increases the likelihood of spurious results, while also arguing the addition of covariates minimizes the likelihood of spurious results. As robustness checks, we implement specifications allowing for a discontinuity or controlling for covariates.

C. Interpretation of the estimates

We interpret our RKD results as reflecting the effects of greater DI transfer payments on mortality. *A priori*, greater DI transfer payments could lead either to decreases or increases (or no change) in mortality. For example, increased DI transfer payments could lead individuals to purchase more of goods that allow them to avoid mortality (*e.g.*, a better diet or treatment for disability-related conditions). On the other hand, increased DI transfer payments could lead individuals to work less (Gelber, Moore, and Strand forthcoming), and working less could lead to increased mortality (see, *e.g.*, Snyder and Evans 2006, Fitzpatrick and Moore 2017).[25] Our estimates should be interpreted in light of the fact that current and future monthly DI and subsequently OASI payments will generally be identical, except when individuals receive DI back pay in the first month of DI receipt to cover retroactively the period between becoming disabled and DI receipt. This is because PIA is highly stable once someone begins to receive DI, and individuals generally collect DI until reaching the OASI Normal Retirement Age between 65 and 66 in the period we study (Gelber, Moore, and Strand 2017).

The group whose "treatment on the treated" effects we identify consists of those with AIME around the bend points. Our estimates represent the effects of changing DI benefit payments while holding other factors constant, thus holding constant variation stemming from the DI application process, the role of Medicare, or DI earnings rules. Like other papers based on local variation, including others in the DI literature, our identification strategy does not attempt to estimate general equilibrium impacts of DI.

[25] We interpret the estimates as income effects, as the changes in DI transfers around the bend points do not create substitution effects (Gelber, Moore, and Strand forthcoming).

It is also important to clarify the role of dependent payments in interpreting the estimates. In our sharp RKD specification at the lower and upper bend points, the first stage only measures payments to the primary beneficiary. Measuring the first stage in this way effectively corresponds to an extreme case in which primary beneficiaries' mortality is not influenced by their dependents' DI benefits. However, it is possible that the primary beneficiary's mortality is also influenced by the benefits paid to his or her dependents. For example, one alternative assumption is a "unitary" model of the family, in which the family acts as if it maximizes a single utility function and therefore pools the unearned income of all family members (Becker 1976). This would have implications for the interpretation of the estimates at each of the bend points.

As discussed in Section II, when considering overall DI payments to the family in the full sample near the lower bend point, the "first stage" relationship between DI benefits and AIME is attenuated, relative to the benefit schedule shown in the solid line in Figure 1 in which the marginal replacement rate changes from 90 percent below the bend point to 32 percent above it. In particular, Figure 1 shows that there is effectively little change in the family benefit marginal replacement rate in the region surrounding the bend point for those with dependents. This implies that, relative to assuming the marginal replacement rate changes from 90 percent to 32 percent for the full sample, in the unitary model the relevant change in the marginal replacement rate measured in the denominator of (1) would be smaller. Since we make the "sharp RKD assumption" that the change in the marginal replacement rate is from 90 percent to 32 percent in the full sample, our estimate of the absolute treatment effect should be interpreted as a *lower bound* on the true absolute effect if dependent benefits affect the primary beneficiary's mortality. This is the first of several reasons described throughout the paper that we estimate lower bounds on the absolute effects. If households are not unitary, for example as in a "collective" model of household bargaining (Chiappori 1992), then payments made to a beneficiary's dependents could have a smaller effect on the beneficiary than his or her own payments.

The family maximum bend point only applies to those with dependents. Thus, at the family maximum bend point our estimates should be interpreted as the impact of variation in dependent benefits on the primary beneficiary's mortality. We find significant effects at this bend point, demonstrating that dependent benefits do indeed affect the primary beneficiary's mortality in this sample.[26]

IV. Data

To apply the RKD, we use administrative data from the 2010 version of the Disability Analysis File (DAF) (previously called the Ticket Research File). The DAF is a compilation of multiple administrative data sources from the Social Security Administration, including the Master Beneficiary Record, Supplemental Security Record, 831 File, Numident File, and Disability Control File. The DAF contains information on all disability beneficiaries who received benefits in at least one month between 1997 and 2010. It includes information on AIME and PIA. The data sources that are used to construct the DAF also provide information on each beneficiary's demographic characteristics, including age, race, and gender; DI program activity, including path to allowance (*e.g.*, whether a claimant was determined to be eligible by the initial disability examiner or through a hearings-level appeal) and the magnitude of disability payments; and exact date of death (day, month, and year) (Hildebrand *et al.* 2012). We obtained updated information on date of death through 2013 in order to extend the period over which we could track beneficiaries' mortality. Annual taxable W-2 wage earnings through 2011 are obtained by linking to the Detailed Earnings Record (DER). We do not have data on assets, total unearned income from other sources, marital status, spousal outcomes, hours worked, or cause of death.[27]

The mortality information in the DAF comes both from the Master Beneficiary Record and the Numident File. SSA receives this information from beneficiaries' family members, as well as from funeral homes, financial institutions, government agencies and postal authorities. SSA also contracts with state vital statistics bureaus to provide dates of death to manage program payments. SSA policy is to verify death reports for DI beneficiaries from sources it considers less accurate. (SSA does not verify deaths for non-DI beneficiaries, implying that mortality is measured with greater error among non-beneficiaries.) SSA data miss a small number of deaths (Government Accountability Office 2013, SSA Office of Inspector General 2012, 2017).

[26] In the unitary model, the change in marginal replacement rates for those with dependents is 50 percent larger at the upper bend point. Although we quote the crowdout estimate based on the primary beneficiary's benefit alone as a benchmark, in a unitary setting the crowdout estimates would be smaller by one third for beneficiaries with dependents (approximately one third of the sample).

[27] In the Current Population Survey over the years 2001-2010, of those reporting that "Disability causes difficulty working," 42.76 percent were married.

However, there is no evidence that the fraction of deaths that are missing varies by DI income, and no SSA policies related to death reporting depend on the size of income payments.[28] Therefore, the degree of measurement error should not change around the bend points and should not confound our variation. However, if SSA data miss a small number of deaths, we may underestimate the causal effect of DI benefits on mortality, suggesting that our estimates represent lower bounds on the true absolute effects.

We choose a sample of individuals who entered DI between 1997 and 2009 and who were aged 21 to 61 years at the time of filing. This allows us to observe whether these individuals died within a follow-up period of four years after beginning to receive DI payments, meaning the four years beginning with the first month in which recipients received DI payments. Four years is also the period following DI receipt that is used in Maestas, Mullen, and Strand (2013) and Gelber, Moore, and Strand (forthcoming). The upper age restriction to those under 61 avoids interactions with rules associated with OASI. To focus on beneficiaries whose DI payments are affected by the bend points, we also limit the sample to DI primary beneficiaries who did not receive SSI at any point in the sample period, thus eliminating dual-eligibles who collect SSI during the DI waiting period and/or on an ongoing basis.

We clean the data by removing records with missing or imputed observations of basic demographic information (*e.g.*, date of birth or sex), which reduces the sample by 2.0 percent. We also remove records in which there is no initial AIME or PIA value, or in which the stated date of disability onset used for the PIA calculation is more than 12 months before the date of filing or 17 months after the date of filing (the range over which documented date of disability onset should lie). This reduces the sample by another 5.5 percent. In addition, we remove individuals who have a PIA based on eligibility for DI under both their record and that of another worker or who had not received DI payments within four years of filing, reducing the sample by another 1.5 percent. We additionally clean the data to remove cases in which the data contain unreliable measures of AIME by removing those with more than four AIME changes, which removes 3.4 percent. The SSA data systems typically have a small number of cases with unusual or implausible records; these sample restrictions are similar to those generally made when using

[28] The role of DI eligibility in mortality reporting could matter if the variation in DI income affects DI exit rates at the bend points. However, in Gelber, Moore, and Strand (forthcoming) we show that the bend points do not affect the likelihood of exiting the DI program in order to return to work.

these data (*e.g.*, von Wachter, Song, and Manchester 2011, Maestas, Mullen, and Strand 2013, Moore 2015, Gelber, Moore, and Strand forthcoming).

At the family maximum bend point, we limit the sample to beneficiaries for whom a dependent benefit is also paid within two months of their own initial payment. This is necessary because the eligibility of dependents can change over time due to changes in marital status, the employment of spouses, and the age and education activities of children (SSA 2017), and we want to minimize error by choosing a sample that is subject to the payment formula during the period of observation. Removing beneficiaries whose auxiliary payments began outside this window removed 27.3 percent of this sample. The samples for lower and upper bend points include both beneficiaries with and without reported dependents.[29]

PIA is measured in pre-tax terms. By examining the effect of pre-tax benefits, we answer the policy-relevant question of how a given change in benefits paid by SSA would affect mortality. Since marital status and total family taxable income are not available in our data, we cannot measure the relevant tax rate. After-tax benefits are slightly smaller than pre-tax benefits—and the marginal replacement rate associated with after-tax benefits should change at the bend point by slightly less—again suggesting that our point estimate of the absolute effect of pre-tax benefits should reflect a lower bound on the absolute effect of after-tax benefits.

Table 1 shows summary statistics. In the full sample, we use data on 3,648,988 observations. Average PIA is $1,360. PIA is a monthly measure of DI payments, so that $1,360 in monthly payments translates into an annualized benefit of $16,315. Annual mortality rates in the four years after first receiving DI range between 2.6 percent (fourth year after program entry) and 7.0 percent (first year after program entry). Average age when applying is 48.6, and 53.1 percent of the sample is male. For approximately half of the sample, the primary disability is either a musculoskeletal condition (29.7 percent) or mental disorder (20.1 percent), with neoplasms (cancer) (11.6 percent) and circulatory conditions (largely heart disease) (10.3 percent) also common.

[29] Although in principle we could restrict the lower bend point sample to beneficiaries without dependents in order to address the measurement issues related to the family maximum rules described above, it would not be prudent to do so because we do not reliably measure the number of dependents around the lower bend point (see the footnote above regarding Appendix Figure A1).

The table also shows the summary statistics for samples around each of the bend points (the lower bend point, the family maximum bend point, and the upper bend point). Those around higher bend points have higher mean PIA. The lowest mortality rates are observed for the family maximum bend point sample; beneficiaries must have a dependent to be included resulting in this relatively young sample. Appendix Figure A2 shows that the lower, family maximum, and upper bend points correspond to the 4^{th}, 30^{th}, and 84^{th} percentiles of the AIME distribution, respectively.[30]

We also use data from the Consumer Expenditure Survey (CES) and Survey of Income and Program Participation (SIPP). Appendix Table A2 shows the summary statistics for samples of individuals/households whose DI income would put them close to each of the bend points (calculated by transforming observed DI income into AIME), as well as for individuals/households not receiving DI income.[31] The summary statistics show that the DI beneficiary samples have substantially lower total expenditures and net worth than does the non-DI sample, particularly for individuals or households whose DI income places them close to the lower and family maximum bend points. However, relative to the non-DI sample, health expenditures are much higher among DI beneficiaries around the family maximum and upper bend points, and are comparable around the lower bend point.

V. Graphical and Regression Analysis

In using these data, we begin our analysis with validity checks on our empirical method. Next, we estimate our main results, demonstrate their robustness, and estimate heterogeneous effects by time period and demographic group.

V.a. Preliminary analysis

As an initial validity check, Figure 2 shows that the density of the number of observations in each bin, and its slope, appear continuous around the bend points. Appendix Figure A1 shows that at AIME levels around the family maximum bend point, the fraction of the full sample with reported dependents also appears smooth. Appendix Figure A3 shows the distributions of the

[30] An AIME at the 30^{th} percentile of the distribution for the full population (combining both those with and without dependents) puts beneficiaries with dependents at the family maximum bend point.

[31] DI beneficiaries are not directly identified in the CES. However, Moore and Ziebarth (2014) show that Social Security payments are nearly always to DI beneficiaries when everyone in the household is aged under 60. Note that the CES does not necessarily capture all forms of household expenditure. For discussion of the measurement issues associated with the CES, see Meyer and Sullivan (2011) and Bee, Meyer and Sullivan (2015).

means of six predetermined covariates available in the administrative data: fraction male, fraction black, fraction allowed via hearing, fraction whose disability is a mental disorder, fraction whose disability is a musculoskeletal condition, and average age when applying for DI. All of these appear smooth through all three of the bend points. Appendix Figure A4 shows a "first stage" graph: as expected, measured PIA in the dataset shows changes in slope at the bend points in AIME in precisely the ways the policy dictates.

Our regressions in Table 2 confirm that the number of observations, these predetermined covariates, and the fraction of the potential sample that receives SSI in our sample period (shown in Appendix Figure A5), are all smooth in the region of the bend points. We adopt an approach similar to Card *et al.* (2015) by examining whether the first derivative changes at the bend point, as measured by coefficient β_2, when we run separate regressions with polynomials in AIME of order between three and five. For each dependent variable, we select the polynomial order that minimizes the finite-sample (corrected) Akaike Information Criterion (AICc) and report the change in slope at the bend point for that specification. We use our baseline specification with binned covariates and outcomes, without additional controls, and with no discontinuity in the dependent variable at the bend point. Out of 24 regressions (eight outcomes for each of three bend points), only one estimate of the change in the slope at the bend point is significantly different from zero at the ten percent level. As expected, the coefficients in these regressions are jointly insignificant around each bend point separately, and among all three bend points pooled. Appendix Table A3 verifies that there is no evidence of a change in the level of the density of the running variable around each of the three bend points. Appendix Table A1 also verifies that there is no change in the level or slope of the fraction of the sample with dependents in the full sample with AIME around the family maximum bend point. We further show in Appendix Table A4 that there is no evidence for "bunching" in the density of initial AIME.[32] Other literature has found an effect of DI payment size on DI applications and receipt (von Wachter, Song, and Manchester 2011, Black, Daniel, and Sanders 2002, Autor and Duggan 2003). Our finding, by contrast, is that we find no effect or payment variation on DI receipt locally around the bend points in

[32] We calculate "bunching" in the way described in detail in Gelber, Moore, and Strand (forthcoming), similar to the method in Saez (2010) or Chetty *et al.* (2011). Working more will not lead to higher DI income if earnings are not in the highest-earning years used to calculate AIME. The incentives around working while on DI are discussed in detail in Gelber, Moore and Strand (forthcoming).

particular; this is consistent with the expectation that the policy variation appears difficult to understand and not particularly salient.[33]

All of these results suggest that individuals do not appear to locate their AIME strategically and RKD methods are appropriate for estimating causal treatment effects. As we discussed above, it is not surprising to find that there is no sorting around the bend points given that it is difficult to understand, calculate, and manipulate AIME. In Gelber, Moore, and Strand (forthcoming), we also find that beneficiaries' earnings respond to the transfers after they go on DI, but not before. As we explain in Gelber, Moore, and Strand (forthcoming), this evidence is consistent with the possibility that DI onset occurs relatively unexpectedly, supporting the notion that the effects we document are associated with changes in transfer income that were not anticipated prior to going on DI. This is also consistent with the evidence in the current paper showing the smoothness of the covariates – including the overall density and the densities of different disabilities – and the lack of bunching. This collection of evidence suggests that individuals did not behave as if they anticipate the DI transfers, and did not change health investments in advance of DI receipt based on variation in their anticipated future DI income around the bend points (see Grossman 1972 or Philipson and Becker 1998 on such effects).

V.b. Main Results

Having demonstrated that our empirical strategy passes these tests, in Figure 3 we show the mean yearly mortality rate in the four years after DI allowance around each of the bend points. There appears to be a clear discontinuous increase in the slope of the mortality rate as a function of AIME, above the lower bend point relative to below it (*i.e.*, the negative slope becomes flatter). The estimated change in slope shown in the fitted lines fits the empirical observations well. Around the family maximum bend point, the slope also appears to increase notably at the bend point. These results suggest that a decrease in DI benefits causes an increase in mortality at these bend points. The figure shows that there is little visible change in slope at the upper bend point.

[33] The Social Security Statement workers receive could only provide an approximate measure of their likely benefits (Gelber, Moore, and Strand 2017), implying that around the bend points: (1) actual PIA should be a smooth function of PIA as estimated on the Statement; and (2) it should be difficult to choose earnings to sort around the bend point on the basis of the information provided by the Statement. This does not rule out that the Statement has some general effects on application behavior (Armour 2013).

Table 3 shows the estimated mortality effects at each of the three bend points when implementing regression (2). For ease of interpretation, we report the implied percentage point effect on the mean annual mortality rate of increasing annual DI benefits by $1,000, which corresponds to variation in AIME that lies well within our bandwidths.[34] (Appendix Table A5 shows the full set of coefficients that we rely on to generate the implied effects presented in Table 3.[35]) As the MSE-minimizing bandwidths for the quadratic and cubic specifications may be quite different to our "baseline" bandwidths, we initially report results using the Calonico *et al.* (2014) bandwidths for those specifications.

At the lower bend point, we find that an increase in DI benefits leads to a substantial reduction in mortality. In the linear model, the estimates show an elasticity of mortality to DI payments of -0.56, and an elasticity of -0.76 with respect to DI payments plus earnings (imputed at the bend point using the regressions underlying Table A5). In this specification, a $1,000 increase in DI payments causes the yearly mortality rate to decrease by 0.26 percentage points. The estimated effects are larger in the quadratic and cubic models; all three estimates are statistically significant at the one percent level. Given that we use different MSE-minimizing bandwidths for each model presented in Table 3, it is difficult to compare model fit across specifications, but when we hold the bandwidth constant across specifications we find that the linear specification minimizes the AICc. Thus, we focus most on the results of our baseline linear specification.

Recall that we interpret the (absolute value of) our estimate at the lower bend point as a lower bound. Since we estimate a large effect, the fact that this is a lower bound only strengthens our conclusion that the effect is large. To obtain a sense of the extent to which this reflects a lower bound, note that Appendix Figure A1 shows that up to around 20 percent of the sample reports a dependent once AIME is above the lower bend point in the region in which beneficiaries have an incentive to report dependents. Assuming that the change in the marginal

[34] This corresponds to an increase in the PIA of $83, which occurs at an AIME value of $144 above the lower bend point, $225 above the family maximum bend point, and $490 above the upper bend point.

[35] To calculate the estimated effects in Table 3 on the basis of the Appendix Table A5 regressions, under our sharp RKD framework we divide the estimated β_2 in Appendix Table A5 by the change in slope in the first stage shown in Figure 1. For example, for the lower bend point, we divide the coefficient by -0.58 = 0.90 – 0.32.

replacement rate is zero for those with dependents, this would imply that our reported point estimates under-state the true effect at this bend point by up to 20 percent.

We also find that an increase in DI benefits leads to a substantial reduction in mortality at the family maximum bend point. In this specification, a $1,000 annual increase in household DI payments causes a 0.091 percentage point decrease in the annual mortality rate of the primary beneficiary. The elasticity of mortality with respect to DI payments is -0.57, and the elasticity of mortality with respect to DI payments plus earnings is -0.67.[36] The point estimates are larger in the quadratic and cubic specifications; the standard errors also increase but the estimates retain significance at the ten percent and five percent significance levels, respectively.

At the upper bend point, all three specifications show insignificant impacts of DI payments on the mortality rate. The point estimates are negative, but they are small and imprecisely estimated.

Taken together, these results suggest the largest and most robust impacts of DI payments are on mortality among lowest-income beneficiaries, *i.e.*, at the lower bend point followed by the family maximum bend point. It is perhaps not surprising that the largest effects of DI payments occur among the lowest-income groups, and is consistent with literature from Preston (1975) to Chetty *et al.* (2017) that finds the correlation between income and mortality is strongest at low income levels.

V.c. Robustness and further validity checks

We perform several exercises to further establish the robustness of the mortality estimates. In Figure 4 and Table 4, we show results for four placebo samples. Panel A of Figure 4 shows the mean annual mortality rate in Years 1 to 4 of DI beneficiaries *without* dependents whose AIME puts them in the region of the family maximum bend point. These beneficiaries are unaffected by the family maximum rules, and therefore we should not see a change in the mortality-AIME relationship at the family maximum bend point. The figure suggests that there is no such change, and this is confirmed by the regression results in Column 1 of Table 4.

Figure 4 Panels B through D show the mortality rates for *non*-DI beneficiaries as a function of AIME at each of the three bend points. We create a sample of non-beneficiaries from the 2011 Continuous Work History Sample (CWHS), a one percent sample of active Social

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[36] Like DI payments, here we measure earnings in pre-tax terms.

Security Numbers. The analysis sample consists of living DI-insured workers age 18-57 in 1997 who have never applied for DI. AIME is calculated as if they had become eligible for DI during 1997. We match these data to the Numident and measure mortality from 1998 to 2010.[37] In Figure 4 Panels B through D, there is no clear increase in slope at any of the bend points, and this is confirmed by the regression estimates in Columns 2 to 4 of Table 4 showing insignificant changes in slope.

Several appendix figures show additional robustness exercises, again focusing on the linear specification. Appendix Figure A6 show that the point estimates at the lower and family maximum bend points are fairly stable as the bandwidth is varied. As would be expected, the estimates become statistically significant once a sufficiently large bandwidth is used to achieve sufficient statistical power.[38] Appendix Figure A7 shows the elasticity estimate and 95 percent confidence interval when we run the RKD regression (2) for "placebo" bend points that are located throughout the range of AIME values covered by the bandwidths (in the spirit of Ganong and Jäger 2014). The figure shows that in both the lower bend point and the family maximum samples, the largest (in absolute value) and most statistically significant coefficients occur precisely at the actual location of the bend points. The formal "permutation test" following Ganong and Jäger (2014) shows that the estimate with the kink placed at the actual bend point is statistically significantly larger in magnitude than the distribution of placebo estimates.[39]

Additional appendix tables show further robustness checks. Within the specification for each polynomial, the estimates are similar when we allow a discontinuity at the bend point (Appendix Table A6), or when using a fuzzy RKD in which the "first stage" relates average observed PIA over the initial four years to initial AIME, rather than a sharp RKD (Appendix Table A7).[40] We also show that the estimates are similar when controlling for predetermined covariates at the individual level or removing the impact of covariate means at the bin level (Appendix Table A8). This is mirrored in Appendix Figure A8, where we show that there are sharp changes in the slope of the residualized mortality outcome at both the lower bend point (in the full sample) and the family maximum bend point (in the sample with dependents) after

[37] As we might expect, this non-beneficiary group has much lower mortality rates than the DI samples.
[38] Given the potential for bandwidth to be mis-specified, in Appendix Figure A6 we also vary the bandwidth for the upper bend point sample. The estimates are small and generally not statistically significant at the five percent level.
[39] When using placebo kinks farther from the bend point, we also estimate $p<0.05$.
[40] We describe the fuzzy RKD in greater detail in Appendix 1.

removing the impact of covariates, and over a much wider range of AIME.[41] To explicitly address the binary nature of mortality as an outcome, Appendix Table A9 shows that the results are similar to the baseline when we run a grouped logit model in which the dependent variable is ln[mortality rate/(1 – mortality rate)] and the coefficients are transformed into marginal effects by multiplying them by [(mortality rate)/(1 – mortality rate)]. In Appendix Table A9 we also show nearly identical results to the baseline when we use individual-level data in running our main specification, rather than bin means (Appendix Table A9 Column 3); when we use finer $10 or $25 bins of AIME rather than $50 in our baseline (Appendix Table A9 Columns 4 and 5, and Appendix Figures A9 and A10); and when we remove the sample restriction of excluding beneficiaries with more than four AIME changes (Appendix Table A9 Column 6). Appendix Table A10 shows that our placebo tests still show insignificant results when we use the bandwidths selected by the Calonico, Cattaneo, and Titiunik (2014) procedure separately for these CWHS samples, rather than using our "baseline" bandwidths.

V.d. Effect heterogeneity

Our estimates may vary by time period or sub-group of the population. We first consider how the mortality effects vary by the period receiving DI. Estimates of the cumulative effect by year since going on DI using the linear model are shown in Figure 5, from Year 1 to Year 8.[42] For this figure we restrict the sample to beneficiaries entering DI between 1997 and 2005, so that everyone is followed for eight years. (In Appendix Table A11, we show that the results for the first four years are similar using the main sample.)

At the lower bend point, the point estimates of the *percentage point* effect are significant in each year and grow as further effects accumulate (Panel A).[43] Panel B shows that the *percentage* effect on mortality at the lower bend point is relatively constant throughout the

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[41] Appendix Figure A8 Panel A also shows that, in the full sample, the mortality residuals broadly decline with AIME. This contrasts with Figure 3, which shows that mortality falls with AIME in the region of the lower bend point but rises with AIME at the upper bend point. The reason for the discrepancy relates to the effects of age and other characteristics that are correlated with AIME. In terms of age, older DI beneficiaries are over-represented at high AIME levels – since they have typically had more high earnings years and also benefit from the large adjustments that come from the NAWI when applied over long time periods – and also have higher mortality rates. Appendix Figure A8 Panel B shows that, among DI beneficiaries with dependents, the residualized mortality rate slopes down in AIME below the family maximum bend point, and only begins to slope upward above the bend point, where the slope is affected by the lower marginal replacement rate.

[42] "Year 1" is defined as the first full year beginning with the month an individual starts to receive DI; "Year 2" as the second full year; and so on.

[43] Note that these are the cumulative effects from receiving $1,000 of additional DI payments each year.

period, suggesting that the relative impact remains fairly constant as the underlying annual mortality rate declines.[44] At the family maximum bend point (Panels C and D), the effects become significant at the five percent level beginning in Year 4. After Year 4, the estimates are relatively constant in both percentage point and percent terms (growing slightly in percentage point terms and falling slightly in percent terms).

Table 5 shows the mortality effects at the lower and family maximum bend points in different subgroups of the population, reporting estimates using the linear model that again minimizes the AICc when holding the bandwidth constant across specifications for comparability. Broadly speaking, the absolute values of the point estimates of the effects are usually larger in groups with higher baseline mortality rates. At the lower bend point, the point estimate of the absolute effect on mortality is significantly larger for black relative to non-black beneficiaries, significantly larger for those initially allowed DI through an initial Disability Determination Service (DDS) assessment relative to those allowed via a hearing (after an initial denial), significantly larger for women relative to for men, and significantly smaller for mental or musculoskeletal disorders than for individuals with all other disabilities, particularly cardiovascular conditions. The estimates are insignificantly different for those who entered DI in earlier years (1997-2005) *vs.* later years (2006-9), and insignificantly different for beneficiaries who are older at filing (aged 45 and older) *vs.* younger (aged below 45). The differences in mortality outcomes across these groups are mostly similar at the family maximum bend point, with significantly larger point estimates for those allowed via DDS than a hearing, and significantly smaller for mental and musculoskeletal disorders than all other disabilities.

As our estimates are local to the bend points, it is not possible to determine directly whether the results generalize to the full population of DI recipients. However, Table 1 shows that those allowed via DDS, and those with cancers or circulatory disorders, are under-represented at the lower and family maximum bend points relative to the full DI population. As a result, when we re-weight the population so that its demographic characteristics match those of the full sample, we estimate effects that are modestly larger than the baseline.

V.e. Potential Mechanisms

[44] This is consistent with patterns observed for the mortality of DI beneficiaries, as beneficiaries with cancer and other high-mortality conditions more often die soon after entering the DI program (Zayatz 2015).

The changes in mortality due to income transfers that we document could reflect the effects of changes in labor supply, or in (non-leisure) consumption or investment. Like many other estimates of causal effects, our RKD design is well suited to determine the causal impact of DI payments on mortality, but less well equipped to determine the mechanisms that mediate these impacts.

In our context, we can identify the income effect of DI benefits on earnings using our RKD variation in the payment schedule (Gelber, Moore, and Strand forthcoming). As in Gelber, Moore, and Strand (forthcoming), Appendix Table A12 verifies that there is a strong income effect of DI benefits on earnings at the upper bend point in our sample, but no large or statistically significant effects at the lower or family maximum bend points (both when we do and do not include the deceased in our sample). Thus, the significant effects on mortality we estimate at the lower and family maximum bend points do not appear to be associated with earnings effects in response to changes in DI income.[45]

In Gelber, Moore, and Strand (2017a), we investigate whether DI is associated with changes in expenditures or proxies for consumption. Survey data with relevant information, such as the CES and the SIPP, lack adequate sample sizes to apply an RKD to examine this directly. Power calculations show that our RKD will be (grossly) under-powered to detect the effect of DI payments on expenditures or consumption in these datasets. Thus, we pursue an alternative strategy to develop more suggestive evidence on the association of additional income with expenditures in the DI population.

Using data on DI beneficiaries – and separately non-beneficiaries – in the CES from 1986 to 2012, we regress measures of expenditures on household income, controlling for age, age squared, sex, as well as dummies for self-reported health status, educational attainment, race, and state. When overall expenditure is the dependent variable, the coefficient on current income is large among DI households – and 52 percent higher than for non-DI households. We find larger coefficients on income among DI households relative to non-DI households particularly when the dependent variable is expenditure on food, housing, utilities, health care, and transportation

[45] Although we lack definitive evidence, in principle it is possible that effects on earnings could help explain the lack of an effect on mortality at the upper bend point, for example if the earnings losses due to DI payments at this bend point are associated with lower hours worked and this leads to an increase in mortality as in Snyder and Evans (2006) study of OASI.

(both comparing in absolute and percentage terms). Moreover, we generally find especially large coefficients on income among below-median-income DI households relative to above-median.

Among poorer DI households, then, additional income – including income from DI – could help individuals to afford life-saving consumption or investments, both through additional health expenditures and through other expenditures. Additional health expenditures could be particularly valuable during the initial 24-month waiting period for Medicare eligibility under SSDI; indeed Figure 5 shows that the largest percentage point effects occur initially. Among poorer DI households, higher income could also be associated with lower stress that leads to better health and longevity (*e.g.* Evans and Garthwaite 2015), greater expenditure on utilities could be associated with better heating that helps avoid deaths from diseases like pneumonia (particularly in immunosuppressed populations), or additional expenditures on food could support more nutritious food that lowers the incidence of cardiovascular conditions (Cutler, Glaeser, and Shapiro 2003). Such mechanisms are plausibly consistent with our heterogeneity results in Table 5, showing the largest effects among individuals with cardiovascular conditions and cancers; these are "health-care amenable" conditions in which mortality can be substantially affected by care (Nolte and McKee 2003), and medical and public health literature show that diet and temperature also have important effects on mortality from such conditions (*e.g.* Gasparini *et al.* 2015; Schwingshackl 2017). Meanwhile, mental and musculoskeletal disorders are low-mortality conditions for which it may be difficult to identify mortality effects even when there are broader positive health impacts (Nolte and McKee 2003). Future research can build on this suggestive analysis to continue to illuminate potential mechanisms.

VI. Implications for Welfare Analysis

These estimates have important implications for calculating the cost of saving a life-year through DI payments. Relative to the baseline hazard, we calculate the survival curve under an increase in annual payments of $1 implied by our estimates of the effects of DI income on mortality for each year. We then sum the area between these survival curves, and scale this change in survival by the difference in discounted payments between the two scenarios, using an illustrative 3 percent real rate and taking into account the fact that those who have died no longer receive payments.[46] These results imply that saving a statistical life year requires around $58,574 in additional expenditure at the lower bend point, and $236,626 at the family maximum bend point (both $p<0.05$).[47] In measuring the value of an additional life year, it is important to consider the quality of life – which may be lower for those with medical conditions – as reflected in a Quality Adjusted Life Year (QALY). Neumann, Cohen, and Weinstein (2014) and Neumann *et al.* (2017) have suggested using $100,000 or $150,000 per life year as a benchmark QALY for the general population. They also suggest $50,000 as a "lower boundary" (*p*. 797). Thus, at the lower bend point, our estimates show that the cost of saving an additional life year is in a similar range to the QALY, while at the family maximum bend point the benefits of additional DI payments are also an important factor relative to the additional outlay.[48]

Studies using revealed preference methods have typically found much larger VSLYs in the general population. Viscusi (2010) finds a VSLY in the general population for those age 50 – close to the mean age in our sample – above $500,000, and Murphy and Topel (2006) find estimates in a comparable range well above the one suggested by Neumann *et al*. (2014, 2017). The estimates in Cutler and Richardson (1997) suggest that even after adjusting for life quality, QALYs for those with serious health problems would still be at least twice the Neumann *et al.* (2014, 2017) "lower boundary."[49] This would commensurately raise the gross benefits of DI expenditure, strengthening our argument that the benefits are large.

However, lower-income DI recipients may have lower VSLYs (Viscusi 2010). Moreover, in a full benefit-cost analysis it would also be necessary to value the effect of higher taxes on the lifespan of those taxed to provide the DI benefits. Higher VSLYs will also raise this value, thus raising the opportunity cost of additional DI expenditures. Such an analysis would also require

[46] The results (available upon request) are similar under alternative discount rates from 1 to 5 percent.
[47] This $236,626 at the family maximum bend point is calculated using the combined payments to the primary beneficiary and the dependent; assuming it is only the benefits to the primary beneficiary that reduce that beneficiary's mortality, then saving a statistical life year requires around $157,751 in additional expenditure at the family maximum bend point. The estimates are insignificant and uninformative at the upper bend point.
[48] For context, Almond, Doyle, Kowalski, and Williams (2010) estimate that saving a statistical life through greater Medicaid spending costs around $550,000, or less than the $2.7 million value of a statistical life calculated in Cutler and Meara (2000), while Sommers (forthcoming) finds that saving a statistical life through state Medicaid expansions costs between $327,000 and $867,000. However, this is a substantially different context than ours, involving publicly provided medical care, as opposed to additional income in our setting.
[49] Cutler and Richardson (1997) estimate that the average QALY weights for the conditions in which we estimate the largest effects – cardiovascular conditions and cancers – are 0.77 and 0.70, respectively, which are not far from the average QALY weight for all other conditions, 0.85. Thus, the QALYs in the conditions for which we estimate large effects should be in the same range as the QALYs in the disabled population as a whole.

additional parameters such as the effect of DI income on beneficiaries' Medicare expenditures that presumably are affected along with their health. It is therefore beyond the scope of this paper to provide a full analysis of the costs and benefits of DI payments or their optimal level (*e.g.*, Bound, Cullen, Nichols, and Schmidt 2004, Meyer and Mok 2013, Low and Pistaferri 2015). Rather, what we conclude from our illustrative exercise is that the cost of saving a life-year among the lowest-income groups is in a comparable range to QALY valuations. In Gelber, Moore, and Strand (2017b), we are performing illustrative calculations of the implications of our mortality estimates for the optimal DI replacement rate.

VII. Conclusion

A key policy question regarding DI is the extent to which DI income affects mortality. Our evidence demonstrates that DI income reduces mortality, particularly among lower-income beneficiaries. In particular, at the lower and family maximum bend points, the point estimates of the elasticities of mortality with respect to DI payments are -0.56 and -0.57, respectively, corresponding to annual mortality reductions of 0.26 and 0.09 percentage points per $1,000 of annual DI benefits. Meanwhile, we find no significant effect at the upper bend point. We interpret the estimate at the lower bend point as a lower bound due to the measurement issues described above, and we interpret the estimates at all of the bend points as lower bounds on the effect of after-tax benefits. If anything, these factors strengthen our conclusion that the effects are large for lower-income beneficiaries. The results show that this high-mortality, low-income population in the U.S. responds more than more advantaged groups in developed economies today, but similarly to less developed economies around the world today or in earlier time periods in the U.S.

These results imply that the DI payment outlay associated with saving a life-year through additional DI payments is in a comparable range to the QALY at the lower bend point, and that the benefits of additional DI payments are also an important factor relative to the additional outlays at the family maximum bend point. The lifespan gains are therefore a substantial factor in assessing the welfare effects of DI payments.

As noted, our estimates are local to the region of the bend points. However, our estimates do demonstrate that large mortality benefits of DI payment size are observed among at least some beneficiaries, whereas previous analyses of the benefits of DI have implicitly ignored such mortality benefits. Moreover, the sample near the bend points we study spans a large fraction of all DI recipients and is therefore of great interest in studying the program. At the same time, our mortality effect estimates do not necessarily generalize to non-DI populations – indeed this is a prime motivation for studying the DI program separately. DI recipients have particularly high mortality rates, and their mortality probability might be particularly affected by transfer income.

DI is one important context, but there is a more general lesson from our results: social insurance programs in the modern, developed country context can have large, previously unrecognized welfare benefits due to mortality reductions. This could apply not only in DI but perhaps also in other programs with predominantly high-mortality and/or low-income beneficiaries, such as workers' compensation, sickness insurance, or SSI. Future papers could fruitfully investigate these issues.

References

Aizer, Anna, Shari Eli, Joseph Ferrie, and Adriana Lleras-Muney. "The Long-Term Impact of Cash Transfers to Poor Families." *American Economic Review* 106.4 (2016): 935-971.

Akee, Randall, Emilia Simeonova, William Copeland, Adrian Angold, and E. Jane Costello. "Young Adult Obesity and Household Income: Effects of Unconditional Cash Transfers." *American Economic Journal: Applied Economics* 5.2 (2013): 1-28.

Almond, Douglas, Joseph Doyle, Amanda Kowalski, and Heidi Williams. "Estimating Marginal Returns to Medical Care: Evidence from At-Risk Newborns." *Quarterly Journal of Economics* 125.2 (2010): 591-634.

Ando, Michihito. "How Much Should We Trust Regression-Kink-Design Estimates?" *Empirical Economics*, forthcoming.

Arias, Elizabeth. "United States Life Tables, 2010." *National Vital Statistics Reports 63.7*: Hyattsville MD: National Center for Health Statistics (2014).

Armour, Philip. "The Role of Information in Disability Insurance Application: An Analysis of the Social Security Statement Phase-In." Cornell University working paper.

Autor, David, and Mark Duggan. "The Rise in the Disability Rolls and the Decline in Unemployment." *Quarterly Journal of Economics* 118.1 (2003): 157-206.

Autor, David, Nicole Maestas, Kathleen Mullen, and Alexander Strand. "Does Delay Cause Decay? The Effect of Administrative Decision Time on the Labor Force Participation and Earnings of Disability Applicants." NBER Working Paper No. 20840 (2015).

Autor, David, Andreas Kostøl, Magne Mogstad, and Bradley Setzler. "Disability Benefits, Consumption Insurance, and Household Labor Supply." NBER Working Paper No. 23466 (2017).

Baily, Martin. "Some Aspects of Optimal Unemployment Insurance." *Journal of Public Economics* 10 (1978): 379-402.

Bailey, Michelle Stegman, and Jeffrey Hemmeter. *Characteristics of Noninstitutionalized DI and SSI Program Participants, 2010 Update.* Washington DC: Social Security Administration Office of Retirement and Disability Policy (2014).

Ball, Steffan, and Hamish Low. "Do Self-insurance and Disability Insurance Prevent Consumption Loss on Disability?" *Economica* 81.323 (2014): 468-490.

Barham, Tania, and Jacob Rowberry. "Living Longer: The Effect of the Mexican Conditional Cash Transfer Program on Elderly Mortality," *Journal of Development Economics*, 105 (2013): 226-236.

Bee, Adam, Bruce Meyer, Bruce, and James X. Sullivan. "The Validity of Consumption Data: Are the Consumer Expenditure Interview and Diary Surveys Informative?" In Christopher Carroll, Thomas Crossley, and John Sabelhaus (ed.), *Improving the Measurement of Consumer Expenditures*. Chicago: University of Chicago Press (2015): 204-240.

Black, Dan, Kermit Daniel, and Seth Sanders. "The Impact of Economic Conditions on Participation in Disability Programs: Evidence from the Coal Boom and Bust." *American Economic Review* 92.1 (2002): 27-50.

Borghans, Lex, Anne C. Gielen, and Erzo F.P. Luttmer. "Social Support Substitution and the Earnings Rebound: Evidence from a Regression Discontinuity in Disability Insurance Reform." *American Economic Journal: Economic Policy* 6.4 (2014): 34-70.

Bound, John. "The Health and Earnings of Rejected Disability Insurance Applicants." *American Economic Review* 79 (1989): 482-503.

Bound, John, and Richard V. Burkhauser. "Economic Analysis of Transfer Programs Targeted on People with Disabilities." *Handbook of Labor Economics* 3 (1999): 3417-3528.

Bound, John, Julie Berry Cullen, Austin Nichols, and Lucie Schmidt. "The Welfare Implications of Increasing Disability Insurance Benefit Generosity." *Journal of Public Economics*, 88(12) (2004): 2487-514.

Calonico, Sebastian, Matias Cattaneo, and Rocio Titiunik. "Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs." *Econometrica* 82.6 (2014): 2295-2326.

Campolieti, Michele, and Chris Riddell. "Disability Policy and the Labor Market: Evidence from a Natural Experiment in Canada." *Journal of Public Economics* 96.3-4 (2012): 306-316.

Card, David, Carlos Dobkin, and Nicole Maestas. "Does Medicare Save Lives?" *Quarterly Journal of Economics* 124.2 (2009): 597-636.

Card, David, David Lee, Zhuan Pei, and Andrea Weber. "Inference on Causal Effects in a Generalized Regression Kink Design." *Econometrica* 83.6 (2015): 2453-2483.

Card, David, David Lee, Zhuan Pei, and Andrea Weber. "Regression Kink Design: Theory and Practice." In Matias D. Cattaneo and Juan Carlos Escanciano (ed.), *Regression Discontinuity Designs: Theory and Applications (Advances in Econometrics 38)*. Bingley UK: Emerald Group Publishing (2017): 341-382.

Case, Anne. "Does Money Protect Health Status? Evidence from South African Pensions." In David Wise (ed.), *Perspectives on the Economics of Aging*. Chicago: University of Chicago Press (2004): 287-312.

Cesarini, David, Erik Lindqvist, Robert Ostling, and Bjorn Wallace. "Wealth, Health, and Child Development: Evidence from Administrative Data on Swedish Lottery Players." *Quarterly Journal of Economics* 131.2 (2016): 687-738.

Chandra, Amitabh, and Andrew A. Samwick. "Disability Risk and the Value of Disability Insurance." NBER Working Paper No. 11605 (2005).

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

Chetty, Raj. "Moral Hazard vs. Liquidity and Optimal Unemployment Insurance." *Journal of Political Economy* 116.2 (2008): 173-234.

Chetty, Raj. "A General Formula for the Optimal Level of Social Insurance." *Journal of Public Economics* 90.10-11 (2006): 1879-1901.

Chetty, Raj, and Amy Finkelstein. "Social Insurance: Connecting Theory to Data." In Alan Auerbach, Raj Chetty, Martin Feldstein, and Emmanuel Saez (ed.), *Handbook of Public Economics* 5 (2013): 111-193.

Chetty, Raj, John Friedman, Tore Olsen, and Luigi Pistaferri. 2011. "Adjustment Costs, Firm Responses, and Micro vs. Macro Labor Supply Elasticities: Evidence from Danish Tax Records." *Quarterly Journal of Economics* 126 (2): 749-804.

Chetty, Raj, Michael Stepner, Sarah Abraham, Shelby Lin, Benjamin Scuderi, Nicholas Turner, Augustin Bergeron, and David Cutler. "The Association Between Income and Life Expectancy in the United State, 2001-2014." *Journal of the American Medical Association* 315.16 (2016): 1750-1766.

Cohen, Alma and Liran Einav. "Estimating Risk Preferences from Deductible Choice." *American Economic Review*, 97.3 (2007): 745-788.

Coile, Courtney. "Disability Insurance Incentives and the Retirement Decision: Evidence from the United States." In David Wise (ed.), *Social Security Programs and Retirement Around the World: Disability Insurance Programs and Retirement*. Chicago: University of Chicago Press (2016): 45-80.

Cox, David R. "Regression Models and Life-Tables." *Journal of the Royal Statistical Society, Series B (Methodological)* 34.2 (1972): 187-220.

Cutler, David M., Angus S. Deaton, and Adriana Lleras-Muney. "The Determinants of Mortality." *Journal of Economic Perspectives* 20.3 (2006): 97-120.

Cutler, David M., Edward Glaeser, and Jesse Shapiro. "Why Have Americans Become More Obese?" *Journal of Economic Perspectives* 17.3 (2003): 93-118.

Cutler, David M., and Ellen Meara. "The Technology of Birth: Is It Worth It?" *Frontiers in Health Policy Research* 3 (2000): 33-68.

Cutler, David M., and Elizabeth Richardson. "Measuring the Health of the U.S. Population." *Brookings Papers on Economic Activity* 28(3): 217-282.

Deaton, Angus S. "Health, Inequality, and Economic Development." *Journal of Economic Literature* 16 (2003): 113-158.

Deaton, Angus S., and Christina Paxson. "Mortality, Education, Income, and Inequality among American Cohorts." In David Wise (ed.), *Themes in the Economics of Aging*. Chicago: University of Chicago Press (2001): 129-170.

Deshpande, Manasi. "Does Welfare Inhibit Success? The Long-Term Effects of Removing Low-Income Youth from Disability Insurance." *American Economic Review* 106.11 (2016): 3300-3330.

Diamond, Peter, and Eytan Sheshinski. "Economic Aspects of Optimal Disability Benefits." *Journal of Public Economics* 57 (1995): 1-23.

Duflo, Esther. "Grandmothers and Granddaughters: Old Age Pension and Intra-household Allocation in South Africa." *World Bank Economic Review* 17.1 (2003): 1-25.

Evans, William N., and Craig L. Garthwaite. "Giving Mom a Break: The Impact of Higher EITC Payments on Maternal Health." *American Economic Journal: Economic Policy* 6.2 (2014): 258-290.

Finkelstein, Amy, Erzo Luttmer, and Matthew Notowidigdo. "What Good is Wealth without Health? The Effect of Health on the Marginal Utility of Consumption." *Journal of the European Economic Association* 11.S1 (2013): 221-258.

Finkelstein, Amy, Nathaniel Hendren, and Erzo Luttmer. "The Value of Medicaid: Interpreting Results from the Oregon Health Insurance Experiment." NBER Working Paper 21308 (2015).

Finkelstein, Amy, Sarah Taubman, Bill Wright, Mira Bernstein, Jonathan Gruber, Joseph P. Newhouse, Heidi Allen, Katherine Baicker, and the Oregon Health Study Group. "The Oregon Health Insurance Experiment: Evidence from the First Year." *Quarterly Journal of Economics* 127.3: 1057-1106 (2012).

Fitzpatrick, Maria D., and Timothy J. Moore. "The Mortality Effects of Retirement: Evidence from Social Security Eligibility at Age 62." Cornell University working paper (2017).

French, Eric, and Jae Song. "The Effect of Disability Insurance Receipt on Labor Supply." *American Economic Journal: Economic Policy* 6.2 (2014): 291-337.

Ganong, Peter, and Simon Jäger. "A Permutation Test and Estimation Alternatives for the Regression Kink Design." IZA Discussion Paper No. 8282 (2014).

Garcia-Gomez, Pilar, and Anne Gielen. "Health Effects of Containing Moral Hazard: Evidence from Disability Insurance Reform." IZA Discussion Paper No. 8386 (2014).
Gasparini, Antonio, *et al.* "Mortality Risk Attributable to High and Low Ambient Temperature: A Multicountry Observational Study." *The Lancet* 386 (2015): 369-375.
Gelber, Alexander, Timothy J. Moore, and Alexander Strand. "The Effect of Disability Insurance Payments on Beneficiaries' Earnings." *American Economic Journal: Economic Policy*, forthcoming.
Gelber, Alexander, Timothy J. Moore, and Alexander Strand. "Income and Consumption among Disability Insurance Recipients and Non-Recipients." UC Berkeley working paper (2017a).
Gelber, Alexander, Timothy J. Moore, and Alexander Strand. "Optimal Disability Insurance Replacement Rates with Mortality Effects." UC Berkeley working paper (2017b).
Government Accountability Office. "Social Security Administration: Preliminary Observations on the Death Master File." *Report No. GAO-13-574T.* Washington DC: Government Accountability Office (2013).
Grossman, Michael. "On the Concept of Health Capital and the Demand for Health." *Journal of Political Economy* 80.2 (1972): 223-255.
Gruber, Jonathan. "The Consumption Smoothing Benefits of Unemployment Insurance." *American Economic Review* 87.1 (1997): 192-205.
Gruber, Jonathan. "Disability Insurance Benefits and Labor Supply." *Journal of Political Economy* 108.6 (2000): 1162-183.
Gruber, Jonathan, and Jeffrey Kubik. "Disability Insurance Rejection Rates and the Labor Supply of Older Workers." *Journal of Public Economics* 64.1 (1997): 1-23.
Gubits, Daniel, Winston Lin, Stephen Bell, and David Judkins. "BOND Implementation and Evaluation: First- and Second-Year Snapshot of Earnings and Benefit Impacts for Stage 2." Cambridge MA: Abt Associates (2014).
Hammitt, James K. "Valuing Changes in Mortality Risk: Lives Saved versus Life Years Saved." *Review of Environmental Economics and Policy* 1 (2007): 228-240.
Hildebrand, Lesley, Laura Kosar, Jeremy Page, Miriam Loewenberg, Benjamin Fischer, Dawn Phelps, and Natalie Hazelwood. *User Guide for the Ticket Research File: TRF10.* Washington DC: Mathematica Policy Research (2012).
Hoynes, Hilary, Diane W. Schanzenbach, and Douglas Almond. "Long-Run Impacts of Childhood Access to the Safety Net." *American Economic Review* 106.4 (2016): 903-934.
Jensen, Robert T., and Kaspar Richter. "The Health Implications of Social Security Failure: Evidence from the Russian Pension Crisis." *Journal of Public Economics* 88.1 (2004): 209-236.
Kelley, James W., & Joseph R. Humphreys. "Congressional Intent Concerning the Notch Issue: Legislative Background of the 1977 Social Security Amendments." Appendix to Commission on the Social Security "Notch" Issue, *Final Report on the Social Security "Notch" Issue*.
Kitagawa, Evelyn M., and Philip M. Hauser. *Differential Mortality in the United States: A Study in Socioeconomic Epidemiology.* Cambridge MA: Harvard University Press (1973).
Kostøl, Andreas, and Magne Mogstad. "How Financial Incentives Induce Disability Insurance Recipients to Return to Work." *American Economic Review* 104.2 (2014): 624-55.

Landais, Camille. “Assessing the Welfare Effects of Unemployment Benefits Using the Regression Kink Design.” *American Economic Journal: Economic Policy* 7.4 (2015): 243-278.

Lee, David, and Thomas Lemieux. “Regression Discontinuity Designs in Economics.” *Journal of Economic Literature* 48 (2010): 281-355.

Liebman, Jeffrey B., and Erzo F.P. Luttmer. “Would People Behave Differently If They Better Understood Social Security? Evidence from a Field Experiment.” *American Economic Journal: Economic Policy* 7.1 (2015): 275-299.

Low, Hamish, and Luigi Pistaferri. “Disability Insurance and the Dynamics of the Incentive Insurance Trade-off.” *American Economic Review* 105.10 (2015): 2986-3029.

Maestas, Nicole, Kathleen J. Mullen, and Alexander Strand. “Does Disability Insurance Receipt Discourage Work? Using Examiner Assignment to Estimate Causal Effects of SSDI Receipt.” *American Economic Review* 103.5 (2013): 1797-829.

Manoli, Day, and Nick Turner. “Cash-on-Hand & College Enrollment: Evidence from Population Tax Data and the Earned Income Tax Credit.” NBER Working Paper 19836 (2014).

Meyer, Bruce, and Wallace Mok. “Disability, Earnings, Income, and Consumption.” NBER Working Paper 18869 (2013).

Meyer, Bruce, and James X. Sullivan. “Further Evidence on Measuring the Well-Being of the Poor Using Income and Consumption.” *Canadian Journal of Economics* 44.1 (2011): 52-87.

Moore, Timothy J. “The Employment Effects of Terminating Disability Benefits.” *Journal of Public Economics* 124 (2015): 30-43.

Moore, Timothy J., and Nicolas Ziebarth. “The Consumption Patterns of Disability Beneficiaries.” Cornell University working paper (2014).

Murphy, Kevin, and Robert Topel. “The Value of Health and Longevity.” *Journal of Political Economy* 114.5 (2006): 871-904.

Nielsen, Helena S., Torben Sørensen, and Christopher Taber. “Estimating the Effect of Student Aid on College Enrollment: Evidence from a Government Grant Policy Reform.” *American Economic Journal: Economic Policy* 2.2 (2010): 185-215.

Neumann, Peter J., Joshua T. Cohen, and Milton Weinstein. “Updating Cost-Effectiveness – The Curious Resilience of the $50,000-per-QALY Threshold.” *New England Journal of Medicine* 371 (2014): 796-797.

Neumann, Peter J., Theodore Ganiats, Louise Russell, Gillian Sanders, and Joanna Siegel. *Cost-Effectiveness in Health and Medicine, 2nd Edition* (2017). Oxford: Oxford University Press.

Nolte, Ellen, and Martin McKee. “Measuring the Health of Nations: Analysis of Mortality Amenable to Health Care.” *British Medical Journal* 327.7424: 1129.

Office of Management and Budget. “Budget of the U.S. Government, Fiscal Year 2014.” Washington, D.C.: Government Printing Office (2013).

Philipson, Tomas, and Gary Becker. “Old-Age Longevity and Mortality Contingent Claims.” *Journal of Political Economy* 106.3 (1998): 550 – 574.

Preston, Samuel H. “The Changing Relation between Mortality and Level of Economic Development.” *Population Studies* 29.2 (1975): 231-248.

Preston, Samuel H., and Paul Taubman. “Socioeconomic Differences in Adult Mortality and Health Status.” *Demography of Aging* 1 (1994): 279-318.

Romig, Kathleen, and Dave Shoffner. "Understanding the Social Security Family Maximum." *Social Security Bulletin* 75.3 (2015): 1-13.

Ruhm, Christopher. "Are Recessions Good for Your Health?" *Quarterly Journal of Economics* 115.2 (2000): 617-650.

Saez, Emmanuel. "Do Taxpayers Bunch at Kink Points?" *American Economic Journal: Economic Policy* 2.3 (2010): 180-212.

Salm, Martin. "The Effect of Pensions on Longevity: Evidence from Union Army Veterans." *Economic Journal* 121.552 (2011): 595-619.

Schwingshackl, Lukas, *et al.* "Food Groups and Risk of All-Cause Mortality: A Systematic Review and Meta-Analysis of Prospective Studies." *American Journal of Clinical Nutrition* 105.6 (2017): 1462-1473.

Smith, James P. "Healthy Bodies and Thick Wallets: The Dual Relation between Health and Economic Status." *Journal of Economic Perspectives* 13.2 (1999): 144-166.

Snyder, Stephen, and William N. Evans. "The Effect of Income on Mortality: Evidence from the Social Security Notch." *Review of Economics and Statistics* 88.3 (2006): 482-495.

Social Security Administration. *Annual Statistical Report on the Social Security Disability Insurance Program, 2012*. Washington DC: Social Security Administration Office of Retirement and Disability Policy (2013).

Social Security Administration. 2015. *Annual Statistical Report on the Social Security Disability Insurance Program, 2014*. Washington, D.C.: Social Security Administration Office of Retirement and Disability Policy.

Social Security Administration. *The 2016 Annual Report of the Board of Trustees of the Federal Old-Age and Survivors Insurance and Federal Disability Insurance Trust Funds*. Washington DC: Social Security Administration Office of the Chief Actuary (2016).

Social Security Administration Office of the Inspector General. "Title II Deceased Beneficiaries Who Do Not Have Death Information on the Numident." *Audit Report A-09-11-2271.* Baltimore: Social Security Administration Office of the Inspector General (2012).

Social Security Administration Office of the Inspector General. "Social Security Benefits Paid Before and After an Individual's Death." *Audit Report A-05-16-50123.* Baltimore: Social Security Administration Office of the Inspector General (2016).

Sommers, Benjamin. "State Medicaid Expansions and Mortality, Revisited: A Cost-Benefit Analysis." *American Journal of Health Economics* (forthcoming).

Sullivan, Daniel, and Till Von Wachter. "Job Displacement and Mortality: An Analysis using Administrative Data." *Quarterly Journal of Economics* 124.3 (2009): 1265-1306.

Turner, Lesley. "The Road to Pell Is Paved with Good Intentions: The Economic Incidence of Federal Student Grant Aid." University of Maryland Working Paper (2014).

Viscusi, W. Kip. "Policy Challenges of the Heterogeneity of the Value of Statistical Life." *Foundations and Trends in Microeconomics* 6.2 (2010): 99-172.

Viscusi, W. Kip, and Joseph Aldy. "The Value of a Statistical Life: A Critical Review of Market Estimates throughout the World." *Journal of Risk and Uncertainty* 27.1 (2003): 5-76.

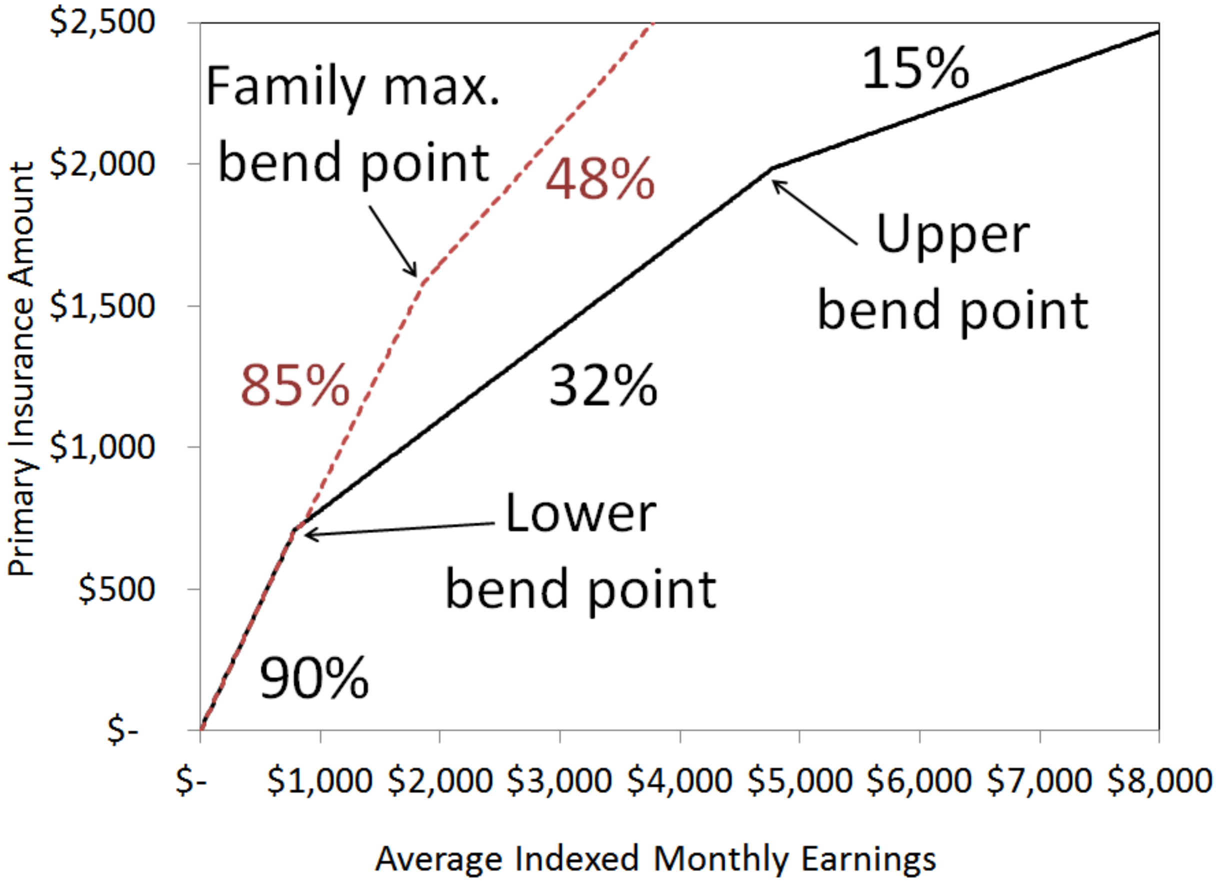
Von Wachter, Till, Jae Song, and Joyce Manchester. "Trends in Employment and Earnings of Allowed and Rejected Applicants to the Social Security Disability Insurance Program." *American Economic Review* 101.7 (2011): 3308-3329.

Weathers, Robert, and Jeffrey Hemmeter. "The Impact of Changing Financial Work Incentives on the Earnings of Social Security Disability Insurance (SSDI) Beneficiaries." *Journal of Policy Analysis and Management* 30.4 (2011): 708-728.

Weathers, Robert, and Michelle Stegman. "The Effect of Expanding Access to Health Insurance on the Health and Mortality of Social Security Disability Insurance Beneficiaries." *Journal of Health Economics* 31.6 (2012): 863-875.

Zayatz, Tim. "Social Security Disability Insurance Program Worker Experience." *Actuarial Study No. 123, SSA Pub. No. 11-11543.* Washington DC: Social Security Administration Office of the Chief Actuary (2015).

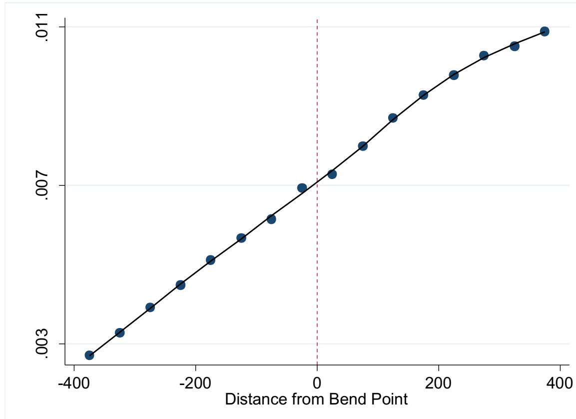
Figure 1. Relationship of Primary Insurance Amount to Average Indexed Monthly Earnings



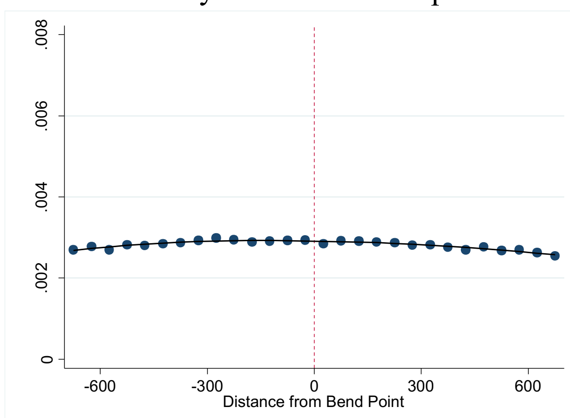
Notes: The solid black line displays the relationship between Average Indexed Monthly Earnings (AIME) and the Primary Insurance Amount (PIA) for beneficiaries. The red dashed line shows the maximum family benefits that can be paid to beneficiaries and their dependents. The family maximum bend point occurs when the binding rule changes from family payments not being larger than 85 percent of AIME to the one that it may not be larger than 150 percent of PIA. This means that the marginal rate changes from 85 percent to 48 percent of AIME (which is equal to 150 percent of the 32 percent replacement rate). The 150 percent rule applies to AIME values higher than this bend point, so at the upper bend point the marginal rate for the family maximum changes from 48 percent (150 percent of 32 percent) to 22.5 percent (150 percent of 15 percent). An AIME at the 30th percentile of the distribution for the full population (combining both those with and without dependents) puts beneficiaries with dependents at the family maximum bend point.

Figure 2. Smoothness of Density around the Bend Points

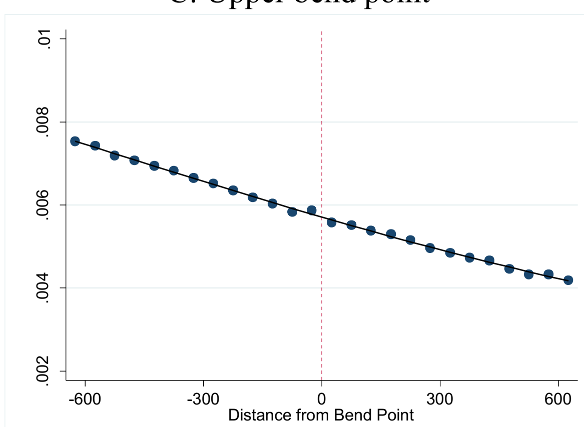
A: Lower bend point



B: Family maximum bend point



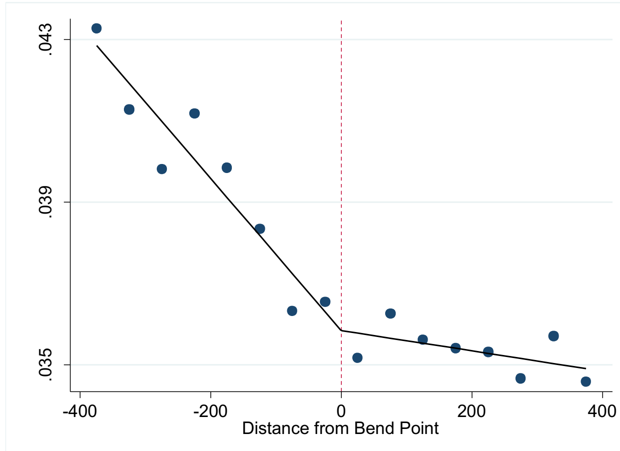
C: Upper bend point



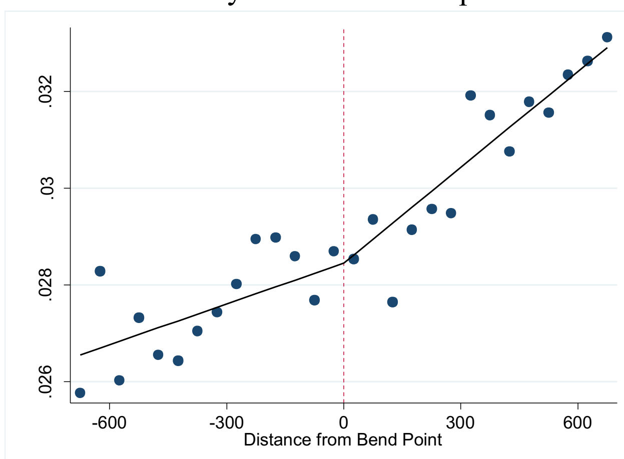
Notes: The figure shows the density of initial AIME in $50 bins as a function of distance of initial AIME to each bend point. The number of observations appears smooth through the bend points, with no sharp change in slope or level. The fraction of the sample in each bin is calculated by dividing the number of beneficiaries in each bin by the total number of beneficiaries in the sample. In each panel, we show a range for the density that spans 0.008. The best-fit line is a cubic polynomial that allows for a discontinuity in the first derivative above the bend point, which is similar to the approach used for Table 2. The data are from SSA administrative records.

Figure 3. Annual Mortality Rates around the Bend Points

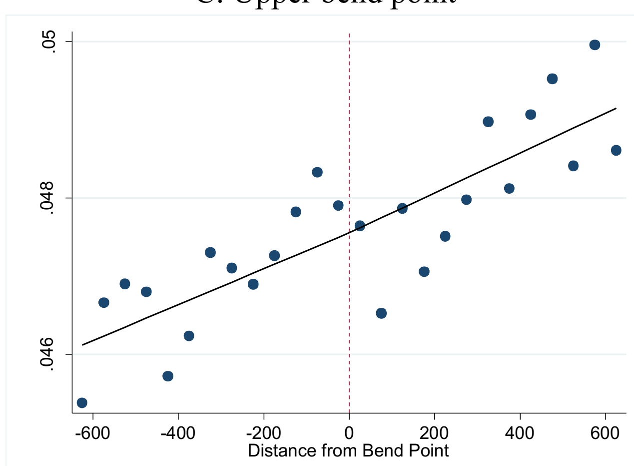
A: Lower bend point



B: Family maximum bend point

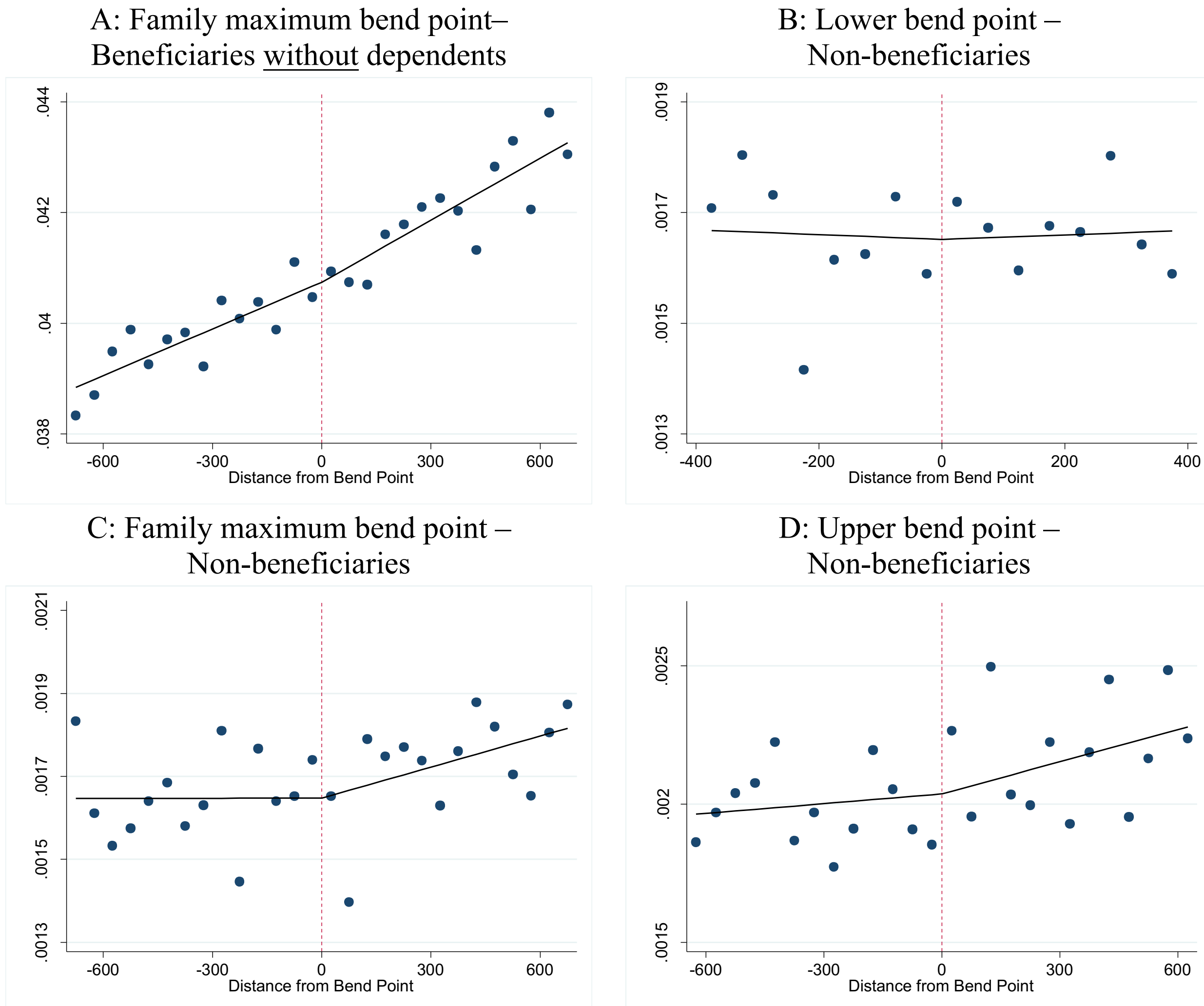


C: Upper bend point



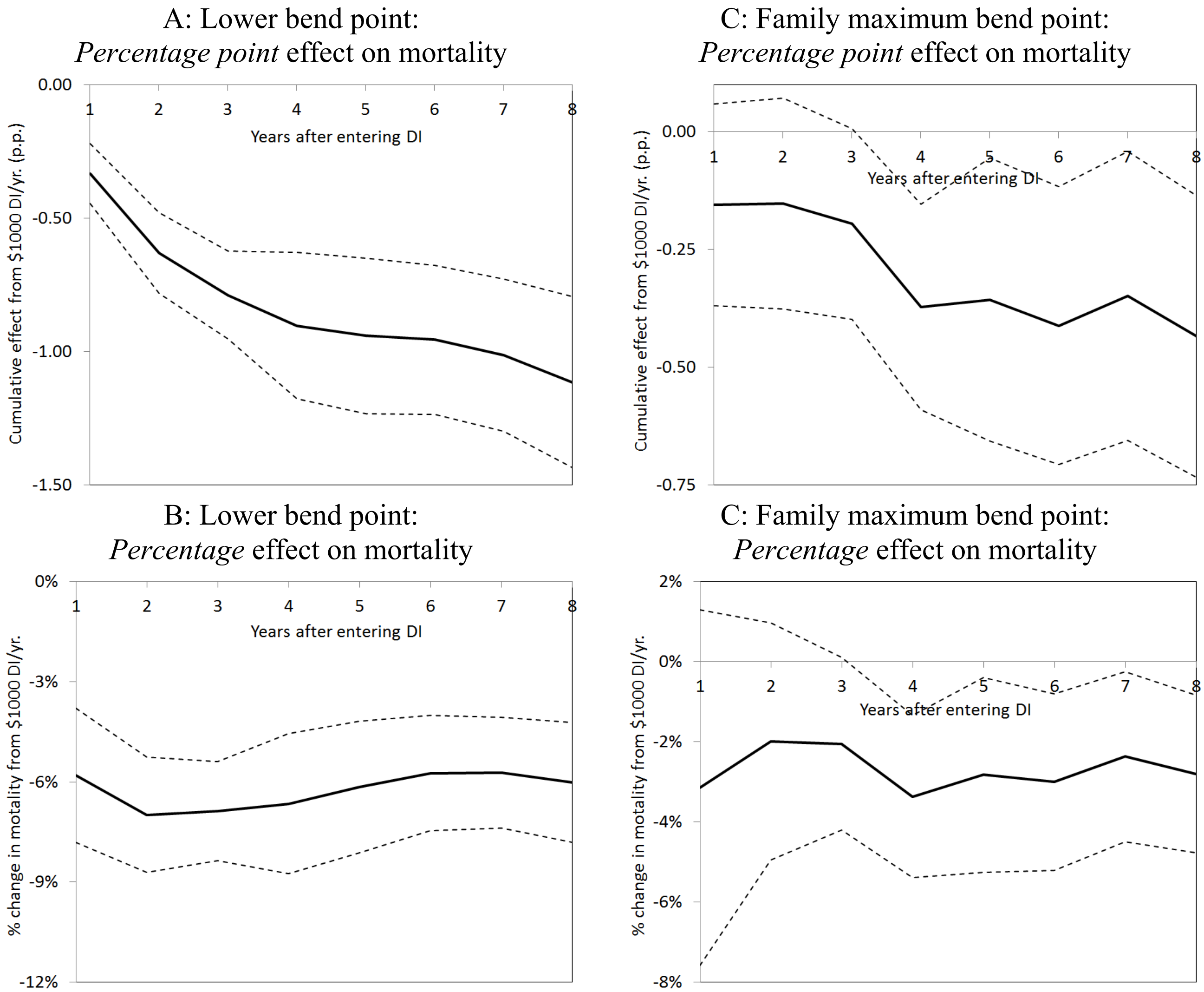
Notes: The figure shows the mean annual mortality rate in the first four years after going on DI, in $50 bins, as a function of distance of AIME from the bend point. The figure shows that, at the lower and family maximum bend points, the mortality rate slopes upward more steeply above the bend point than below it, with fitted lines that lie close to the data.

Figure 4. Placebo Mortality Estimates



Notes: The figure shows that we find no noticeable changes in slope in various placebo samples. Panel A shows the sample of DI beneficiaries without dependents. Panels B through D show results from the Continuous Work History Sample One Percent File around each of the three bend points.

Figure 5. Cumulative Effect of DI Benefits on Mortality, Beneficiaries entering DI 1997-2005



Note: The panels show the cumulative mortality effect for each year after receiving DI from Year 1 to Year 8. In this figure we examine beneficiaries entering DI between 1997 and 2005 because this allows us to examine a consistent sample across all years from 1 to 8.

Table 1. *Summary Statistics*

	Lower bend point		Family max. bend point		Upper Bend point		Full sample	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Demographic Information								
Age when applying for DI (years)	46.9	9.72	40.8	8.04	50.7	7.16	48.6	8.61
Fraction male	0.231	0.421	0.502	0.500	0.720	0.449	0.531	0.499
Fraction black	0.120	0.325	0.165	0.371	0.122	0.327	0.135	0.341
Program Information								
Primary Insurance Amount (PIA)	$675	$126	$1,091	$141	$1,845	$135	$1,360	$480
- Annualized PIA	$8,105	$1,514	$13,098	$1,691	$22,134	$1,614	$16,315	$5,764
Fraction allowed DI via a hearing (after an initial denial)	0.317	0.465	0.324	0.468	0.247	0.432	0.283	0.450
Fraction by disability type:								
Musculoskeletal cond.	0.308	0.462	0.262	0.439	0.293	0.455	0.297	0.457
Mental disorders	0.237	0.425	0.281	0.450	0.166	0.372	0.201	0.401
Other disabilities	0.455	0.498	0.457	0.498	0.541	0.498	0.502	0.500
- Cancers	0.103	0.303	0.098	0.297	0.130	0.337	0.116	0.320
- Circulatory conditions	0.077	0.267	0.072	0.259	0.125	0.331	0.103	0.304
Cumulative Mortality Rates								
1st year after entry	0.062	0.241	0.052	0.222	0.081	0.272	0.070	0.256
2nd year after entry	0.097	0.300	0.080	0.271	0.125	0.331	0.110	0.313
3rd year after entry	0.124	0.329	0.100	0.300	0.160	0.366	0.140	0.347
4th year after entry	0.146	0.353	0.116	0.321	0.190	0.392	0.166	0.372
Observations	412,124		287,723		546,776		3,648,988	

Notes: "SD" denotes the standard deviation. The lower bend point sample includes DI beneficiaries within $400 of the lower bend point; the family maximum bend point sample includes DI beneficiaries with dependents within $700 of the kink induced by the family maximum schedule; and the upper bend point sample includes DI beneficiaries within $650 of the upper bend point. These samples are the same as those considered in our regressions.

Table 2. *Smoothness of the Densities and Predetermined Covariates*

	Density (x100,000)	Predetermined covariates (x 1,000): Age at DI filing	Male	Black	Hearings allowed	Mental disorders	Musculo. conditions	Density of SSI (x100,000) [excluded]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A: Lower bend point								
Estimated kink	0.378	1.871	0.154	0.051	-0.174*	-0.029	-0.044	-1.052
(Std. error)	(0.467)	(2.949)	(0.114)	(0.058)	(0.092)	(0.081)	(0.092)	(1.437)
Poly. degree	5	5	5	5	5	5	5	4
B: Family maximum bend point								
Estimated kink	0.063	0.256	0.029	-0.015	-0.007	-0.015	0.037	0.030
(Std. error)	(0.063)	(0.947)	(0.078)	(0.049)	(0.084)	(0.065)	(0.077)	(0.074)
Poly. degree	5	5	5	5	5	5	5	5
C: Upper bend point								
Estimated kink	0.058	-1.496	-0.023	-0.020	0.002	-0.014	0.072	0.009
(Std. error)	(0.123)	(0.968)	(0.072)	(0.017)	(0.067)	(0.034)	(0.045)	(0.044)
Poly. degree	5	4	5	5	5	5	5	5

Notes: The table shows that the density of the assignment variable (*i.e.*, initial AIME) and distributions of predetermined covariates are smooth around the bend points. We test for a change in slope at the bend point by fitting a polynomial through the data window and allowing for a discontinuity in the first derivative above each bend point. We use cubic, quartic, and quintic polynomials, and report the coefficient and standard error from the polynomial order that minimizes the corrected Akaike Information Criterion (AICc). Robust standard errors [* p<0.10, ** p<0.05, *** p<0.01] are shown in parentheses.

Table 3. *Effect of DI Benefits on Mortality Rates*

	RKD estimates					Elasticities [linear model]	
	Linear model	Quadratic model	Cubic model	Annual DI pay at bend point	Annual mortality at bend point (p.p.)	In terms of DI payments	In terms of DI pay + earnings
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A: Lower bend point							
p.p. change per $1,000 of DI	-0.261***	-0.422***	-0.520***	$8,543	3.58	-0.556***	-0.764***
	(0.045)	(0.133)	(0.120)			(0.096)	(0.127)
Bandwidth	$400	$450	$550				
B: Family maximum bend point							
p.p. change per $1,000 of DI	-0.091***	-0.148*	-0.153**	$12,648	2.85	-0.570***	-0.667***
	(0.034)	(0.090)	(0.078)			(0.217)	(0.245)
Bandwidth	$700	$850	$950				
C: Upper bend point							
p.p. change per $1,000 of DI	-0.014	-0.012	-0.075	$20,777	4.76	-0.063	-0.099
	(0.079)	(0.228)	(0.171)			(0.353)	(0.530)
Bandwidth	$650	$750	$1000				

Notes: The table contains coefficients and standard errors showing the estimated effect of increasing annual DI benefit payments by $1,000 on the annual mortality rate at each bend point. The estimates are based on the regression kink design model (2) in the text. The full set of regression coefficients for the linear model is reported in the Appendix. For the family maximum bend point, the annual DI pay at the bend point refers to the mean annual pay to the primary beneficiary; mean annual pay to dependents is $6,324. See other notes to Table 1. Robust standard errors [* p<0.10, ** p<0.05, *** p<0.01] are shown in parentheses.

Table 4. *Placebo Estimates*

	Family maximum:	Non-beneficiaries		
	DI beneficiaries *without* dependents	Lower bend point	Family max. bend point	Upper bend point
	(1)	(2)	(3)	(4)
p.p. change per $1,000 DI	-0.023	-0.0012	-0.0056	-0.0133
	(0.022)	(0.0053)	(0.0051)	(0.0176)
Mortality rate at bend point (p.p)	4.07	0.165	0.165	0.204

Notes: The table shows that we find no significant "effects" in various placebo samples. Column 1 shows the sample of DI beneficiaries without dependents, who show no significant effect of DI benefits on mortality around the family maximum bend point. Columns 2 through 4 show results from samples of non-beneficiaries constructed using the Continuous Work History Sample One Percent File. These placebo samples also show no significant effects. We use the baseline linear specification throughout. Robust standard errors [* p<0.10, ** p<0.05, *** p<0.01] are shown in parentheses.

Table 5. *Heterogeneity in the Mortality Effects*

		Lower bend point			Family maximum bend point		
Category	Subgroup	p.p. change per $1,000 of DI (1)	Annual mortality at bend point (p.p.) (2)	*p*-value on equality of coefficients in group (3)	p.p. change per $1,000 of DI (4)	Annual mortality at bend point (p.p.) (5)	*p*-value on equality of coefficients in group (6)
All		-0.261*** (0.045)	3.58		-0.091*** (0.034)	2.85	
Type of DI allowance	Initial DDS allowance	-0.223*** (0.051)	4.69	0.03	-0.140*** (0.050)	3.76	0.02
	Hearings allowance	-0.082** (0.033)	1.25		0.018 (0.029)	0.95	
Race	Nonblack	-0.257*** (0.059)	3.57	0.04	-0.102*** (0.037)	2.80	0.42
	Black	-0.504*** (0.150)	3.72		-0.048 (0.101)	3.06	
Sex	Males	-0.064 (0.104)	3.69	<0.01	-0.149** (0.057)	2.90	0.18
	Females	-0.315*** (0.034)	3.55		-0.044 (0.055)	2.79	
Year began on DI	1997-2005	-0.302*** (0.065)	4.39	0.74	-0.065 (0.045)	3.01	0.32
	2006-2009	-0.257*** (0.050)	2.66		-0.129** (0.053)	2.56	
Category of primary disability	Mental disorders	-0.054 (0.045)	1.00	<0.01	-0.007 (0.033)	0.73	0.03
	Musculo. Conditions	-0.031 (0.029)	1.01		0.032 (0.027)	0.76	
	All other disabilities	-0.372*** (0.085)	6.71		-0.210*** (0.072)	5.35	
	- Cancers	-0.615 (0.404)	17.5		-0.560*** (0.219)	16.2	
	- Cardiovascular conditions	-0.219*** (0.076)	3.98		-0.037 (0.110)	2.95	
Age when filing DI	Age < 45 yrs.	-0.153*** (0.038)	2.03	0.29	-0.053 (0.039)	2.25	0.32
	Age ≥ 45 yrs.	-0.249*** (0.065)	4.39		-0.129 (0.083)	4.12	

Notes: See notes to Tables 1 and 3. The mean mortality rate in Column 2 is measured by the constant in the regression. Column 3 shows the *p*-value from a test of the hypothesis that the coefficients are equal within each category. Robust standard errors [* p<0.10, ** p<0.05, *** p<0.01] are shown in parentheses.

APPENDIX: FOR ONLINE PUBLICATION ONLY

Appendix 1. Fuzzy RKD specification

Initial AIME is fixed. However, in certain cases AIME can change while a beneficiary is on DI. First, the documented date of disability onset may change through the DI application and award process, thus changing the years on which the AIME calculation is based. This accounts for more than 80 percent of adjustments to AIME. Second, SSA observes earnings with a lag, so additional information on pre-DI earnings may be provided and change the AIME calculation. Third, beneficiaries may have sufficient earnings while on DI to have their AIME updated; our tabulations show that in approximately five percent of cases, AIME is updated for this reason.

The adjustments to AIME are typically minor, so initial AIME measures AIME in subsequent years with only modest error. To account for AIME changes, we also estimate a "fuzzy RKD," where the "reduced form" model remains (2) but it is scaled by the "first stage" estimates of the change in the slope of mean realized DI benefits while a beneficiary is on DI:

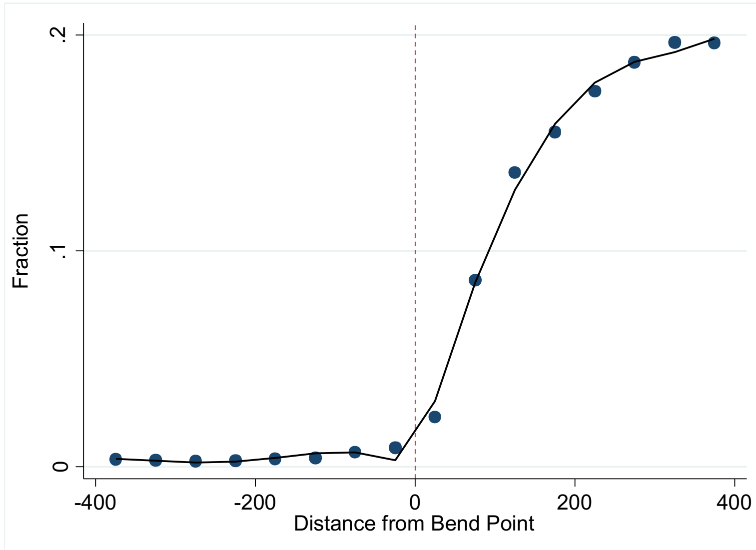
$$Benefits_i = \alpha_0 + \alpha_1(A_i - A_0) + \alpha_2(A_i - A_0)D_i + \varepsilon_i$$

The effect of a dollar of DI benefits on average earnings is then given by β_2/α_2. However, some of the measured changes in AIME once on DI could be due to measurement error rather than true changes, potentially leading to lack of precision in the first stage.

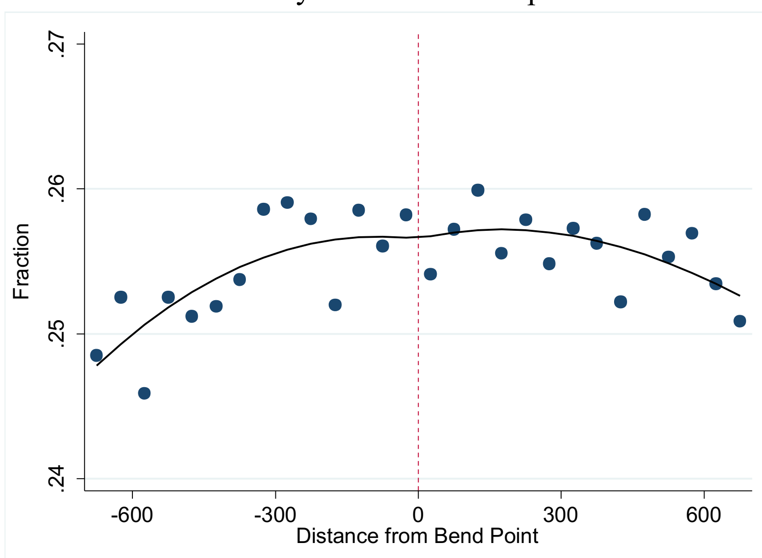
In practice, AIME changes are sufficiently minor that we obtain essentially identical results using the sharp and fuzzy RKD. We use the sharp RKD as our baseline, while also showing the results using the fuzzy RKD.

Figure A1 Fraction of Beneficiaries with Reported Dependents

A: Lower bend point

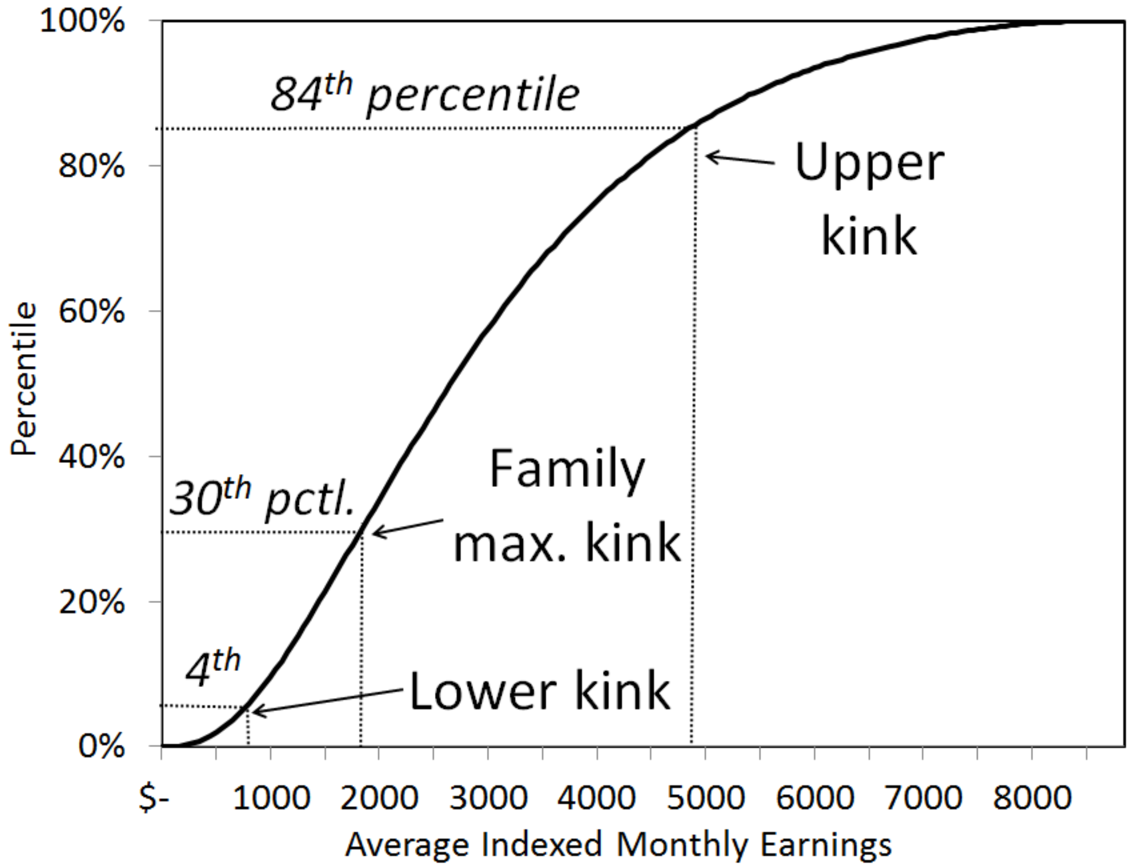


B: Family maximum bend point



Notes: The figure shows the number of reported dependents in each $50 bin around the lower and family maximum bend points. Panel A shows that the number of beneficiaries with reported dependents rises sharply above the lower bend point, precisely where there are increased incentives to report additional dependents. This is why we cannot select the sample based on number of reported dependents at the lower bend point. By contrast, Panel B shows that the number of reported dependents is smooth around the family maximum bend point, suggesting that the changes in family maximum rules do change the probability of claiming dependents.

Figure A2 Cumulative Distribution Function of the Average Indexed Monthly Earnings of new Disability Insurance Beneficiaries



Notes: The source is SSA administrative records on new DI beneficiaries from 2001 to 2007. See the text for sample restrictions and Table 1 for the characteristics of this full sample.

Figure A3a Distribution of Predetermined Covariates – Lower Bend Point

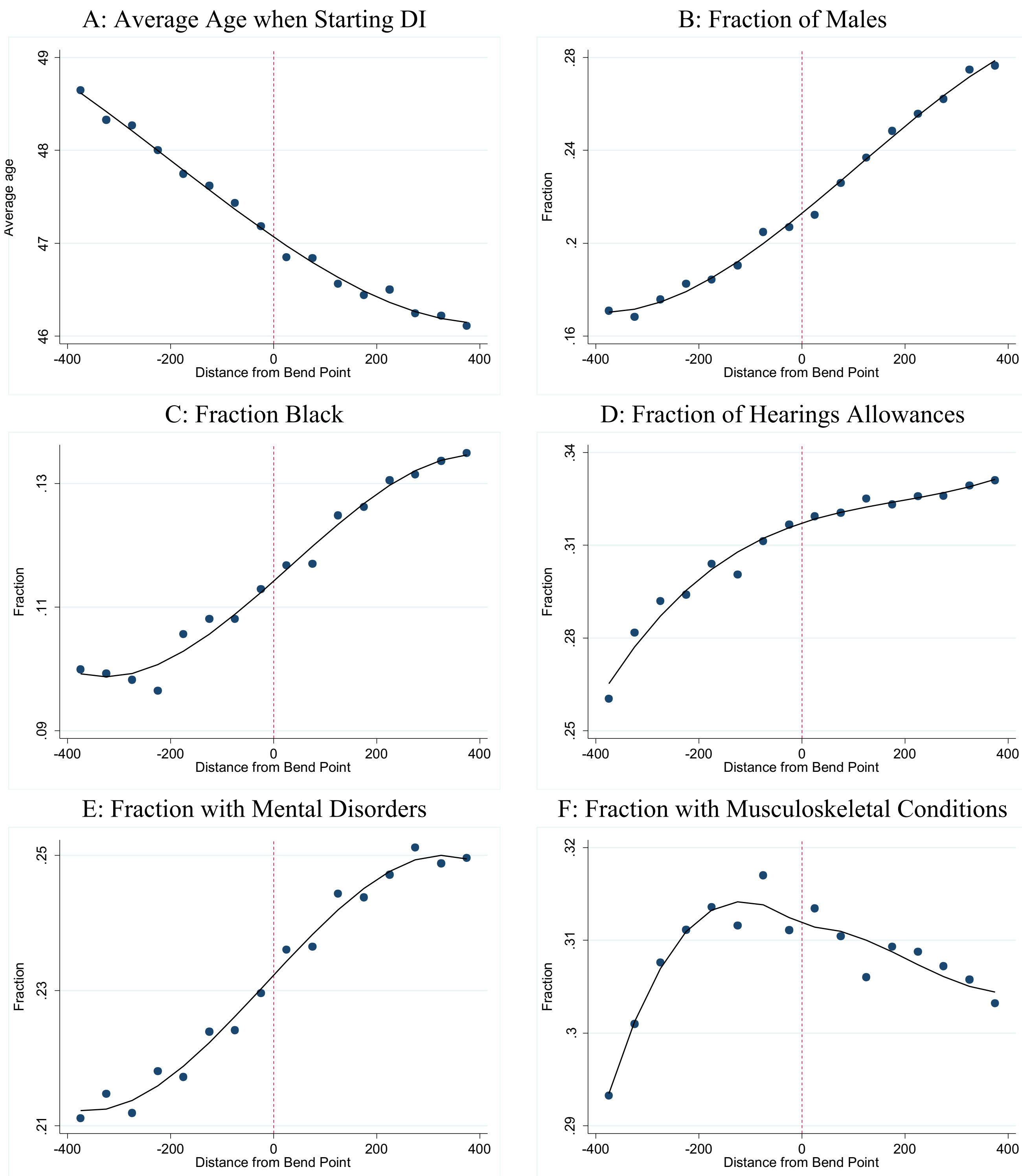


Figure A3b Distribution of Predetermined Covariates – Family Maximum Bend Point

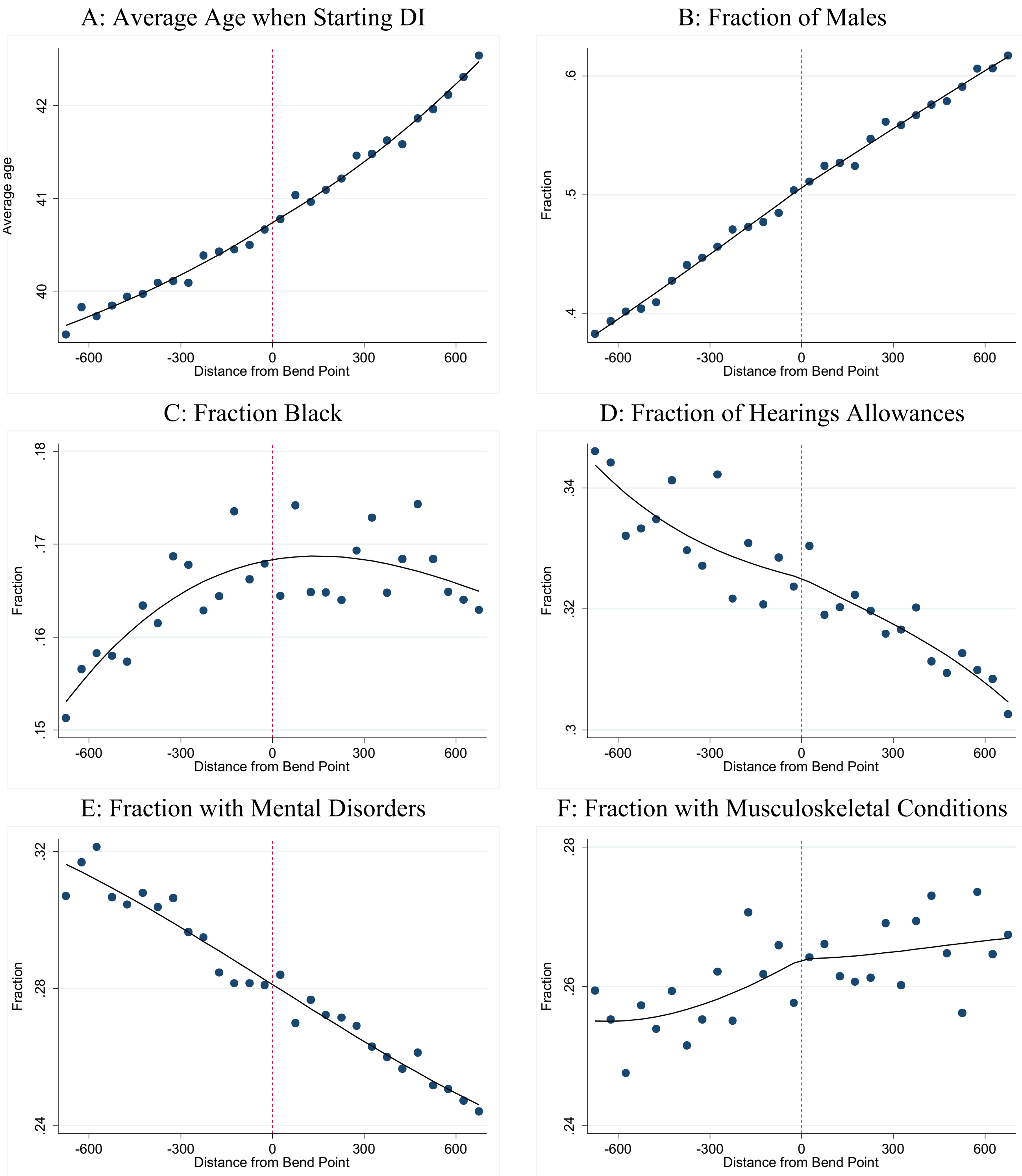
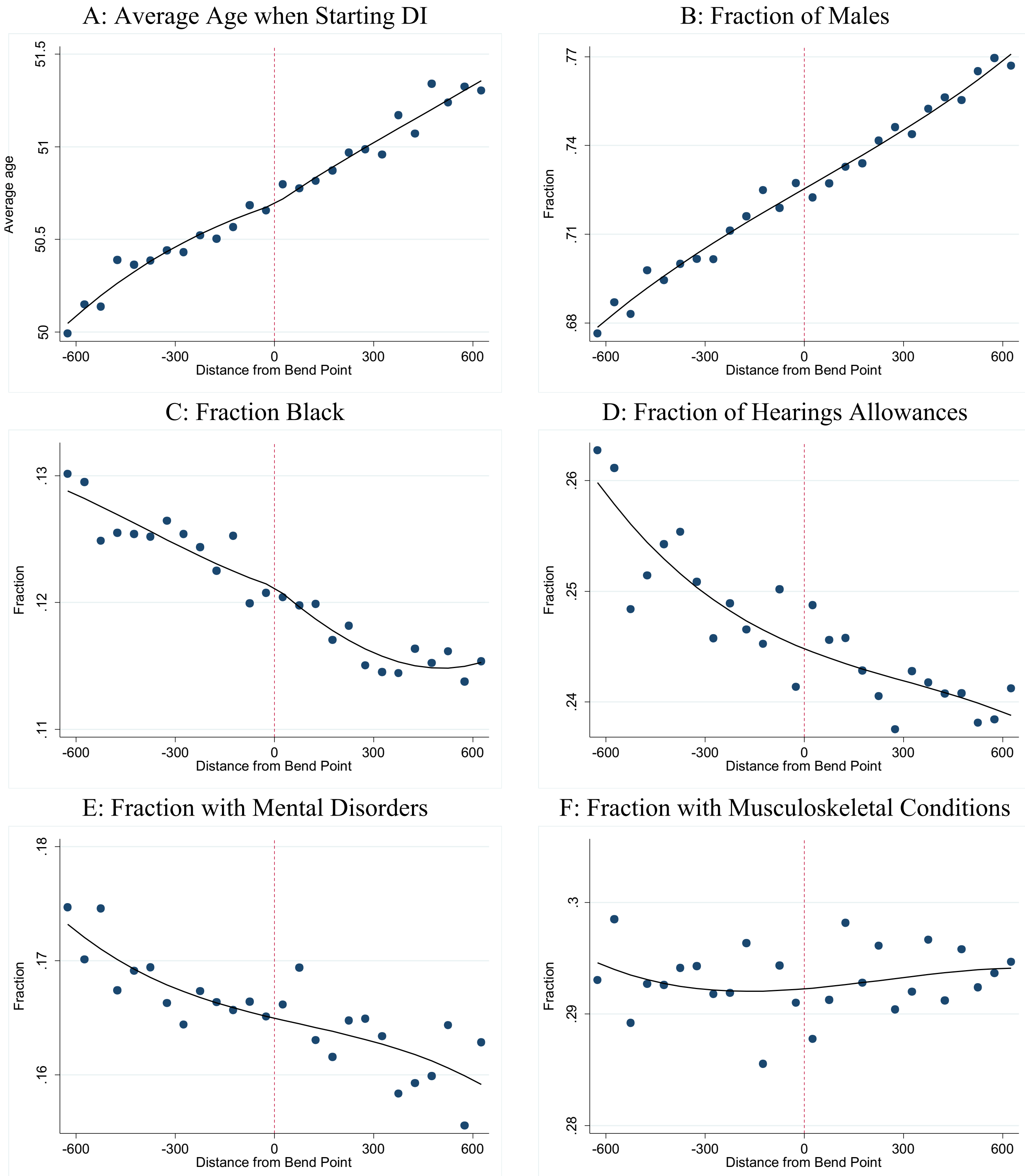
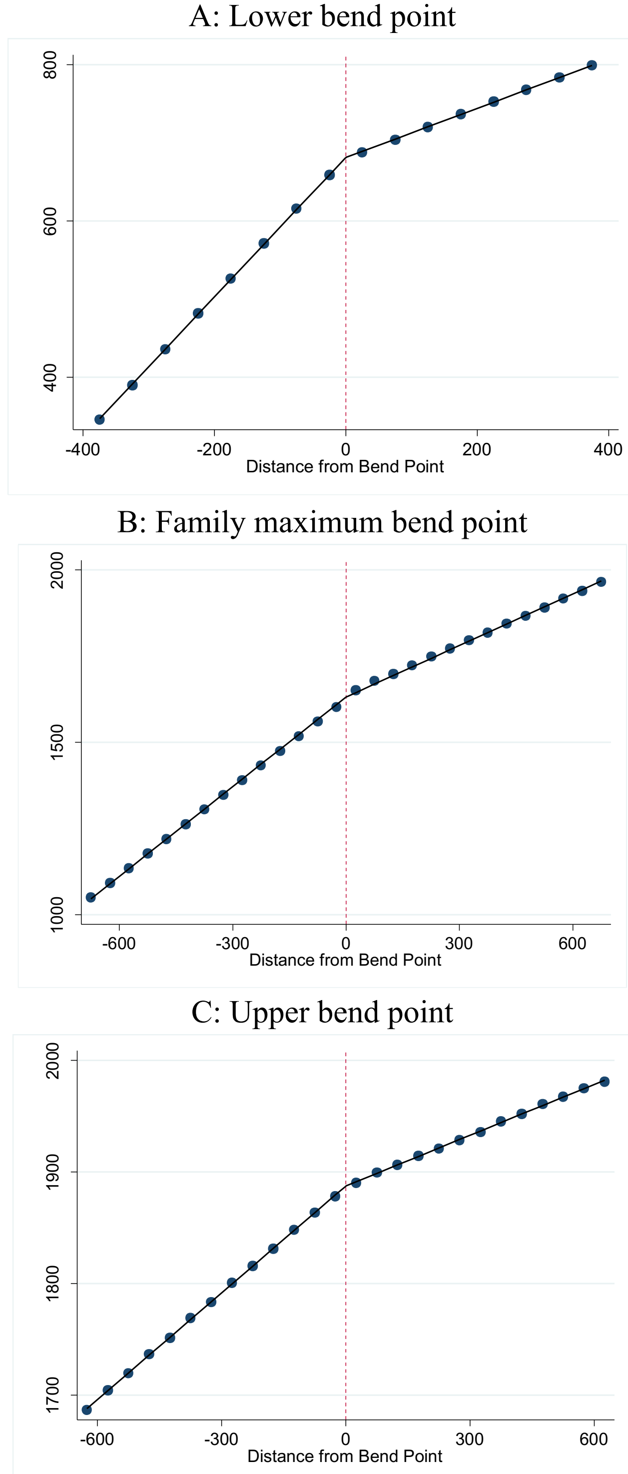


Figure A3c Distribution of Predetermined Covariates – Upper Bend Point



Notes: These figures show the distributions of predetermined covariates in $50 bins as a function of distance from each bend point. They show that these distributions are smooth in the region of the bend point. The best-fit lines are cubic polynomials.

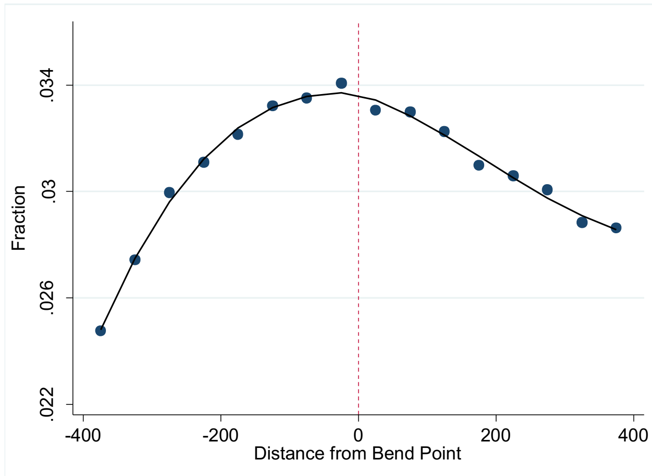
Figure A4 Observed Monthly DI Payments as a Function of Average Indexed Monthly Earnings



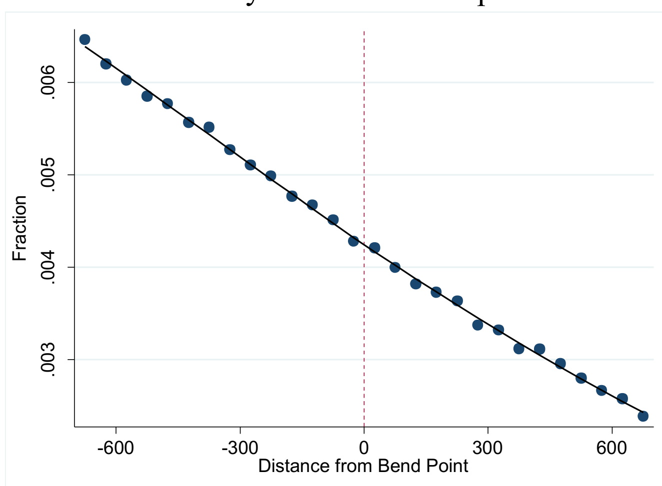
Notes: The figure shows actual DI payments (as measured in our data) as a function of AIME. The figure shows that the effective marginal replacement rate is very close to those indicated by the formulating translating AIME to PIA.

Figure A5 Smoothness of Density of Dual DI/SSI Recipients [Excluded from Main Sample]

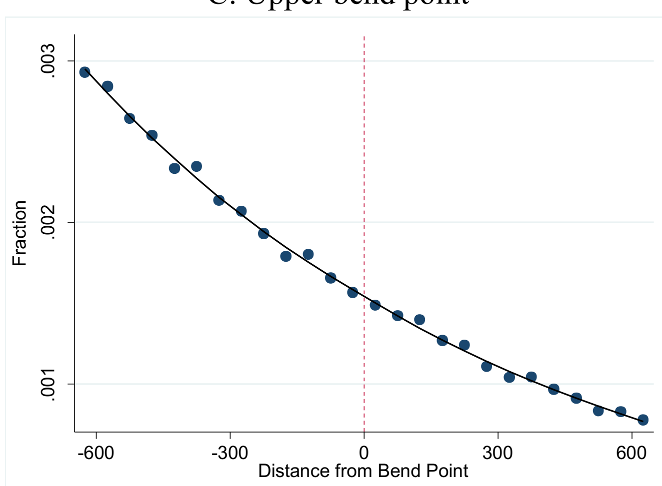
A: Lower bend point



B: Family maximum bend point

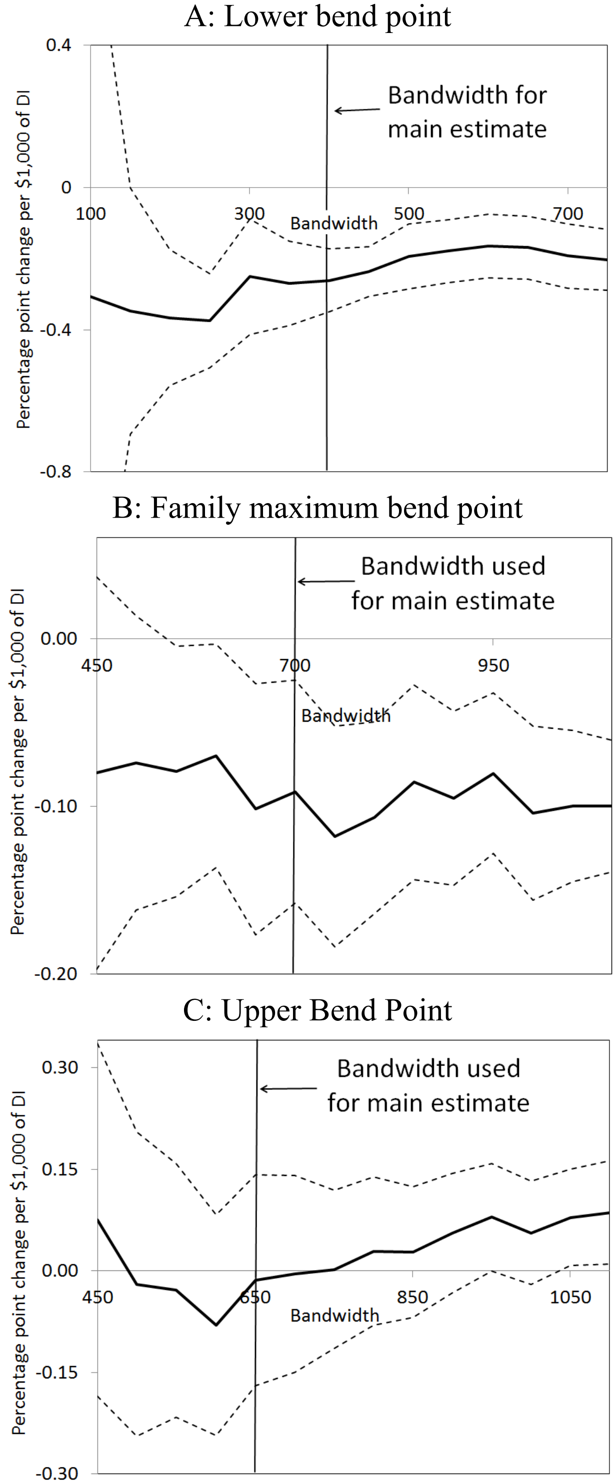


C: Upper bend point



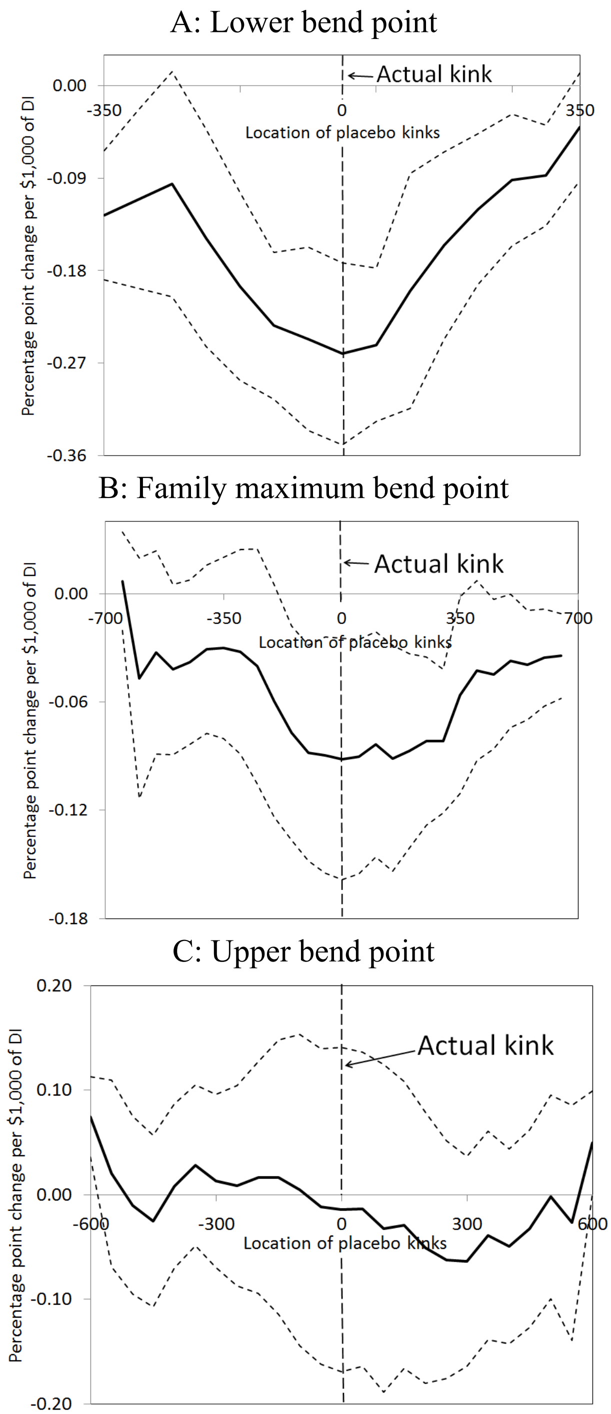
Note: See notes to Figure A2.

Figure A6 Mortality Estimates using Varying Bandwidths



Notes: The figure shows that the point estimates at the lower bend point and family maximum bend point are relative stable as a function of the bandwidth chosen.

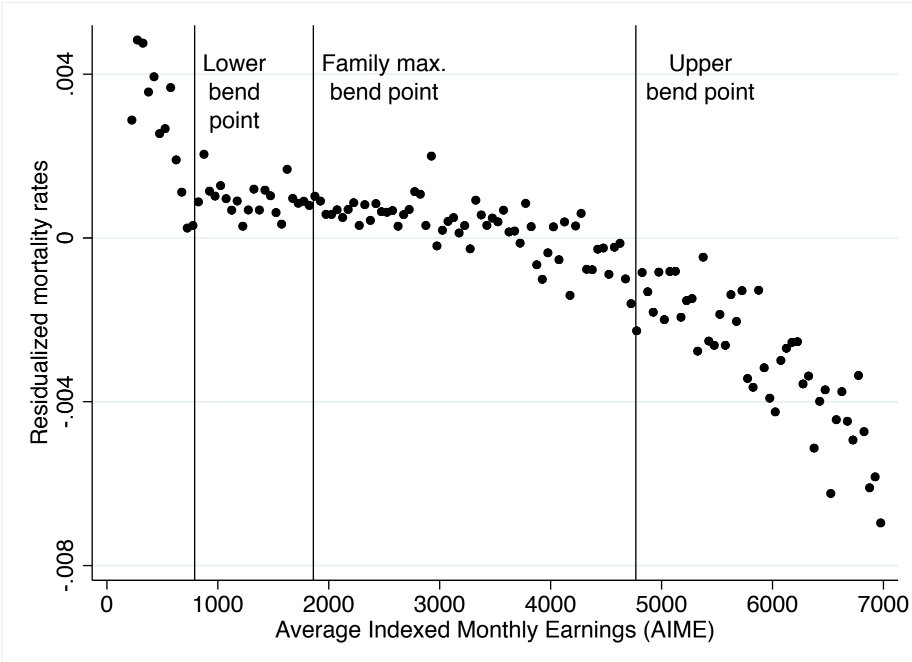
Figure A7 Mortality Estimates for Placebo Bend Point Locations



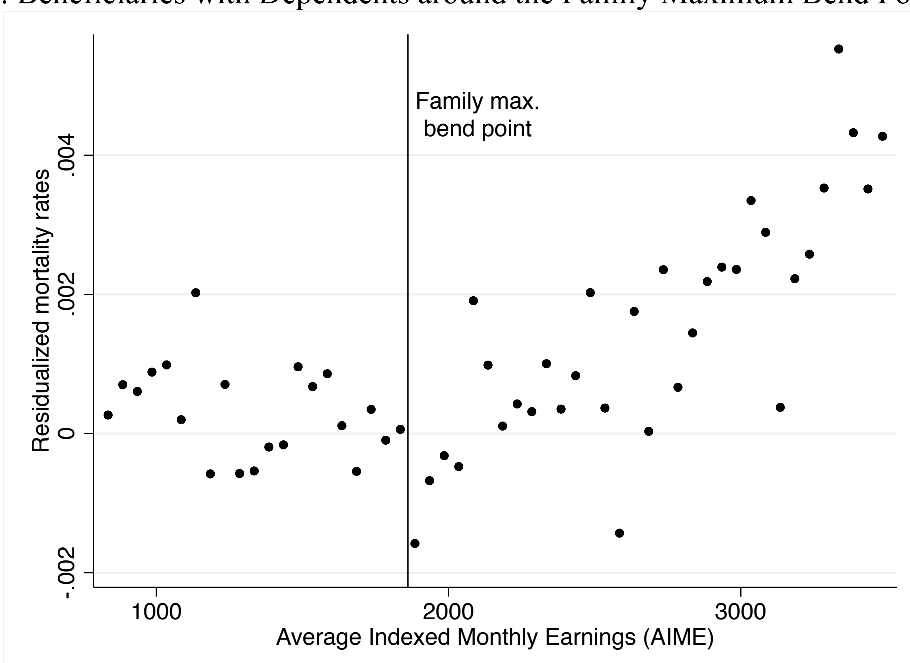
Notes: The figure show the point estimates and 95 percent confidence intervals for the effect of a $1,000 increase in annual DI payments on mortality in the first four years on DI that is implied by replacing the true bend point in model (2) with "placebo" bend point locations relative to the true bend point (normalized to zero). We use the baseline linear specification. The figure shows that, at the lower and family maximum bend points, the absolute value of the coefficient is maximized at the actual bend point (*i.e.* the coefficient itself is minimized at the actual bend point), supporting the contention that there is in fact a change in slope occurring at the true bend point.

Figure A8 Distribution of Mortality Rate Residuals Controlling for Age, Year of Entry, State, Male, Black, Allowance Level

A: All Beneficiaries

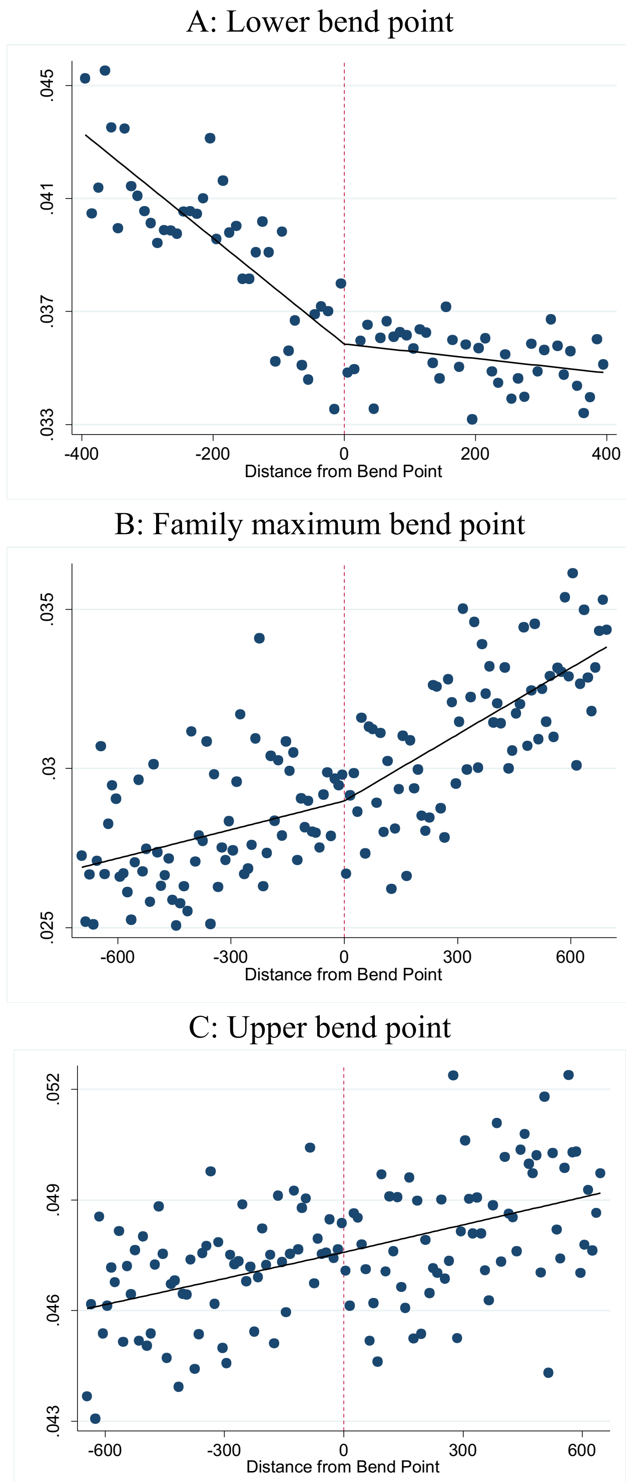


B: Beneficiaries with Dependents around the Family Maximum Bend Point



Notes: The vertical lines in the figures show the locations of the bend points. Panel A shows the residuals of the mortality rate after controlling for covariates, over the full range of AIME. The figure shows a clear, large discontinuity in the slope of the mortality rate at the lower bend point. Allowance level refers to whether the DI beneficiary was allowed at the DDS or hearings stage of disability determination. Panel B shows a clear increase in slope at the bend point when limiting the sample only to beneficiaries with dependents.

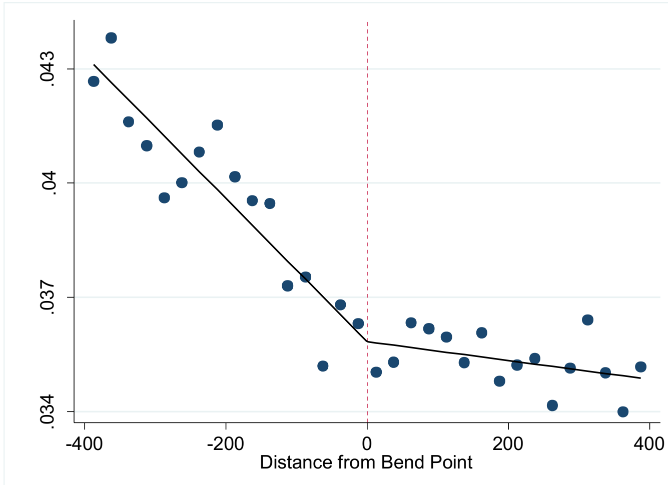
Figure A9 Annual Mortality Rates around the Bend Points – Using $10 bins



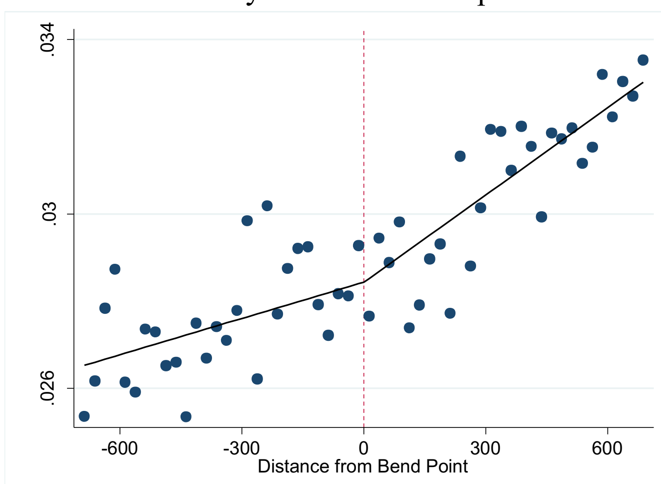
Note: The figure is identical to Figure 3 but uses $10 bins rather than $50 bins.

Figure A10 Annual Mortality Rates around the Bend Points – Using $25 bins

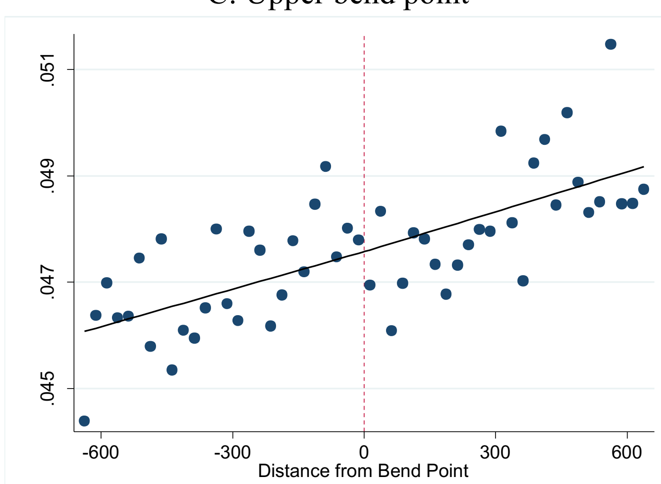
A: Lower bend point



B: Family maximum bend point



C: Upper bend point



Note: The figure is identical to Figure 3 but uses $25 bins rather than $50 bins.

Appendix Table A1. Assessing Smoothness of the Fraction with Dependents

	Testing for a discontinuity in fraction with dependents (x10)		Testing for a kink in fraction with dependents (x100)
	Linear model	Quadratic model	
	(1)	(2)	(3)
A: Lower bend point			
Estimated discontinuity	0.856***	0.282	--
(Std. error)	(0.259)	(0.521)	
Estimated kink	--	--	0.151***
(Std. error)			(0.027)
Polynomial degree	1	2	5
B: Family maximum bend point			
Estimated discontinuity	-0.017	-0.020	--
(Std. error)	(0.020)	(0.027)	
Estimated kink	--	--	0.002
(Std. error)			(0.004)
Polynomial degree	1	2	5

Notes: The table shows that there is a discontinuity in the level and slope of the fraction of the full sample with dependents at the lower bend point, but no such discontinuity at the family maximum bend point. Robust standard errors [* p<0.10, ** p<0.05, *** p<0.01] are shown in parentheses. Around the family maximum bend point, the sample includes both those with and without dependents. See notes to Tables 1, 2, and 3.

Appendix Table A2. Summary Statistics for the Consumer Expenditure Survey and Survey of Income and Program Participation: Expenditure, Net Worth, and Debt

	Respondents receiving DI income			Respondents not receiving DI income
Dependent variable	Lower bend point (1)	Family max. bend point (2)	Upper bend point (3)	(4)
A. Consumer Expenditure Survey				
Total expenditures	$4,716.63	$8,129.89	$8,338.48	$9,020.61
	(5,510.45)	(8,714.61)	(7,524.57)	(9,076.37)
Food	$771.49	$1,335.38	$1,180.05	$1,227.14
	(910.72)	(1,181.07)	(922.06)	(1,110.72)
Housing	$1,663.23	$2,632.73	$2,757.46	$2932.32
	(1,812.64)	(2,635.57)	(2,559.51)	(3,078.09)
Utilities	$467.74	$723.91	$647.30	$602.26
	(418.69)	(547.48)	(400.18)	(494.01)
Home furnishings	$127.81	$273.71	$441.01	$324.05
	(540.89)	(713.05)	(979.12)	($1,117.34)
Apparel	$117.70	$369.22	$331.96	$353.98
	(222.83)	(547.47)	(521.85)	(899.08)
Transportation	$997.30	$1,667.24	$1,796.98	$1,755.98
	(3,178.57)	(5,391.49)	(4,411.48)	(4,657.57)
Health care	$357.51	$448.84	$777.46	$365.77
	(662.98)	(617.24)	(902.91)	(683.90)
Entertainment	$189.82	$406.64	$488.05	$486.29
	(470.97)	(650.82)	(1,413.77)	(1,429.43)
Personal care	$31.50	$58.77	$51.62	$63.27
	(64.44)	(96.90)	(74.06)	(98.25)
B. Survey of Income and Program Participation				
Total net worth	$126,161.57	$99,056.02	$223,035.51	$231,977.14
	(316,241.11)	220,494.98	(614,541.22)	(1,555,208.42)
Total debt	$33,981.51	$59,641.90	$67,383.23	$95,752.60
	(75,705.32)	(90,830.45)	(107,425.92)	(156,291.68)

Note: For the Consumer Expenditure Survey (CES), expenditures refer to total expenditures last quarter. See text for details.

Appendix Table A3. Assessing Smoothness of the Densities

	Density of sample (x1,000)		Density of SSI recipients [excluded] (x1,000)	
	Linear model	Quadratic model	Linear model	Quadratic model
	(1)	(2)	(3)	(4)
A: Lower bend point				
Estimated kink	-0.296	-0.372	-0.097	1.122
(Std. error)	(0.805)	(1.518)	(1.124)	(1.600)
B: Family maximum bend point				
Estimated kink	-0.026	-0.017	-0.005	0.108
(Std. error)	(0.029)	(0.043)	(0.139)	(0.268)
C: Upper bend point				
Estimated kink	-0.020	-0.126	0.015	-0.006
(Std. error)	(0.089)	(0.153)	(0.071)	(0.127)

Notes: The table shows that there is no discontinuity in the *level* of the number of observations per bin, considered as a function of AIME distance to the bend point at any of the bend points. Robust standard errors [* p<0.10, ** p<0.05, *** p<0.01] are shown in parentheses. Around the family maximum bend point, the sample is limited to those with dependents. See notes to Tables 1, 2, and 3.

Appendix Table A4. Estimates of Excess Mass in Initial AIME

	Baseline	8^{th}-degree polynomial	Excluded region \$200
	(1)	(2)	(3)
A. Lower bend point			
γ (x 10,000)	0.543	-0.651	-0.820
	(1.376)	(1.523)	(0.612)
B. Family maximum bend point			
γ (x 10,000)	-0.373	-0.213	-0.195
	(0.385)	(0.402)	(0.286)
C. Upper bend point			
γ (x 10,000)	0.376	0.563	0.181
	(0.770)	(0.802)	(0.448)

Notes: The table shows the point estimates and 95 percent confidence interval on the coefficient on the dummy for initial AIME being near the bend point (reflecting the excess mass per bin near the bend point). For readability, the reported value of γ is the true value multiplied by 10,000. "Baseline" refers to estimating a seventh-degree polynomial through the earnings distribution and estimating the kink from a region within \$100 of the bend point. "Eighth-degree polynomial" (Column 2) estimates an eighth-order polynomial through the density rather than a seventh-order. "Excluded region \$200" (Column 3) refers to estimating the kink from a region of \$200 around the bend point, rather than \$100. Robust standard errors [* p<0.10, ** p<0.05, *** p<0.01] are shown in parentheses.

Appendix Table A5. Effect of DI Benefits on Mortality Rates: Reporting Full Set of Covariates

	Lower bend point			Family max. bend point			Upper bend point		
	Linear model (1)	Quadratic model (2)	Cubic model (3)	Linear model (4)	Quadratic model (5)	Cubic model (6)	Linear model (7)	Quadratic model (8)	Cubic model (9)
p.p. change per $1,000 of DI	-0.261***	-0.422***	-0.520***	-0.091***	-0.148*	-0.153**	-0.014	-0.012	-0.075
	(0.045)	(0.133)	(0.120)	(0.034)	(0.090)	(0.078)	(0.079)	(0.228)	(0.171)
β_2	0.162***	0.263***	0.327***	0.038***	0.062*	0.064**	-0.003	-0.002	-0.014
(x10^4)	(0.028)	(0.083)	(0.076)	(0.014)	(0.037)	(0.032)	(0.014)	(0.041)	(0.031)
AIME	-0.187***	-0.238***	-0.290***	0.028***	0.016	0.014	0.023***	0.020	0.017
(x10^4)	(0.018)	(0.043)	(0.044)	(0.010)	(0.021)	(0.018)	(0.008)	(0.021)	(0.015)
AIME^2		-0.131	-0.233***		-0.015	-0.016		0.002	-0.013
(x10^7)		(0.077)	(0.073)		(0.024)	(0.017)		(0.025)	(0.015)
AIME^3			0.230***			0.005			-0.009
(x10^10)			(0.073)			(0.010)			(0.008)
Constant	0.358***	0.355***	0.353***	0.285***	0.283***	0.283***	0.476***	0.476***	0.475***
(x 10)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
R-squared	0.935	0.951	0.936	0.874	0.897	0.918	0.697	0.684	0.774
Bandwidth	$400	$450	$550	$650 $700	$850	$950	$650	$750	$1000

Notes: The table contains the full results of model (2) for all three specifications at the three bend points. β_2 refers to the change in slope at the bend point, from regression (2) in the main text. The estimates in the first row are equal to β_2 scaled by the decrease in the slope of PIA as a function of AIME at each bend point. Robust standard errors [* p<0.10, ** p<0.05, *** p<0.01] are shown in parentheses. For more information, see notes to Tables 1 and 3.

Appendix Table A6. Effect of DI Benefits on Mortality Rates with Discontinuity at Bend Point

	Linear specification		Quadratic specification		Cubic specification	
	Base model	With discontinuity	Base model	With discontinuity	Base Model	With discontinuity
	(1)	(2)	(3)	(4)	(5)	(6)
A: Lower bend point						
p.p. change per $1,000 of DI	-0.261***	-0.261***	-0.422***	-0.423***	-0.520***	-0.537***
	(0.045)	(0.047)	(0.133)	(0.139)	(0.120)	(0.146)
Bandwidth	$400		$450		$550	
B: Family maximum bend point						
p.p. change per $1,000 of DI	-0.091***	-0.092***	-0.148*	-0.148	-0.153**	-0.154*
	(0.034)	(0.034)	(0.090)	(0.098)	(0.078)	(0.083)
Bandwidth	$700		$850		$950	
C: Upper bend point						
p.p. change per $1,000 of DI	-0.014	-0.029	-0.012	0.004	-0.075	-0.106
	(0.079)	(0.072)	(0.228)	(0.215)	(0.171)	(0.163)
Bandwidth	$650		$750		$1000	

Notes: The table is identical to the baseline estimates, except that this table adds a dummy reflecting a potential change in the level of the outcome at the bend point. The table shows similar results to the baseline in Table 3. See other notes to Table 3.

Appendix Table A7. Effect of DI Benefits on Mortality Rates – Fuzzy RKD Estimates

	Sharp Linear RKD (1)	Fuzzy Linear RKD (2)
A: Lower bend point		
Change in DI replacement rate at bend point	-0.58	-0.577***
		(0.004)
p.p. change per $1,000 of DI payments	-0.261***	-0.262***
	(0.045)	(0.045)
B: Family maximum bend point		
Change in DI replacement rate at bend point	-0.37	-0.368***
		(0.037)
p.p. change per $1,000 of DI payments	-0.091***	0.092***
	(0.034)	(0.035)
C: Upper bend point		
Change in DI replacement rate at bend point	-0.17	-0.167***
		(0.002)
p.p. change per $1,000 of DI payments	-0.014	-0.014
	(0.079)	(0.081)

Notes: In certain cases, AIME can change while a beneficiary is on DI. To account for AIME changes, we also estimate a "fuzzy RKD," where the "reduced form" model remains (2) but it is scaled by the "first stage" estimates of the change in the slope of mean realized DI benefits while a beneficiary is on DI. The adjustments to AIME are typically minor, so initial AIME measures AIME in subsequent years with only modest error. Thus, the results are similar to the baseline results reported in Table 3.

Appendix Table A8. Effect of DI Benefits on Residualized Mortality Rates or Using Individual-Level Controls

	Base results: unadjusted mortality rates (1)	Using residuals (2)	Using individual controls (3)
A: Lower bend point			
p.p. change per $1,000 of DI payments	-0.261***	-0.149***	-0.141***
	(0.045)	(0.043)	(0.040)
B: Family maximum bend point			
p.p. change per $1,000 of DI payments	-0.091***	-0.062**	-0.067*
	(0.034)	(0.032)	(0.035)
C: Upper bend point			
p.p. change per $1,000 of DI payments	-0.014	-0.014	-0.035
	(0.079)	(0.063)	(0.066)

Notes: The table shows the baseline estimates (Column 1), except that this table adds two specifications. First, in Column 2 we use the residuals of mortality after controlling for the bin means of age, as well as dummies for year of entry into DI, state, male, black, and whether the DI beneficiary was allowed at the DDS or hearings stage of disability determination. Second, in Column 3 we run the regressions at the individual level while controlling for age, as well as dummies for year of entry into DI, state, male, black, and whether the DI beneficiary was allowed at the DDS or hearings stage of disability determination. The alternative specifications show similar results to the baseline. Robust standard errors [* p<0.10, ** p<0.05, *** p<0.01] are shown in parentheses. See other notes to Table 3.

Appendix Table A9. Robustness of the Mortality Effects

	Main estimate (1)	Grouped logit model (2)	Changing aggregation: Individual-level data (3)	Changing aggregation: Using $10 bins (4)	Changing aggregation: Using $25 bins (5)	Including those with >4 AIME changes (6)
A. Lower bend point						
p.p. change per $1,000	-0.261***	-0.241***	-0.263***	-0.263***	-0.262***	-0.243***
of DI payments	(0.045)	(0.044)	(0.041)	(0.042)	(0.039)	(0.039)
B. Family maximum bend point						
p.p. change per $1,000	-0.091***	-0.078**	-0.094***	-0.096***	-0.094***	-0.094***
of DI payments	(0.034)	(0.035)	(0.034)	(0.031)	(0.029)	(0.037)
C. Upper bend point						
p.p. change per $1,000	-0.014	-0.009	-0.006	-0.007	-0.008	0.042
of DI payments	(0.079)	(0.079)	(0.078)	(0.078)	(0.079)	(0.083)

Notes: The table shows that the baseline results on the effect of DI benefits on mortality are robust to other specifications. See the main text for explanations of each specification, as well as other notes to Table 3. We re-present the main results in Column 1. Robust standard errors [* p<0.10, ** p<0.05, *** p<0.01] are shown in parentheses.

Appendix Table A10. Placebo Tests of Non-beneficiaries using CCT Bandwidths

	Non-beneficiaries		
	Lower bend point (1)	Family max. bend point (2)	Upper bend point (3)
p.p. change per $1,000 of DI	-0.0034	-0.0007	-0.0025
	(0.0051)	(0.0058)	(0.0041)
Mortality rate at bend point (p.p)	0.0016	0.0017	0.0021
CCT bandwidth	$500	$600	$1,550
Number of non-beneficiaries within range	153,293	277,071	351,266

Notes: The table shows that the placebo tests of non-beneficiaries are robust to using the bandwidths selected by the procedure of Calonico, Cattaneo, and Titiunik (CCT) (2014) in the Continuous Work History Sample One Percent File that we use, rather than using the same bandwidths as our main specification as we do in Table 4.

Table A11. Cumulative Effect of DI Benefits on Mortality by Years Receiving DI

	After 1 year receiving DI (1)	After 2 years receiving DI (2)	After 3 years receiving DI (3)	After 4 years receiving DI (4)
A: Lower bend point				
Change from $1,000 of DI each year (p.p.) *(a)*	-0.393***	-0.725***	-0.920***	-1.044***
	(0.063)	(0.095)	(0.108)	(0.181)
Cumulative mortality rate at bend point (p.p) *(b)*	6.11	9.56	12.12	14.33
Percentage change in mortality *[row (a) / (b)]*	-6.43***	-7.58***	-7.59***	-7.28***
	(1.06)	(1.02)	(0.92)	(1.31)
B: Family maximum bend point				
Change from $1,000 of DI each year (p.p.) *(a)*	-0.162	-0.143	-0.182	-0.365***
	(0.114)	(0.120)	(0.121)	(0.136)
Cumulative mortality rate at bend point (p.p) *(b)*	5.08	7.90	9.84	11.38
Percentage change in mortality *[row (a) / (b)]*	-3.20	-1.81	-1.84	-3.21***
	(2.29)	(1.54)	(1.25)	(1.22)

Notes: The table shows the cumulative mortality effect for each year after receiving DI from Year 1 to Year 4, around each of the bend points. Robust standard errors [* p<0.10, ** p<0.05, *** p<0.01] are shown in parentheses. See other notes to Table 3.

Appendix Table A12. Effect of DI Benefits on Earnings

	Removing dead from sample		Including dead in sample	
	Mortality bandwidth	GMS earnings bandwidth	Mortality bandwidth	GMS earnings bandwidth
	(1)	(2)	(3)	(4)
A: Lower bend point				
Cents / $1 change in DI	-0.41	-7.03*	1.66	-4.83
(Std. error)	(2.02)	(4.27)	(2.86)	(4.08)
Bandwidth	$300	$500	$350	$500
B: Family maximum bend point				
Cents / $1 change in DI	3.73	--	-1.20	--
(Std. error)	(3.38)		(2.67)	
Bandwidth	$850		$1000	
C: Upper bend point				
Cents / $1 change in DI	-21.33**	-20.26***	-20.55***	-18.90***
(Std. error)	(10.77)	(2.31)	(6.96)	(1.84)
Bandwidth	$600	$1500	$650	$1500

Notes: The table shows that we estimate robust significant effects of DI on earnings only at the upper bend point, consistent with our results in Gelber, Moore, and Strand (forthcoming). The estimates differ very slightly from those in Gelber, Moore, and Strand due to slightly different sample selection criteria described in the main text. Robust standard errors [* p<0.10, ** p<0.05, *** p<0.01] are shown in parentheses.