Disability Insurance Income Saves Lives*

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Abstract

We show that higher payments from US Social Security Disability Insurance (DI) reduce mortality. Using administrative data on new DI beneficiaries, we exploit discontinuities in the benefit formula through a regression kink design. We estimate that $1,000 more in annual DI payments decreases the annual mortality rate of lower-income beneficiaries by approximately 0.18 to 0.35 percentage points, implying an elasticity of mortality with respect to DI income of around -0.6 to -1.0. We find no robust evidence of an effect of DI income on the mortality of higher-income beneficiaries. The mortality effects imply large welfare benefits of disability insurance.

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1 Introduction

Disability insurance is a key part of the social safety net. It protects workers and their families from the economic risks associated with disabilities that prevent or limit work. Social Security Disability Insurance (DI) currently insures 175 million American adults against these risks, and in 2020 paid $144 billion to 10 million disabled workers and their families (Social Security Administration or SSA 2021*a*). Beneficiaries are heavily dependent on these payments: 82% are in households that receive more than half of their income from DI, and 37% are in households that had no income other than from DI (Bailey and Hemmeter, 2015). DI beneficiaries are also in poor health: 14% of those who began to receive DI between 2006 and 2010 died within four years, a rate roughly ten times higher than 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. To the best of our knowledge, none of the existing literature has studied the causal effects of DI payments on health outcomes in the US. Indeed, as Chetty and Finkelstein (2013) note: "One particularly important program that has received relatively little attention in terms of measuring benefits. . . is disability insurance" (p. 189).

The primary goal of this paper is to examine how DI income affects beneficiaries' mortality. We estimate the causal effect of income on mortality by using a regression kink design (RKD) applied at three "bend points" (BPs) in the formula that determines payments. The monthly DI payment—known as the Primary Insurance Amount (PIA)—is a progressive function of Average Indexed Monthly Earnings (AIME), which is based on a beneficiary's past earnings. As shown in Figure 1, the marginal rate at which PIA depends on AIME changes from 90% to 32% at the "lower BP" and from 32% to 15% at the "upper BP." Family payment rules create a third "family BP" at which the combined payments to the primary beneficiary and dependents changes from 85% to 48% of AIME. The lower, family and upper BPs occur, respectively, at the fourth, 30th and 84th percentiles of AIME. It is important to note that program rules do not vary around the bend points, which means we estimate the impact of DI income rather than DI eligibility *per se*.

Our primary outcome is the average annual mortality rate during the first four years on DI. We use SSA data on 3.6 million new DI beneficiaries from 1997 to 2009. Intuitively, the RKD allows us to assess whether there are changes in the relationship between mortality and AIME (our assignment variable) that correspond to the sharp changes in DI payments as a function of AIME at the bend points. We previously used this identification strategy and context to examine the effect of DI income on beneficiaries' earnings (Gelber et al., 2017).[1]

We find that DI payments reduce mortality among lower-income beneficiaries. At the lower BP, where average annual DI income in our sample is $10,368, our point estimates imply that an increase of $1,000 in annual DI payments decreases beneficiaries' annual mortality rate by 0.21 to 0.35 percentage points (p.p.).[2] At the family BP, where the average annual DI income for the primary beneficiary is $14,596 and a further $7,298 is paid for dependent(s), our point estimates imply that an increase of $1,000 in annual DI payments decreases beneficiaries' annual mortality rate by 0.18 to 0.26 p.p. At both bend points, the effects are largest among beneficiaries awarded DI by initial disability examiners (rather than upon appeal); among those with a primary disability that is not a musculoskeletal condition or mental disorder (such as cancers and heart disease); and when beneficiaries first receive DI payments. At the upper BP, where the primary beneficiary receives an annual DI income of $28,896 per year, we find no evidence of mortality effects.

The estimates are robust to the choice of bandwidth, the inclusion of covariates, and other RKD specification choices. We verify there are no mortality effects at the family BP for DI beneficiaries without dependents, nor at any of the three bend points using other placebo tests.

Our estimates imply that it costs between $36,000 and $59,000 to save an additional life year at the lower BP, and between $47,000 and $65,000 at the family BP. The "lower boundary" on the value of a life year recommended by the latest major expert panel is $50,000 (Neumann et al. 2014, Neumann et al. 2017). Therefore, the gains in life expectancy we document represent an important benefit of DI not recognized in previous estimates of optimal disability insurance benefit levels.

[1] Here we add the family BP, further address potential confounders at the lower BP, and incorporate recent RKD estimation techniques. Using all of these features, we re-estimate the impact of DI income on earnings, confirm the key results from Gelber et al. (2017), and demonstrate no significant impact on earnings at the family BP.

[2] All dollar amounts are expressed in 2020 dollars, unless otherwise noted.

In considering the potential benefits of DI, existing 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.[3] Empirical evidence on the health effects of DI income is limited to a study using Dutch disability reforms that found opposite-signed effects of income on mortality for men and women (García-Gómez and Gielen 2017), and a study of US veterans receiving payments for mental disorders that found a reduction in self-reported pain but—consistent with our results for mental disorders—no effects on mortality (Silver and Zhang 2022).

To our knowledge, evidence on the overall impact of DI receipt on mortality—which reflects the combined effects of changes in income, work activity, and health insurance—is limited to a study by Black et al. (2021), who use judge assignment as an instrument for DI allowances among initially denied applicants who appeal this decision. They find that DI receipt increases mortality for marginally allowed beneficiaries at this stage of the process, while DI decreases mortality for sicker, inframarginal beneficiaries. They argue that the increased mortality in the former group may occur because working is beneficial to health, while for the latter group this effect is dominated by health gains resulting from DI income and Medicare eligibility. Our findings support this interpretation. Moreover, we find that immediately allowed beneficiaries—who have no need to appeal and therefore are not in the Black et al. (2021) data—account for the mortality reductions we observe. Our results are complementary, because we examine the effect of DI income on its own, which is relevant for calculating the optimal DI replacement rate (as implied by Chetty 2006).

The scant evidence on the causal health effects of DI contrasts with the large and growing literature quantifying the costs associated with the reduction in work due to disability insurance.[4]

[3]For example, see Bound et al. (2004), Chandra and Samwick (2005), Ball and Low (2014), Low and Pistaferri (2015), Meyer and Mok (2019), Autor et al. (2019), and Deshpande and Lockwood (2021). Deshpande (2016) also examines how Supplemental Security Income (SSI) for low-income youth affects income volatility, while Deshpande et al. (2021) documents how DI reduces financial distress. See Diamond and Sheshinski (1995) for a theoretical exploration of optimal DI. As we discuss later, in some models it would be sufficient to observe only non-health consumption to calculate the welfare effects of DI, while in others it would be necessary to observe mortality (as well as other aspects of health consumption).

[4]For example, see Bound (1989), Gruber and Kubik (1997), Gruber (2000), Black et al. (2002), Autor and Duggan (2003), Chen and van der Klaauw (2008), von Wachter et al. (2011), Campolieti and Riddell (2012), Maestas et al. (2013), Borghans et al. (2014), French and Song (2014), Kostøl and Mogstad (2014), Autor et al. (2015), Moore (2015), Coile (2016), and Gelber et al. (2017). For a review of earlier work, see Bound and Burkhauser (1999).

Other evidence is limited to the larger literature on how income affects health in non-DI contexts.[5] That larger literature provides little guidance for evaluating DI, however, as beneficiaries' high mortality rates and low income levels make them different from other populations. Direct estimates of the impact of DI income on health are also relevant to current policy, as changing the DI payment formula is considered in policy discussions (e.g., CBO 2020).

By identifying a group of Americans for whom income strongly affects mortality, our findings also inform the broader literature on the economic determinants of health. Studies of the effect of income on mortality in developed countries generally find that income has little to no effect on reducing mortality in the general population (Cutler et al. 2006, Chandra and Vogl 2010, Clark and Royer 2013). However, these studies do not focus on vulnerable populations. In contrast, our estimates are similar to those found in studies of high-mortality, low-income groups in other contexts, such as old-age pensioners in Russia (Jensen and Richter 2004) and rural China (Cheng et al. 2018), and US Union Army veterans receiving pensions in the early 1900s (Salm 2011). In relative terms, our estimated causal effect of $1,000 in DI income is similar to the income-mortality gradient for US taxpayers in the bottom 5% of taxable household income (Chetty et al. 2016), which—like our causal estimates at the three bend points—declines with income levels.[6].

Given that DI provides income to approximately 4% of the working-age population, the direct effects we document represent substantial improvements in life expectancy. Our results also highlight the more general importance of incorporating health-related benefits in evaluating income support through social insurance programs, even in modern developed economies.

[5] An extensive set of studies spanning many disciplines has found a strong positive correlation between income and health, including reduced mortality and morbidity (e.g. Kitagawa 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), Hoynes et al. (2016), Cheng et al. (2018), and Miglino et al. (2022). For examples of studies that use other types of income, see Preston (1975), Preston and Taubman (1994), Ruhm (2000), Deaton and Paxson (2001), Case et al. (2002), Akee et al. (2013), and Cesarini et al. (2016). There is related research on how employment and retirement affect health (e.g, Sullivan and von Wachter 2009, Fitzpatrick and Moore 2018).

[6] The mortality effects of $1,000 in DI income are also similar in relative terms to providing non-disabled individuals with health insurance or healthcare access (Miller et al. 2021, Goldin et al. 2021)

2 Policy Environment

Rules determining DI cash payments form the basis for our identification strategy. DI is designed to provide payments based on past earnings. Each beneficiary's "Average Indexed Monthly Earnings" (AIME) is based on their annual earnings since age 21, converted to current dollar values. This is used to calculate their monthly payment, or "Primary Insurance Amount" (PIA). Details about DI, including eligibility, Medicare, and its interaction with SSI, are provided in Appendix A.1.

The formula converting AIME to PIA is progressive, providing higher replacement rates when AIME is low. For DI beneficiaries who became eligible in 2020, PIA was equal to 90% of the first $960 of AIME, plus 32% of the next $4,825 of AIME, plus 15% of AIME over $5,785; see the solid line in Figure 1. The formula creates kinks at $960 of AIME, where the marginal replacement rate changes from 90% to 32%, and at $5,785 of AIME, where it changes from 32% to 15%. We follow SSA terminology by referring to these as "bend points" (BPs): the initial change is the "lower BP" and the second one is the "upper BP." They were set through the 1977 Social Security Act Amendments to provide progressive and financially sustainable DI income (Kelley and Humphreys 1994). BP values are adjusted annually using a national wage index.

A third kink in the relationship between AIME and DI payments is created by the rules around the maximum benefits paid to the primary beneficiary and their dependents. The DI benefits a family receives from a worker's earnings record cannot be more than 85% of AIME or 150% of PIA (Romig and Shoffner 2015). For DI beneficiaries with any dependents, the "family BP" occurs when the binding rule changes from 85%-of-AIME below the bend point to 150%-of-PIA above it. As shown in Figure 1, in 2020 this occurs where AIME is $2,257. In terms of total family benefits, the marginal replacement rate for each dollar of AIME changes from 85% (under the 85%-of-AIME rule) to 48% (i.e., 150% of the 32% replacement rate). DI beneficiaries without dependents are unaffected. Around 90% of dependents are children aged under 18, who cannot be paid directly. Thus, it is common for all DI income to be paid to the primary beneficiary.

We therefore have three bend points at which the marginal relationship between DI income and AIME changes: the lower and upper BPs that directly affect the DI payment to the primary

beneficiary, and the family BP that affects the total family DI payments via dependent payments.

Using this variation in a RKD is only valid if beneficiaries do not adjust their AIME in response to the bend points. Such adjustments are unlikely, as it is difficult to determine and change AIME. First, AIME is based on up to 35 years of earnings, and the average DI applicant has a relevant earnings history lasting 29 years (SSA 2021*a*). Second, the wage index used to update earnings is applied with a two-year lag (e.g., 2008 earnings are scaled by 2006 values). Third, up to five of the lowest-earning years are excluded from the AIME calculation. Most workers' earnings decline prior to applying for DI, so those years are often dropped (von Wachter et al. 2011; Gelber et al. 2017). Consequently, manipulating AIME in response to the bend points requires an applicant to make detailed calculations about their earnings history and precise forecasts about the location of the bend points several years before applying for DI.[7] Even then, adjusting AIME is difficult except by working at relatively high levels. Changing AIME is very different to responding to marginal tax rates, which are published ahead of time and only depend on current earnings (Kleven, 2016).

The relationship between AIME and payments is complicated when beneficiaries receive SSI. SSI provides cash, Medicaid, SNAP (food stamps) and home energy assistance to disabled individuals who, apart from a home and a car, have less than $2,000 in assets. Payments are based on "countable income," which depends on their assets, living arrangements and earnings.

Individuals eligible for DI and SSI receive only DI, with two exceptions. First, SSI is paid during the DI waiting period, which is five months from the documented date of disability onset (SSI has no waiting period). Second, beneficiaries with a PIA less than their SSI federal benefit rate receive DI and SSI on an ongoing basis, with total payments equal to the relevant SSI rate (e.g., $783 per month for individuals in 2020). These payments do not depend on AIME.

We remove DI/SSI beneficiaries from our main sample in order to isolate the AIME-induced income variation. However, in Appendix B we verify that the probability of being dually eligible for DI and SSI is smooth at each bend point and also report estimates for dually eligible beneficiaries.

[7] Workers are sent a Social Security Statement that provides an approximate measure of their likely DI benefits. While its receipt has been found to affect application behavior (Armour 2018), Statement estimates are unlikely to be precise enough to determine actual AIME within the ranges used in our analysis.

3 Empirical Strategy and Interpretation of Estimates

3.1 Identification Strategy

We exploit the variation in the DI income formula using a "fuzzy" RKD, which leverages a change in the slope of treatment intensity to identify a local "treatment-on-the-treated" parameter (Card et al. 2015). In our context, the treatment intensity (B) is the size of DI payments (i.e., PIA plus dependent payments), the assignment variable (A) is AIME when the individual first applies for DI, and our primary outcome variable (Y) is the mortality rate of beneficiaries after receiving DI.

When a non-negligible fraction of the population follows the statutory benefit formula, we can use the fuzzy RKD estimand:

$$\frac{\lim_{a\to a_0^+} \frac{\mathrm{d}E[Y|A=a]}{\mathrm{d}a} - \lim_{a\to a_0^-} \frac{\mathrm{d}E[Y|A=a]}{\mathrm{d}a}}{\lim_{a\to a_0^+} \frac{\mathrm{d}E[B|A=a]}{\mathrm{d}a} - \lim_{a\to a_0^-} \frac{\mathrm{d}E[B|A=a]}{\mathrm{d}a}} \tag{1}$$

to identify a weighted average of the marginal effects of B and Y at bend point a_0 (Card et al. 2015). The weight reflects the probability of complying with the benefit formula.

The key identifying assumption in an RKD is the smoothness of the assignment variable distribution: conditional on the unobserved individual "type," the density of AIME is continuously differentiable in a neighborhood of a bend point (Card et al. 2015). This assumption may not hold if there is sorting in relation to the bend points. However, as discussed in Section 2, such sorting appears implausible in our context given how AIME is calculated. In Appendix B, we also document smoothness in the distribution of the assignment variable and the means of predetermined covariates at the bend points, which further assuages concerns about sorting.

3.2 RKD Implementation

Following the standard in the literature, we implement RKD estimation via local polynomial regressions. We separately estimate the four quantities in (1). For $\lim_{a\to a_0^+} \mathrm{d}E[Y|A=a]/\mathrm{d}a$, we

obtain its estimator $\hat{\beta}_1^+$ by using observations above a_0 (denoted by the + superscript) to solve:

$$\{\hat{\beta}_j^+\} = \arg\min_{\beta_j^+} \sum_{i=1}^{n^+} \{Y_i^+ - \sum_{j=0}^{p} \beta_j^+ (A_i^+)^j\}^2 K\left(\frac{A_i^+}{h}\right). \tag{2}$$

We can analogously define $\hat{\beta}_1^-$ as the estimator for $\lim_{a \to a_0^-} \mathrm{d}E[Y|A=a]/\mathrm{d}a$. The resulting estimator for the kink in the outcome is $\hat{\beta}_1^+ - \hat{\beta}_1^-$. We similarly obtain the first-stage kink by replacing Y with B in equation (2) and estimating it above and below a bend point. The fuzzy RKD estimator is simply the ratio of the outcome kink estimator to the first-stage kink estimator.

We follow the literature to choose the three ingredients of (2): bandwidth h, polynomial order p and kernel K. For h, we employ the mean-squared-error (MSE) optimal bandwidth from Calonico et al. (2014), as implemented in the Stata package `rdrobust` (Calonico et al. 2017).[8] Following Card et al. (2017), we use a local linear specification ($p = 1$). For K, we use a uniform kernel.

With an MSE-optimal bandwidth, the asymptotic distribution of the RKD estimator is not centered at the true treatment effect. We address this using the method of Calonico et al. (2014), which corrects for the asymptotic bias in the local linear estimator using a quadratic approximation and constructs a robust standard error by accounting for the sampling variation in the bias estimator. For point estimates, we report the conventional and bias-corrected local linear estimates, as the former may have a lower MSE (Card et al. 2017). We rely solely on the latter for inference.

In an RKD, the inclusion of covariates is not needed for consistency. However, we follow Calonico et al. (2019) to locally control for covariates and document their limited impact on our estimates. The method amounts to adding covariates in the local regressions of (2), while restricting their effects to be the same on both sides of a bend point.

3.3 Interpretation of the Estimates

Our RKD approach measures the effects of changing DI income at the bend points while holding other factors constant, including DI screening, Medicare eligibility, and employment rules. Our

[8] Card et al. (2015, 2017) document that the regularization term adapted from the Imbens and Kalyanaraman (2012) RD bandwidth selector, which is asymptotically negligible but guards against large bandwidths, can be very large in RKD applications. This is also true in our case, so we follow Card et al. (2017) and remove the regularization term.

estimand reflects the change in average mortality rates resulting from a $1 increase in DI benefit payment. Since the marginal change in income varies across bend points, for ease of interpretation we report the implied changes in mortality rates from increasing DI payments by $1,000 per year.

Two aspects of this measure are important for interpretation. First, while we use current DI income, the variation induced by the bend points has persistent effects on lifetime income. PIA and dependent payments only change with annual cost of living adjustments, and fewer than 1% of DI beneficiaries exit DI to return to the labor force each year. Second, DI income is measured in pre-tax terms and we answer the policy-relevant question of how a change in DI benefits would affect mortality. We cannot account for tax rates, as total family taxable income is not available in our data. However, as discussed in Appendix A.1, few beneficiaries have their DI income taxed. To the degree that after-tax benefits are slightly smaller than pre-tax benefits—and the marginal replacement rates associated with after-tax benefits change by slightly less—our estimates will be lower bounds on the absolute effects of after-tax benefits.

4 Data and Analysis Sample

We use SSA administrative data and 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 (see Appendix A.2 for details about the data). The upper age restriction to those under 61 avoids interactions with rules associated with retirement insurance. As mentioned in Section 2, we restrict our main sample to DI primary beneficiaries who did not receive SSI, but also conduct analysis on dually eligible DI/SSI beneficiaries. We measure mortality from the month an individual begins to receive DI payments. We use a follow-up period of four years, which is also the period used in Maestas et al. (2013) and Gelber et al. (2017). DI beneficiaries' mortality rates are especially high when first receiving payments, before declining and remaining stable beyond the second year of eligibility (Zayatz 2015). We consider the timing of mortality effects in our heterogeneity analysis.

At the family BP, we limit the sample to beneficiaries whose dependent benefit starts at the same time as their own payment. Using initial dependent status avoids concerns that changes in dependent eligibility vary around the bend point (e.g., due to changes in marital status or a child's

schooling). The other samples include beneficiaries with and without reported dependents.

Our full sample includes 3,648,988 beneficiaries. We provide their summary statistics in Appendix Table A2. Average PIA is $1,507 per month, or $18,084 annually. Family payments average $19,176 annually. Mortality rates in the first four years after receiving DI decline over time, with 7.0% dying in the first year and 2.0% dying in the fourth year. Average age when applying is 48.6 years, and 53.1% of the sample is male. For approximately half of the sample, the primary disability is either a musculoskeletal condition (29.7%) or mental disorder (20.1%), with the next most common other categories being cancers (11.6%) and cardiovascular conditions (10.3%).

The table also shows summary statistics for the samples around each bend point. Average DI income is lowest around the lower BP and highest around the upper BP. The lower and family BP samples have lower mortality rates than the upper BP sample, which has a higher average age and a larger fraction with cardiovascular conditions. The lower, family, and upper BPs correspond to the 4th, 30th, and 84th percentiles of the AIME distribution, respectively (Appendix Figure A2).

5 Results

5.1 Main Results

In Appendix B, we show that the densities and covariate distributions are smooth around each bend point. The results suggest that individuals do not appear to locate their AIME strategically and that RKD methods are appropriate for estimating causal treatment effects. We also observe kinks in DI income payments at the bend points that closely match the PIA and family maximum formulas.

We graphically present our key result in Figure 2, where we plot the mean annual mortality rate for the four years after DI allowance around each of the bend points. In this and subsequent figures—unless noted—the bins are selected to minimize Integrated MSE using the quantile-spacing method of Calonico et al. (2015). There is a visible discontinuous increase in the slope of the mortality rate as a function of AIME above the lower BP relative to below it (i.e., the negative slope becomes flatter). Around the family BP, 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. There is no visible change in slope at the upper BP.[9]

Table 1 shows the estimated mortality effects. We report the implied percentage point change in the annual mortality rate from an extra $1,000 per year. We report local linear estimates with and without quadratic bias correction, and the corresponding estimates adjusted locally for covariates (i.e., age, sex, race, how awarded DI, and disability type). We report large first-stage effects on DI payments throughout. We also report robust standard errors, the optimal bandwidth and effective number of observations used, as well as the mean annual mortality rate at each bend point.

We find that higher DI payments reduce mortality at the lower and family BPs. At the lower BP, the baseline estimate is -0.24 p.p. per $1,000 of DI income, and -0.37 p.p. with quadratic bias correction. The covariate-adjusted estimates are slightly smaller, at -0.21 and -0.35 p.p. respectively. At the family BP, the equivalent point estimates are -0.25, -0.32, -0.18 and -0.26 p.p. All eight estimates are statistically significant at the 5% level. Relative to the mean mortality rates near the bend points, these point estimates imply decreases in annual mortality of 5 to 10% per $1,000 of DI income. In contrast, at the upper BP, all of the estimates are small and not statistically significant at conventional levels.

We document the robustness of our main estimates to the choice of bandwidth in Figure 3. We focus on the specification with quadratic bias correction, robust standard error, and covariate adjustment, and present estimates using bandwidths of up to $800 for the lower BP—which occurs at $960 of AIME—and $1200 for the other two bend points. At the lower BP, where the MSE-optimal bandwidth is $156, the estimates are stable and statistically significant using bandwidths of between $150 and $800. At the family BP, where the MSE-optimal bandwidth is $587, the estimates are statistically significant using bandwidths between $390 and $810, and above $860.

[9]Figure 2 shows that mortality falls with AIME in the region of the lower BP but rises with AIME at the family and upper BPs. Older DI beneficiaries are over-represented at higher AIME levels—since they have typically had more high-earnings years and also benefit from large wage-index adjustments over long time periods—and also have higher mortality rates. Figures B2 to B4 show that average age varies in ways that closely match these mortality patterns.

Some of the pattern may also be due to selection into DI based on health. The proportion of income replaced by DI is falling with AIME, which would be expected to result in marginal (and average) applicants with worse health. Such selection is consistent with models of optimal DI, in which poor health decreases utility from work (Diamond and Sheshinski 1995, Autor and Duggan 2003). Any such selection appears unrelated to the local changes in marginal replacement rates at the bend points, so does not change our interpretation of the RKD estimates. Moreover, we show that controlling for age and other covariates makes little difference to the results.

At both bend points, the point estimates shrink slightly with more data, stabilizing at around -0.30 p.p. at the lower BP (compared to -0.35 p.p.) and -0.22 p.p. at the family BP (compared to -0.25 p.p.). At the upper BP, the estimates remain small and not statistically different from zero for all bandwidths. We present further robustness and placebo tests in Appendix B. Taken together, the results suggest that DI payments reduce the mortality of the lowest-income beneficiaries.

5.2 Effect Heterogeneity

We consider how the mortality effects vary by how DI was awarded, sex, race, age at filing, year started on DI, primary disability, and time on DI. Table 2 shows these heterogeneity results at the lower and family BPs, estimated with quadratic bias correction and local adjustment for the other covariates not used in defining the sample.[10]

The estimated mortality reductions are generally larger in groups with higher baseline mortality rates. The clearest difference is between initial awardees and those awarded via a hearing (after an initial denial). Initial awardees, who have a mortality rate roughly four times that of hearings-level awardees, have large and statistically significant reductions in mortality at both bend points. In contrast, there are no apparent mortality changes for hearings-level awardees.

Estimates for other subgroups are generally similar, and become even more so when the samples are restricted to beneficiaries awarded DI at the initial stage. The exception is disability type, with the largest estimates for beneficiaries with cancers and those with disabilities not in the four largest categories (mental, musculoskeletal, cancers and cardiovascular).[11] Consistent with the results for how DI was awarded, these two groups have the highest baseline mortality rates.

We compare estimates for the first and second years on DI to the third and fourth. The estimated mortality reductions decline with time on DI at the lower BP, although the differences are not statistically significant. While single-year estimates are imprecise, the point estimates at both bend points are lowest in the fourth year of DI.[12] While this suggests the effects decline over time, underlying mortality rates also fall with time on DI and make it harder to detect treatment effects.

[10] We assess heterogeneity at the upper BP in Appendix Table B4, but do not find any statistically significant effects.

[11] Dividing "other disabilities" into finer subgroups results in samples that are too small to be informative.

[12] The estimates for the first and fourth years are -0.66 and -0.07 (lower BP) and -0.30 and -0.11 (family BP), although none are statistically different from zero or from each other.

5.3 Potential Mechanisms

In this section, we examine potential mechanisms that mediate the mortality impacts of DI income. First, we rule out changing labor supply as a mechanism. Second, we argue that a likely mechanism is that higher DI income leads to spending that protects health: we provide suggestive evidence that the mortality effects are muted among recipients with access to SSI, which comes with eligibility for Medicaid, SNAP (food stamps) and home energy subsidies.

To explore DI's impacts on labor supply, we use the same RKD variation and present the estimated changes in earnings at each bend point in Appendix Table B5. As in Gelber et al. (2017), we find DI income reduces earnings at the upper BP but has no statistically significant effects at the lower or family BPs. [13] This suggests different mechanisms to studies that find the receipt of DI and Social Security can lower labor force participation and increase mortality (e.g., Black et al. 2021, Fitzpatrick and Moore 2018, Kuhn et al. 2020).[14]

A likely mediator of the income-mortality nexus is spending that protects health. Many DI-only beneficiaries are poor: Livermore and Bardos (2014) estimate that around 28% live in poverty. Low-income DI beneficiaries report delaying healthcare, moving to cheaper housing, skipping meals, and having limited food (Meyer and Mok 2019, Coe et al. 2014, Livermore et al. 2010). More DI income may limit these hardships and improve health. For example, cheaper heating has been found to reduce mortality (Chirakijja et al., 2019), and more food expenditure improves nutrition and lowers the incidence of cardiovascular conditions (Cutler et al., 2003).

Healthcare spending may be especially valuable, as beneficiaries are in poor health and are not eligible for Medicare up to 24 months after DI payments begin. While all SSI recipients have access to Medicaid, only around 15% of DI-only beneficiaries receive Medicaid during this period (Rupp and Riley 2012). New DI beneficiaries are less likely to have health insurance than non-beneficiaries, and around 20% report delaying medical care due to cost (Livermore et al. 2010).

[13] We further establish that earnings responses do not affect our mortality estimates by using the sum of DI income and earnings in the denominator of (1). These results, presented in Appendix Table B6, are similar to those in Table 1.

[14] It is possible that effects on earnings could explain the lack of mortality effects at the upper BP, if DI income reduces work and offsets other benefits on health. Such a mechanism would be consistent with Snyder and Evans (2006), who find that more income led to lowered employment and higher mortality using the Social Security "notch".

DI income may also be protective after beneficiaries become eligible for Medicare, as healthcare utilization has been found to be sensitive to income payments among seniors with Medicare and veterans with little to no direct monetary costs (Gross et al. 2022, Silver and Zhang 2022).

We assess the mortality effects among beneficiaries that receive both DI and SSI—who are not included in our main sample—to gain insight into this channel. DI/SSI beneficiaries are immediately eligible for Medicaid, which has been found to reduce mortality among non-disabled individuals (e.g., Borgschulte and Vogler 2020, Miller et al. 2021). Most receive SNAP benefits, which have also been found to reduce mortality (Bailey et al. 2020). DI/SSI beneficiaries typically receive these in-kind benefits even after the DI waiting period (Rupp et al. 2008).

Results based on our main empirical approaches are presented in Appendix Figure B11 and Table B7. We focus on mortality after the DI waiting period, when payments around the family and upper BPs match the DI formula.[15] At the lower BP, "top-up" SSI payments weaken the link between AIME and payments on an ongoing basis: the first-stage relationship between AIME and DI / SSI payments is an imprecise 0.001 per dollar of AIME. The mortality estimate is -0.42 p.p. per $1,000, but the 95% confidence interval is wide (-4.2 to 3.3 p.p.). At the family BP, there is a strong first stage. The estimated reduction in mortality of -0.05 p.p. contrasts with -0.26 p.p. for the main sample (p-value for the equality of coefficients is 0.12). This provides suggestive evidence that in-kind benefits may weaken the relationship between disability income and mortality.

There are some mechanisms we are unable to explore. For example, being single or having few assets limits self-insurance options and may contribute to the mortality effects we observe (Autor et al. 2019, Meyer and Mok 2019, Coe et al. 2014). Survey data indicate that DI beneficiaries near the lower and family BPs have much lower assets than beneficiaries near the upper BP. However, we are unable to link such information to our data and estimate the mortality effects along these dimensions.[16] Future research can suggest and further explore potential mechanisms.

[15] During the waiting period, SSI payments do not vary with AIME. While individuals may respond to variation in future (higher) DI payments, many low-income recipients are liquidity constrained and may be unable to do so (Coe et al. 2014). We find no kinks in mortality rates during the DI waiting period.

[16] Descriptive information is available from Survey on Income and Program Participation (SIPP) panels (1996, 2001, 2004 and 2008) linked to SSA and IRS files via the SIPP Synthetic Beta process. We use SSA payment data for SIPP respondents aged between 21 and 61 years to identify DI beneficiaries near each BP based on the CDF of DI payments

6 Implications

Our results show large reductions in mortality among lower-income DI beneficiaries. At the lower BP, when covariates are included, the point estimates per $1,000 of DI income are -0.21 p.p. (conventional) and -0.35 p.p. (bias-corrected) . These imply an elasticity of mortality with respect to DI income in the region of -0.56 to -0.94, and to DI income plus earnings of -0.63 to -1.0. Using household information from the SIPP, we obtain an elasticity of mortality with respect to household income in the region of -0.76 to -1.3.[17] At the family BP, the equivalent point estimates are -0.18 p.p. and -0.26 p.p., implying mortality elasticities in the region of -0.69 to -0.99 for DI income, -0.77 to -1.1 for DI income plus earnings, and -1.1 to -1.6 for household income.

While we are the first to document that cash transfers to disabled workers increases their longevity, our results are similar to estimates for how transfer income affects mortality in other vulnerable populations. For example, the estimated elasticities of mortality with respect to individual income are around -1.2 for rural old-age pensions in China (Cheng et al., 2018) and -0.6 for US Union Army pensions in the early 1900s (Salm, 2011). The estimated elasticity of mortality with respect to household income is around -0.9 for Russian old-age pensions (Jensen and Richter, 2004). Even studies that find smaller effects, such as -0.4 for old-age pensions in Chile (Miglino et al., 2022) and -0.2 for cash transfers to seniors in Mexico (Barham and Rowberry, 2013), are comparable given that they use intent-to-treat estimates.[18] Consistent with our discussion of potential mechanisms, studies finding large mortality reductions from cash payments find that they improve nutrition and increase health care utilization (Jensen and Richter 2004, Cheng et al. 2018).

that match the BP locations (at the family BP, we also condition on having a dependent child). Results from the "Completed Gold Standard Files" provide information on a limited number of variables for samples of DI beneficiaries near the lower, family and upper BPs of 81, 101 and 115 respondents, respectively. Among DI beneficiaries near the lower BP, median housing wealth is $21,838 and median non-housing wealth is $10,750. The respective median values for beneficiaries near the family BP are 47% and 48% higher, while they are 129% and 228% higher for beneficiaries near the upper BP. The fraction of DI beneficiaries that are single is 35% at the lower BP, 27% at the family BP, and 39% at the upper BP. It is not surprising that beneficiaries affected by the family BP have the most children under 18 years (an average of 2.7), but the average at the lower BP is also high (2.0) compared to the upper BP (1.6).

[17] We use the public SIPP files for 1996, 2001, 2004 and 2008, and identify households with DI beneficiaries near each BP based on the CDF of DI payments that match the BP locations (at the family BP, we also condition on having a dependent child). We scale DI plus earnings by additional household income.

[18] See Feeney (2017) and Miglino et al. (2022) for more details. Snyder and Evans (2006) find a mortality elasticity with respect to individual income of 0.6 for Social Security to seniors, which they attribute to changes in work activity.

Other benchmarks are also informative. In terms of AIME-mortality gradient we observe before any of the bend points, our lower BP estimates account for around 90% of the observed relationship and the family BP around 75% of it. We can also compare our estimates to the income-mortality gradient in the general population. In relative terms, our causal estimates of the impact of $1,000 are similar to the gradient for taxpayers in the bottom five percent of taxable household income (Chetty et al., 2016).[19] Compared to documented effects for other policy interventions, in relative terms our estimated effects for $1,000 of DI are similar to providing non-disabled individuals with health insurance or healthcare access.[20] These comparisons point to low-income DI beneficiaries being most similar to vulnerable populations with limited resources.

Our results have important implications for calculating the cost of saving a life-year through DI payments. To estimate the value of a statistical life-year (VSLY), we use SSA actuarial estimates of DI beneficiaries' life expectancy and discount future years of life using an illustrative 3% rate.[21] The mortality reductions over the four years imply that saving a statistical life year requires around $33,000 to $55,000 in extra income at the lower BP, and $45,000 to $65,000 at the family BP.

These ranges are below VSLY benchmarks used by the Department of Health and Human Services, which rose from around $116,000 in 1998 to $369,000 more recently (Kniesner and Viscusi, 2019). 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 et al. (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). Finkelstein et al. (2019) use $25,000 for a Medicaid recipient's valuation of their own life-year.[22]

[19] Using their posted data and regressing mortality rates on household income (with age and year fixed effects), the change in mortality per $1,000 for taxpayers below the 6th percentile is -6% of the mean rate for the lowest percentile. If we restrict the data to taxpayers below the 4th percentile, the estimated mortality change per $1,000 is -11% of the baseline rate. For data, see: `https://opportunityinsights.org/paper/lifeexpectancy/`.

[20] For example, our 5-10% decrease in mortality per $1,000 of DI income is comparable to a -9% change in adult mortality due to Medicaid expansions (Miller et al., 2021), a -10% change in taxpayers' mortality among from more health insurance coverage Goldin et al. (2021), and a mortality change of around -10% among due to the introduction of Community Health Centers in the 1960s Bailey and Goodman-Bacon (2015).

[21] The actuarial estimates are from Zayatz (2015). We use the covariate-adjusted conventional and bias-corrected point estimates, and the average ages for the estimation samples. We use life-years because DI beneficiaries have a relatively low life expectancy (Kniesner and Viscusi, 2019).

[22] These are nominal values, as some of these authors argue that these thresholds are sticky (real values are similar).

In a full benefit-cost analysis, it would be necessary to value the opportunity cost of additional DI income, including the effect of higher taxes on the lifespan of those taxed to fund it. Such an analysis would also require estimates of additional unknown parameters, such as the effect of DI income on beneficiaries' Medicare expenditures. It is therefore beyond the scope of this paper to provide this analysis or the optimal level of DI payments (e.g., Bound et al. 2004, Meyer and Mok 2019, Low and Pistaferri 2015). What we conclude from our illustrative exercise is that the life expectancy gains of low-income DI beneficiaries is in a comparable range to QALY valuations.[23]

7 Conclusion

A key policy question regarding DI is the extent to which DI income affects mortality. Our evidence demonstrates that DI income reduces mortality among lower-income beneficiaries. In particular, at the lower and family BPs, the estimated reductions in annual mortality are around 0.18 to 0.35 p.p. per $1,000 of annual DI benefits. Meanwhile, we find no significant effect at the upper BP.

As noted, our estimates are local to the bend points. We find mortality effects at the fourth percentile of DI income and—for beneficiaries with dependents—at the 30th percentile of DI income. Our estimates are stable to different bandwidths, although there is considerable uncertainty about at what income level such effects fade. However, even under conservative assumptions the effects are large: if our estimates apply to 10% of all DI beneficiaries and one third of DI beneficiaries with dependents, $1,000 more income to each new DI beneficiary would have saved around 830 to 1,340 lives each year during our sample period.[24]

There is also 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.

[23]The optimal income replacement rate is judged by trading off the protections provided by reducing consumption risk against moral hazard costs (Chetty and Finkelstein 2013). If individuals are optimizing, the optimal rate should be the same whether using health or non-health consumption to calibrate the Baily-Chetty formula. However, this need not be the case if individuals are not optimizing. We explore this further in Gelber and Moore (2021).

[24]We base this on the same conventional and bias-corrected covariate-adjusted point estimates as before.

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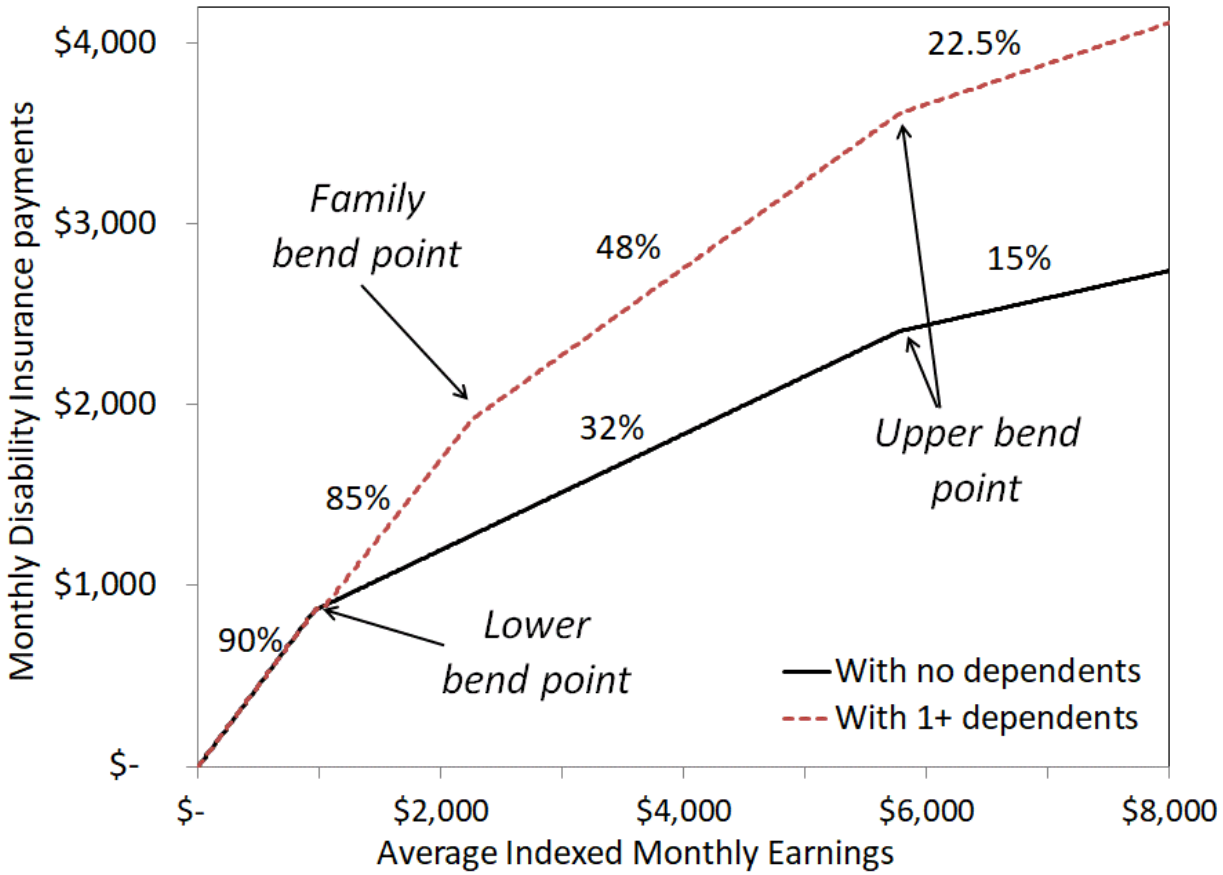
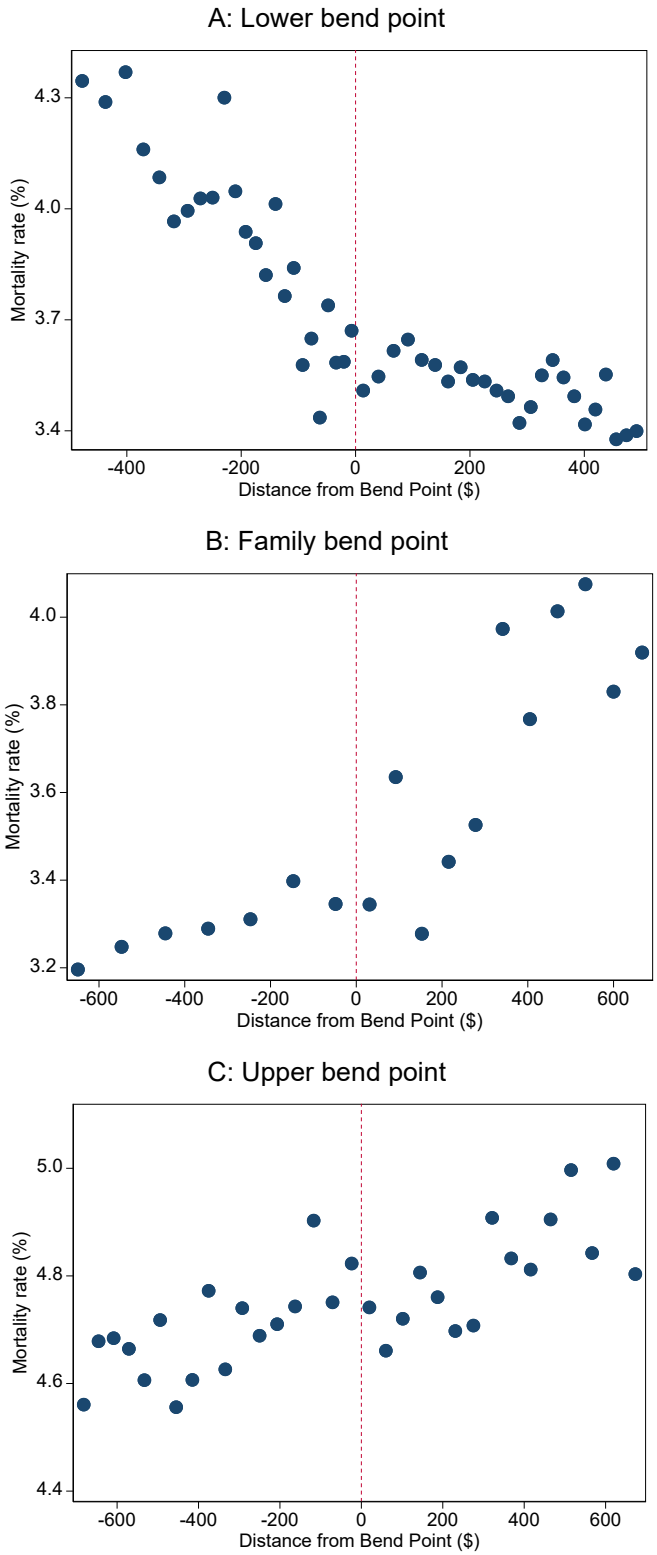
Figure 1 Social Security Disability Insurance payments to Average Indexed Monthly Earnings



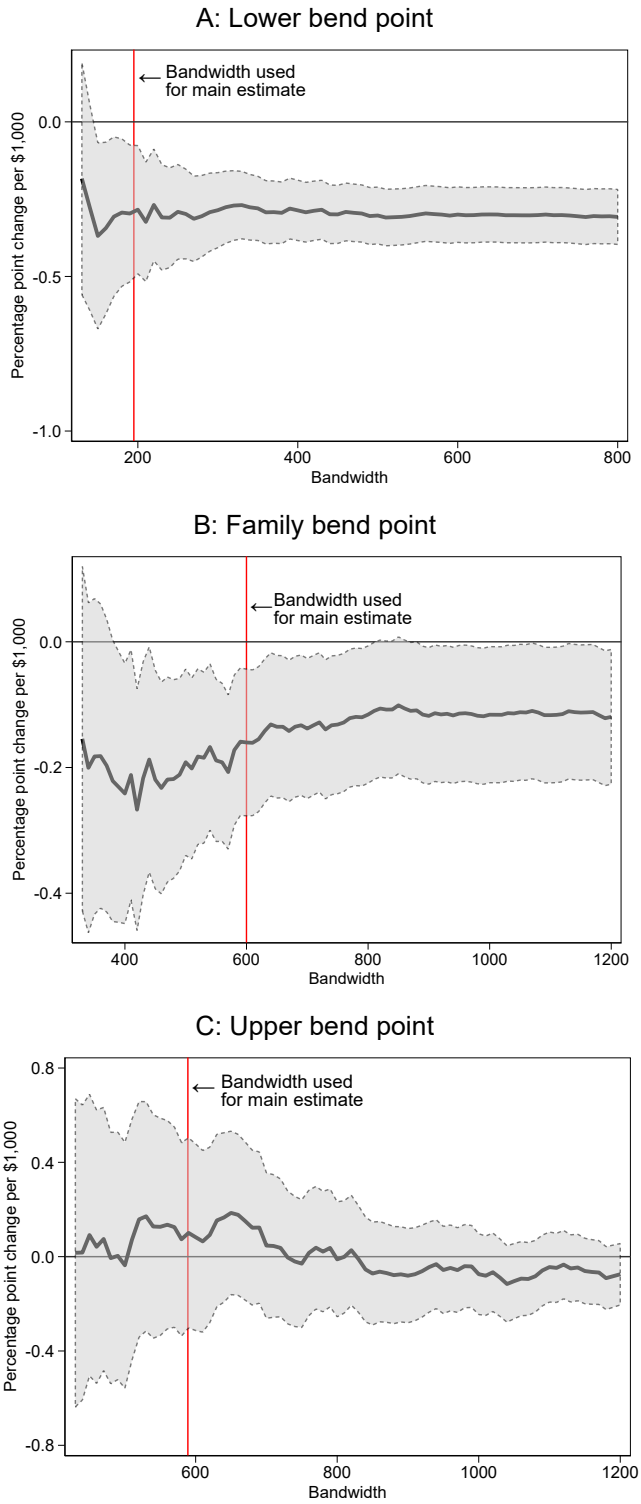
Notes: The solid black line displays the relationship between Average Indexed Monthly Earnings (AIME) and the Primary Insurance Amount (PIA) for beneficiaries. The red dashed line shows the maximum family benefits that can be paid to primary beneficiaries and their dependents. All values are in 2020 dollars. The kink in the family maximum occurs when the binding rule changes from family payments not being larger than 85% of AIME to the one that it may not be larger than 150% of PIA. This means that the marginal rate changes from 85% to 48% of AIME (which is equal to 150% of the 32% replacement rate). The 150% 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% (150% of 32%) to 22.5% (150% of 15%).

Figure 2 Mortality rates around the bend points



Notes: The figure shows the mean annual mortality rates in the first four years after going on DI as a function of distance of AIME from the bend point. Note that AIME is a monthly measure of past earnings. Bin numbers and widths are chosen using the IMSE-optimal quantile-spaced selector of Calonico et al. (2015).

Figure 3 Mortality estimates using varying bandwidths



Notes: The figure shows the coefficients and 95% robust confidence intervals as a function of bandwidth at each bend point. The estimates represent the change in annual mortality rates from increasing annual DI benefit payments by $1,000. We use a local linear RKD specification with quadratic bias correction, predetermined covariates and robust standard errors; see the text for more details. The vertical red lines show the MSE-optimal bandwidths.

Table 1. Effect of Disability Insurance payments on mortality rates

	Without covariates		With covariates		
	Local Linear	+ Quadratic bias correction	Local linear	+ Quadratic bias correction	Bend point mean (p.p.)
	(1)	(2)	(3)	(4)	(5)
Lower bend point					
First-stage estimates	-0.517	-0.506	-0.532	-0.527	
(DI pay change per $1 AIME)	(0.003)	(0.001)	(0.003)	(0.002)	
Mortality change per $1,000 DI (p.p.)	-0.241	-0.371	-0.209	-0.346	3.86
	(0.077)	(0.140)	(0.096)	(0.145)	
Bandwidth	194.48	194.48	156.21	156.21	
Effective no. of observations	182,275	182,275	146,116	146,116	
Family bend point					
First-stage estimates	-0.369	-0.370	-0.369	-0.369	
(DI pay change per $1 AIME)	(0.001)	(0.001)	(0.001)	(0.001)	
Mortality change per $1,000 DI (p.p.)	-0.254	-0.319	-0.184	-0.255	3.65
	(0.063)	(0.100)	(0.061)	(0.094)	
Bandwidth	599.57	599.57	586.91	586.91	
Observations	128,071	128,071	125,485	125,485	
Upper bend point					
First-stage estimates	-0.169	-0.165	-0.169	-0.161	
(DI pay change per $1 AIME)	(0.010)	(0.006)	(0.024)	(0.006)	
Mortality change per $1,000 DI (p.p.)	-0.033	-0.113	-0.025	0.097	4.92
	(0.086)	(0.139)	(0.082)	(0.327)	
Bandwidth	588.94	588.94	579.44	579.44	
Observations	445,600	445,600	438,311	438,311	

Notes: p.p.= percentage points. The table contains coefficients and standard errors showing, at each bend point, the first-stage effects on DI payments and the estimated effect of increasing annual DI benefit payments by $1,000 on the annual mortality rate. This table provides additional information to Table 1. We use the local linear RKD specification described in the text. We show the effects of including quadratic bias correction and controlling for predetermined covariates. We use MSE-optimal bandwidths and report Calonico et al. (2014) robust standard errors for the bias-corrected estimates. For comparison, we report the mean annual mortality rate for beneficiaries at AIME values from $10 below the bend point to the bend point itself.

Table 2. Heterogeneity in the mortality effects at the lower and family bend points

		Lower bend point				Family bend point			
Category	Subgroup	Full sample		DDS examiner awardees only		Full sample		DDS examiner awardees only	
		Estimate (p.p.)	Mean (p.p.)	Estimate (p.p.)	Mean (p.p.)	Estimate (p.p.)	Mean (p.p.)	Estimate (p.p.)	Mean (p.p.)
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
How DI awarded	DDS examiner awardees (a)	-0.373	5.00	--		-0.227	4.29	--	
		(0.138)				(0.075)			
	Hearings level awardees (b)	0.294	1.36	--		0.062	1.04	--	
		(0.364)				(0.071)			
	p-value: (a)=(b)	0.09				0.01			
Sex	Females (c)	-0.422	3.86	-0.475	5.22	-0.142	3.94	-0.230	4.87
		(0.184)		(0.170)		(0.082)		(0.104)	
	Males (d)	0.348	3.83	-0.137	4.21	-0.148	3.40	-0.190	3.78
		(1.017)		(0.272)		(0.083)		(0.101)	
	p-value: (c)=(d)	0.46		0.29		0.95		0.78	
Race	Non-black (e)	-0.321	3.81	-0.424	4.96	-0.181	3.53	-0.207	4.14
		(0.123)		(0.149)		(0.066)		(0.082)	
	Black (f)	0.201	4.20	0.410	5.19	(0.140)	4.28	-0.082	5.07
		(0.358)		(1.54)		-0.181		(0.170)	
	p-value: (e)=(f)	0.17		0.59		0.39		0.51	
Age at filing	Age < 45 yrs. (g)	-0.031	2.16	-0.358	2.85	-0.206	2.83	-0.332	3.42
		(0.900)		(0.495)		(0.070)		(0.094)	
	Age ≥ 45 yrs. (h)	-0.212	4.74	-0.280	5.94	-0.021	5.32	-0.001	5.93
		(0.211)		(0.14)		(0.107)		(0.125)	
	p-value: (g)=(h)	0.84		0.88		0.15		0.13	
Year started on DI	1997-2005 (i)	-0.351	4.74	-0.771	6.08	-0.213	3.86	-0.274	4.48
		(0.494)		(0.344)		(0.084)		(0.101)	
	2006-2009 (j)	-0.398	2.82	-0.411	3.59	-0.044	3.35	-0.069	3.98
		(0.169)		(0.152)		(0.084)		(0.110)	
	p-value: (i)=(j)	0.93		0.34		0.15		0.17	
Primary disability	Mental (k)	0.649	1.10	0.144	1.16	-0.117	0.65	-0.137	0.67
		(0.487)		(0.466)		(0.057)		(0.064)	
	Musculoskeletal (l)	0.047	0.83	-0.247	1.04	0.002	0.72	-0.061	0.66
		(0.250)		(0.186)		(0.063)		(0.095)	
	Cancers (m)	-1.505	18.05	-0.428	18.97	-0.171	18.99	-0.281	19.40
		(1.055)		(0.226)		(0.224)		(0.231)	
	Cardiovascular (n)	-0.077	4.18	-0.557	5.18	-0.020	1.79	-0.035	2.00
		(0.870)		(0.946)		(0.201)		(0.232)	
	All other disabilities (o)	-0.541	7.80	-0.589	9.41	-0.211	6.93	-0.236	8.55
		(0.370)		(0.245)		(0.117)		(0.135)	
	p-value: (k)=…=(o)	0.34		0.70		0.71		0.72	
Time on DI	Years 1 & 2 (p)	-0.503	5.15	-0.819	6.86	-0.107	5.16	-0.142	4.48
		(0.254)		(0.319)		(0.096)		(0.120)	
	Years 3 & 4 (q)	-0.116	2.56	-0.183	3.12	-0.145	2.15	-0.193	3.98
		(0.064)		(0.195)		(0.077)		(0.095)	
	p-value: (p)=(q)	0.14		0.09		0.76		0.74	

Notes: p.p.=percentage points. The table shows group-specific estimates of increasing annual DI payments by $1,000 on the mortality rate. We use a local linear RKD specification with quadratic bias correction, predetermined covariates and robust standard errors; see the text for more details. We report the mean annual mortality rates for beneficiaries from –10 to 0 of AIME relative to the bend point. Columns (3)-(4) and (7)-(8) show the results when the samples are restricted to those awarded DI at the first stage of assessment conducted by Disability Determination Services (DDS).

Appendix (For Online Publication Only)

A Policy Environment and Data: Additional Details

A.1 Details on the Policy Environment

In this appendix, we provide more background on Social Security Disability Insurance (DI), and especially how DI payments are calculated. We also provide details about Supplemental Security Income (SSI) and how it interacts with DI. Unless otherwise noted, this appendix draws upon information in SSA (2021*a*) and SSA (2021*b*).

DI eligibility. DI insures workers for disabilities that limit their ability to work. To be eligible, applicants must (i) be insured for benefits and (ii) have qualifying disabilities. To be insured for DI, an individual needs at least 20 "quarters of coverage" in the previous ten years, although fewer quarters are required for workers aged 30 years or younger. In 2020, each $1,410 in annual earnings contributed a quarter of coverage (up to a maximum of four per year). The threshold for quarters of coverage is updated annually using the National Average Wage Index (NAWI), as are an applicant's prior years of earnings. In practice, insured workers have generally worked at least half of the decade prior to applying for DI.

Section 223(d) of the Social Security Act 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." Substantial gainful activity is judged based on an earnings threshold that is updated annually using the NAWI; in 2020, it was $1,260 per month. Disability examiners work at state Disability Determination Services and assess eligibility using Social Security Administration (SSA) policies and information based on earnings, medical evidence, and vocational factors (age, education and work experience) (Wixon and Strand, 2013). Applicants denied DI eligibility have several options. In some states, applicants can ask for a reconsideration by a different disability examiner. In all states, applicants can request a hearing before an Administrative Law Judge. There are also further appeal options that are less commonly used.

DI benefit calculations. An individual's monthly cash benefit from DI is calculated when an individual applies. The first step is to calculate their Average Indexed Monthly Earnings (AIME). All years between age 21 and an applicant's year of DI eligibility are included in the calculation. Earnings are indexed to the year before DI eligibility. This is done using the NAWI with a two-year lag (e.g., 2007 earnings are scaled by NAWI values for 2005). Then, the lowest one-fifth of years in terms of earnings are dropped from the calculation. These dropped years are rounded down to the next lowest integer and capped at five years. Disabled workers who have fewer than three years dropped can drop up to three additional years if they had been living with a child aged under three and had no earnings (based on child care). At least two years must be used in the AIME computation. Earnings in the remaining years are averaged and converted to months to calculate an applicant's AIME. The second step is to calculate an applicant's Primary Insurance Amount (PIA), which is the monthly payment to the primary beneficiary. As described in Section 2, this is based on their AIME using a progressive formula with two bend points. In 2020, this was equal to 90% of the first $960 of AIME, plus 32% of the next $4,825 of AIME, plus 15% of AIME over $5,785. There are alternative calculations based on steady levels of low earnings and access to other pensions for employment not covered by Social Security, but these are rarely made.

The third step is to calculate dependent payments. DI dependent payments are the same regardless of whether there are one or multiple dependents; note that this is not the case for retirement and survivors benefits, where the payment rules are different. Dependent payments can be made for children who are aged under 18, school students aged 18 or 19, or adults disabled before age 22. They are also available for spouses and divorced spouses if they care for children aged under 16, or if they are aged 62 or older. In 2020, 93% of dependent payments were made for children, with 7% of dependent payments for spouses or divorced spouses. Minors cannot receive DI payments directly. DI benefits can be paid jointly to the primary beneficiary and their dependents when living at the same address; otherwise, they are made as separate checks or deposits.

There are "family maximum" rules that determine the maximum combined payments to the primary beneficiary and their dependents (Romig and Shoffner, 2015). The total DI benefits a

family receives from a worker's earnings record cannot be greater than the minimum of 85% of AIME or 150% of PIA. It also cannot be less than PIA, which is relevant at low levels of AIME. For DI beneficiaries with dependents, what we call the family BP occurs at the AIME level at which the binding rule changes from the 85-percent-of-AIME rule below the bend point, to the 150%-of-PIA rule above the bend point. In 2020, this occurred where AIME was $2,257. At the bend point, the marginal replacement rate for each dollar of AIME changes from 85% (under the 85%-of-AIME rule) to 48% (i.e., 150% of the 32% replacement rate). DI beneficiaries without dependents are not affected by the family maximum rules.

Payment of DI benefits. DI payments are made monthly. Each December, they are increased by the cost-of-living adjustment (COLA). The COLA is the percentage increase in the consumer price index for urban wage earners and clerical workers (CPI-W) measured from the average over July, August, and September of the preceding year to the average for the same three months in the current year. DI beneficiaries receive retirement benefits upon reaching the full retirement age. Their primary payments do not change, as they are based on the same PIA and the same COLA indexation; DI beneficiaries with dependents are subject to different rules that may increase dependent payments.

DI payments are increasd if there is an increase in AIME. (AIME is only ever adjusted upwards.) This can occur if information on earnings that was not available when applying for DI results in a higher AIME (under the rules and calculations discussed above). Earnings once on DI can also increase AIME; however, given that DI beneficiaries earn relatively little, this occurs infrequently and generally does not lead to large changes in AIME. We use initial AIME to avoid any endogenous earning responses based on the AIME values that applicants receive.

DI payments begin after a five-month waiting period. This is based on the documented date of disability established by SSA. Applicants who can establish that their disability began before applying for DI can receive up to 12 months of retroactive DI payments. This maximum is reached when a date is established that is 17 months before the date at which the application was filed (i.e., 12 months plus the DI waiting period of five months). Some applicants may not establish their date

of disability onset until they provide more information to SSA during the determination process; the onset date can be up to 12 months after the date of filing.

Retroactive payments are also made if there is time between the end of the five-month waiting period and when DI eligibility is determined. The average length of time to a decision by the initial disability examiner is three months (Autor et al., 2015), so retroactive payments occur more frequently for applicants allowed DI after appealing an initial denial. Qualified disability advocates and attorneys can collect representation fees of up to 25% of a successful applicant's retroactive payments, up to a maximum of $6,000.

The taxation of DI benefits. Most DI beneficiaries only pay taxes if they have other sources of income. In 2020, DI beneficiaries who were individual filers paid no federal taxes if their total income was less than $25,000; DI income is well below this level in the regions of the lower and family BPs (inclusive of dependent payments). If an individual filer's total income was between $25,000 and $34,000, the tax liability was on 50% of DI income, while for total income above $34,000 the tax liability was on 85% of DI income. These discounts are not applied to non-DI income. The equivalent thresholds for a DI beneficiary filing jointly are below $32,000 (no taxes on DI income), between $32,000 and $44,000 (taxed on 50% of DI income), and above $44,000 (taxed on 85% of DI income). In terms of state taxes, 30 states and the District of Columbia exempt DI income from state income taxes and another seven states have no income taxes. The remaining 13 states tax apply discounts similar or larger than those applied to federal taxation (CRS, 2020).

Medicare eligibility. Medicare provides substantial in-kind benefits to DI beneficiaries after a waiting period. DI beneficiaries are eligible for Medicare two years after DI eligibility, or 29 months after the documented date of disability onset (i.e., 24 months plus the five-month waiting period). Some DI beneficiaries have access to private health insurance or Medicaid, although they report relatively high rates of uninsurance through the first three years of DI receipt (Livermore et al., 2010).

Supplemental Security Income (SSI). SSI provides means-tested benefits to disabled individuals. The program is managed by SSA and uses the same medical eligibility criteria as DI (i.e., an

applicant must have disabilities that are expected to last more than one year or result in death that prevent work above substantial gainful activity levels). The application and assessment process is the same as DI. Applicants generally apply for DI and SSI at the same time; applications are done on a common form and individuals are encouraged to apply for both DI and SSI if they may be eligible for both programs.

Unlike DI, there are no SSI eligibility requirements related to previous earnings. However, there is an assets test. An applicant's "countable resources" must be less than $2,000 for an individual or $3,000 for a couple. This does not include a house, personal effects or a vehicle, but most other resources are counted (including a portion of resources held by family members "deemed" to be available to the applicant).

SSI payments do not depend on AIME. In 2020, the federal SSI monthly rate was $783 for an individual and $1,175 for a couple if both are eligible for SSI. There are no additional payments for dependents. Payment reductions are based upon an SSI recipient's living arrangements, income and other factors. For example, SSI recipients living in other people's houses and receiving room and board generally have their SSI benefits reduced by one third. Earnings above $65 a month (or $85 a month with no other income) result in SSI payments being reduced by 50% (i.e., every two dollars of earnings reduced SSI payments by one dollar). In December 2020, the average monthly payment was $586 (SSA, 2021*b*). SSI payments are increased annually using the same cost-of-living adjustment (COLA) that is applied to DI payments.

There is no waiting period for SSI. SSI payments are based on when an applicant filed for benefits, rather than the documented date of disability onset upon which DI is based. Retroactive payments are made for SSI based on the date of filing.

Income supplements are provided to SSI recipients by 45 states and the District of Columbia; 12 of these states use SSA to manage these payments, while the rest manage the supplemental payments themselves. Each state has its own income and eligibility rules for these payments. States generally grant SSI recipients eligibility for Medicaid, Supplemental Nutrition Assistance Program (SNAP, previously known as "food stamps"), and heating and cooling subsidies through

the Low Income Home Energy Assistance Program (LIHEAP). These programs provide substantial in-kind benefits, which are generally available to SSI recipients without any waiting periods.

The interaction of DI and SSI. As the disability criteria are the same for DI and SSI, individuals can be eligible for both DI and SSI by (i) having enough work credits to be insured for DI, and (ii) being below the relevant SSI "countable resources" threshold. Most individuals eligible for both will receive only DI, as it provides most beneficiaries with higher monthly payments than SSI. When this is the case, DI income crowds out all SSI payments.

As discussed in Section 2, there are two exceptions to this. First, some DI beneficiaries have to wait for DI payments to begin (because, at the time they are judged to be eligible for DI, less than five months has passed since the date of disability onset). Beneficiaries who are eligible for SSI can claim SSI benefits during the DI waiting period. When the waiting period ends, DI beneficiaries with a PIA greater than the relevant SSI benefit rate only receive DI (although they may continue to have access to Medicaid, SNAP and LIHEAP, depending on state rules and their own circumstances). These dually eligible beneficiaries are known as "serial beneficiaries," because they transition from SSI to DI (Rupp et al., 2008).

Second, some DI beneficiaries have a PIA that is less than their relevant 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 set to be equal to their SSI federal benefit rate (with the SSI program paying the difference between their DI benefit and the SSI federal benefit rate). These beneficiaries are subject to SSI rules around earnings, assets and living arrangements on an ongoing basis. (DI is not means tested and does not have equivalent benefit penalties). These dually eligible beneficiaries are known as "concurrent beneficiaries" (Rupp et al., 2008). This second exception creates a "program discontinuity" beyond the DI waiting period. Below it, eligible concurrent DI/SSI beneficiaries receive both DI and SSI and are subject to the rules of both programs. Above it, eligible DI/SSI beneficiaries receive only DI benefits and are not affected by SSI policies.

Figure A1 shows the relationship between federal disability payments (i.e., SSI plus DI pay-

ments) and AIME during and after the DI waiting period for dually eligible beneficiaries. During the DI waiting period, Panel A shows that there is no relationship between AIME and federal disability payments. After the DI waiting period, shown in Panel B, there is no relationship between AIME and federal disability payments to the left of the gray shaded area, while to the right of the shaded area the relationship matches the DI payment rules. The shaded area shows where relationship varies depending on the year used. This variation occurs because SSI payments are indexed by COLA and initial DI payments depend on a formula that is updated using the NAWI to adjust for wage levels (with ongoing DI payments increased using COLA). In fact, the range over which SSI interacts with DI can be even wider, as we use the federal individual SSI payment rate in this figure, but a beneficiary may only be eligible for lower SSI payments because of their living arrangements and countable income (which lowers the level at which the SSI "top-up" is made).

Panel B of Figure A1 shows that there is benefit variation at the family BP beyond the DI waiting period, as there are only serial DI/SSI beneficiaries in that region of AIME. This is also the case for the upper BP, which is to the right of the AIME range used in this figure. However, DI and SSI interact on an ongoing basis in the region of the lower BP. Table A1 makes that clear by showing—for all years in the sample period—the AIME and PIA values at the lower BP, together with the individual federal benefit rate for SSI. In 2020 dollars, the SSI "program discontinuity" occurs between eight dollars below the lower BP and $365 above it; as discussed in the previous paragraph, in practice there is more individual-level variation in terms of where DI and SSI interact (with most factors leading to the program interaction occurring at even lower AIME values). In the paper, we estimate the RKD at the lower BP, which may recover the causal effect of DI income on mortality if the variation related to the DI/SSI program interaction is separate from the DI income induced by the lower BP. However, as discussed in Section 5.3 and shown in Appendix Table B7, at the lower BP there is no "first stage" variation in federal disability income (i.e., DI plus SSI payments) among DI beneficiaries who are also eligible for SSI. This is due to the "gray zone" in Appendix Figure A1. Thus, it is not possible to estimate the effect of disability payments on mortality for this group around the lower BP.

A.2 Details on the Data and Sample Construction

Our main data come from the Disability Analysis File, which is a compilation of SSA administrative data. We use the 2010 version, which contains information on beneficiaries with any DI or SSI benefits between 1997 and 2010. It includes each beneficiary's AIME and PIA; age, race, and sex; DI program activity, including primary disability and how DI was awarded (e.g., by the initial disability examiner or via a hearings-level appeal); and date of death updated through 2013 (Hildebrand et al. 2012). We obtained annual taxable W-2 wage earnings through 2013 from the Detailed Earnings Record. Our data do not include information on assets, total unearned income from other sources, marital status, spousal outcomes, hours worked, or cause of death.

SSA receives mortality information from relatives of beneficiaries, funeral homes, financial institutions, postal authorities and state vital statistics bureaus (GAO 2013). Population coverage is high: Black et al. (2021) estimate that, over the 1997-2013 period we use, the Numident File captures 98.6% of all deaths among those 20 years and older.[1] There is no evidence that reporting of deaths varies by DI income, which means that any measurement error should not change around the bend points and confound our variation. SSA does not record dependents' mortality.

SSA data systems typically have a small fraction of cases with missing or implausible values. We remove them using restrictions similar to those in the existing literature (e.g., von Wachter et al. 2011, Maestas et al. 2013, Gelber et al. 2017). We drop beneficiaries: 1) missing demographic information; 2) missing AIME or PIA values; 3) with a date of disability onset outside of the statutory window (i.e., 12 months before or 17 months after filing); 4) eligible under multiple worker records; 5) who had not received DI payments within four years of filing; and 6) with five or more changes in initial AIME. These restrictions remove 12% of the records from our sample.

[1] See Black et al. (2021), Table A2. Our data also include mortality data from SSA's internal systems (GAO 2013).

B Design Validity and Placebo Tests

B.1 Design Validity

First, the RKD identifying assumptions imply that the distribution of the assignment variable is smooth at a BP. Indeed, the number of observations appear to move smoothly across the bend points (Appendix Figure B1). At each bend point, we test for a kink in the density using the minimum chi-squared method following Card et al. (2012). In particular, we fit polynomial models of order one, two, and three via minimum chi-squared to the AIME histogram within the bandwidths of our main regressions without covariates (i.e., the bandwidths from the first two columns of Table 1). For each model, we test it against a nested counterpart that imposes no kink. The minimum chi-squared objective is equivalent to a optimally weighted minimum distance objective for the multinomial-distributed histogram frequencies (Lindsay and Qu 2003), and our test accounts for the correlation across these frequencies.

We report the p-values for these tests in Appendix Table B1. For the AIME distribution around the lower BP, all three models fail to reject that there is no kink in the density. For the family and upper BPs, the linear model finds a statistically significant kink. However, consistent with our reliance on the Calonico et al. (2014) robust confidence intervals for our main results, which is akin to adopting a quadratic specifications, we put more weight on the quadratic model. This and the cubic model do not indicate a statistically significant kink in the density at any of the three BPs.

Next, we assess the smoothness of the conditional means of predetermined covariates at the bend points, which also follows from the RKD identifying assumptions. We have six covariates available in the data: age when applying for DI; male; black; whether awarded DI via a hearing; primary disability is a mental disorder; and primary disability is a musculoskeletal condition. As shown in Appendix Figures B2-B4, the conditional means appear smooth through all three bend points. We test for kinks in these covariates at the bend points using our primary RKD specification based on equation (2), which includes quadratic bias correction and robust standard errors. The results are presented in Appendix Table B2. None of the estimates are statistically significant at

conventional levels.

Finally, to assess whether SSI eligibility changes at the bend points, we use the same visual and regression approaches to test for kinks in the proportion of DI beneficiaries that receive SSI. This sample includes dually eligible DI/SSI beneficiaries. At each bend point, the fraction of DI beneficiaries who receive SSI appears smooth and there are no statistically significant kinks (Appendix Figure B5 and Table B2).

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 in detail in Appendix A.1, it is not surprising to find no sorting around the bend points given that it is difficult to understand, calculate, and manipulate AIME. In Gelber et al. (2017), we also find that there are no kinks in beneficiaries' earnings before they go on DI.

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). Other literature has found an effect of DI payment size on DI applications and receipt (e.g., Black et al. 2002, Autor and Duggan 2003, von Wachter et al. 2011). By contrast, we find no effect of payment variation on DI receipt locally around the bend points; this is consistent with such variation being difficult to understand and not particularly salient, in contrast to the larger and clearer variation used in this previous literature.

B.2 Placebo Tests

We present results from a series of placebo tests. First, we show RKD mortality estimates using several placebo groups. Figure B7 shows the mean annual mortality rate over the first four years on DI for beneficiaries without dependents whose AIME puts them in the region of the family BP. These beneficiaries are not affected by the family maximum rules. As expected, there is no visually apparent change in the mortality-AIME relationship at the family BP. As shown in the top panel of Appendix Table B3, the estimated kink is small and not statistically significant at conventional levels.

Second, in Appendix Figure B8 we show predicted mortality rates around each bend point using the six predetermined covariates, which effectively combines the covariates into a single index. Again, there is no discernible change at any bend point, and the kink estimates shown in the middle panel of Appendix Table B3 are small and not statistically significant.

Third, we assess the placebo mortality rates of non-DI beneficiaries in relation to their estimated AIME. We create a sample of living DI-insured workers who have never applied for DI using the Continuous Work History Sample, a 1% sample of active Social Security Numbers matched to the Numident File. AIME is calculated as if they had become eligible for DI during 1997, and we measure mortality from 1998 to 2010 (this non-beneficiary group has much lower mortality rates than the DI samples). As shown in Appendix Figure B9, we find no change in mortality at the bend points. Again, the kink estimates shown in the bottom panel of Appendix Table B3 for these placebo samples are small and not statistically significant.[2]

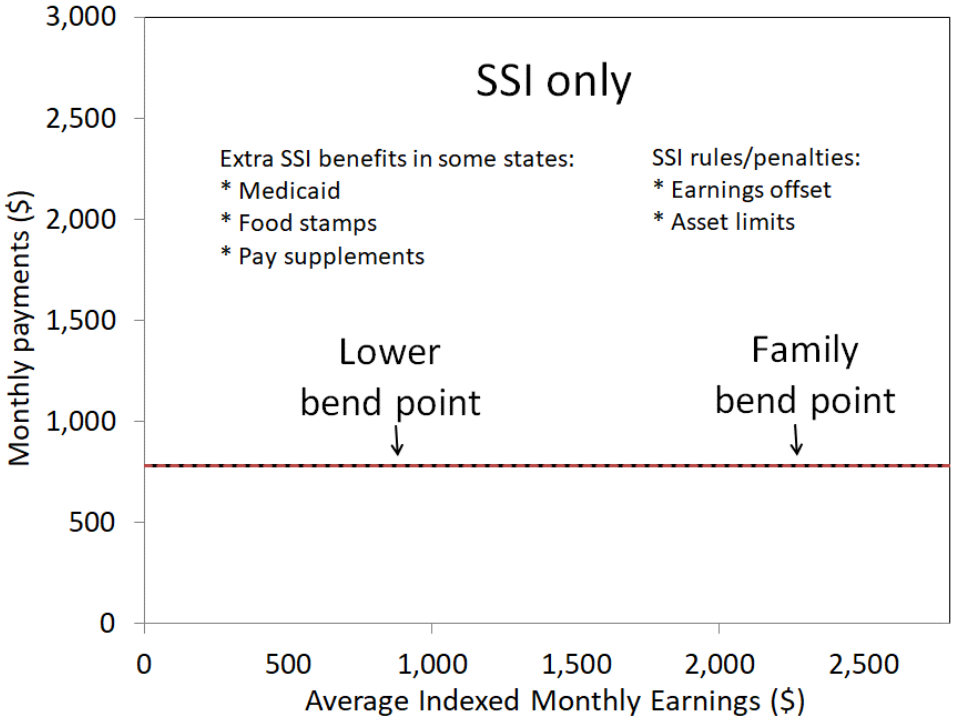
Fourth, we report results from the Ganong and Jäger (2018) permutation test (Appendix Figure B10), which implicitly relies on global homogeneity assumptions regarding the underlying data generating process (Card et al., 2017 Section 4.4.4). At each bend point, we draw 200 placebo thresholds and estimate reduced-form kinks using data that does not include the true policy threshold. For these placebo regressions, we use the same optimal bandwidths as in Table 1. We plot the cumulative distributions of the placebo robust t-statistics. At the lower and family BPs, the t-statistic for the actual reduced-form estimate is larger in absolute value than the placebo t-statistics. In contrast, at the upper BP, the actual t-statistic lies within the range of placebo t-statistics.

In summary, our analyses pass a series of placebo tests. We do not see the RKD mortality effects manifest in groups not subject to a kinked DI benefit schedule.

[2]Rejected DI applicants are another natural placebo group. Unfortunately, we do not have access to data that identifies rejected applicants and their mortality outcomes. Instead, we present placebo tests using beneficiaries and non-beneficiaries (whether or not they had been rejected for DI previously). Given that the average health of rejected DI applicants should lie between these two groups, placebo tests only using rejected DI applicants would be expected to generate similar findings.

Figure A1 The relationship between DI bend points and SSI eligibility

A: Benefits to SSI-eligible beneficiaries during DI waiting period



B: Benefits to SSI-eligible beneficiaries after DI waiting period

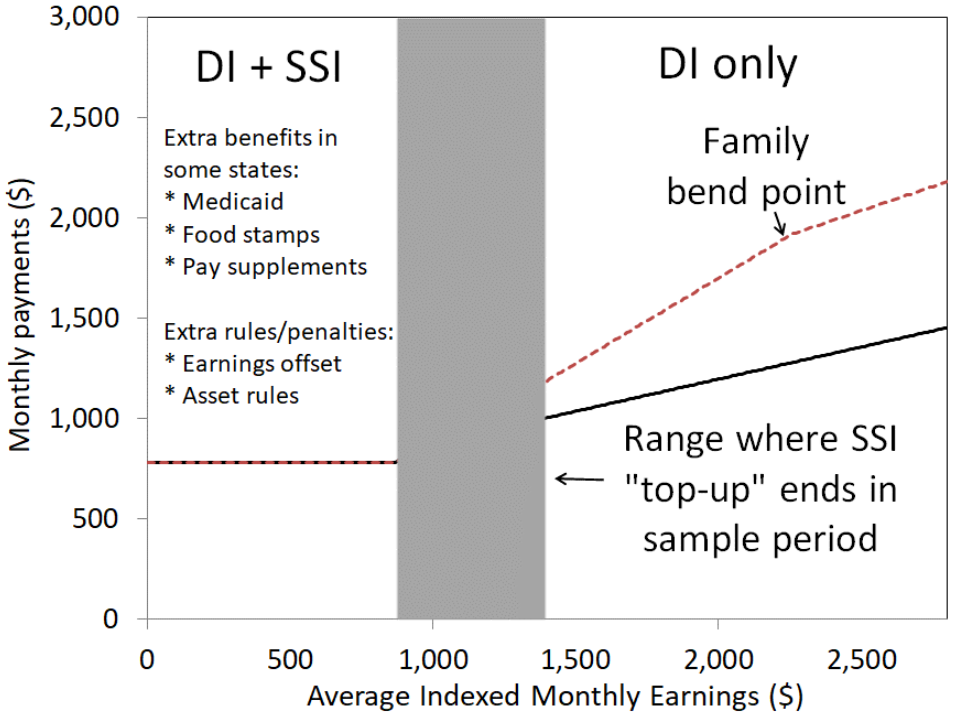
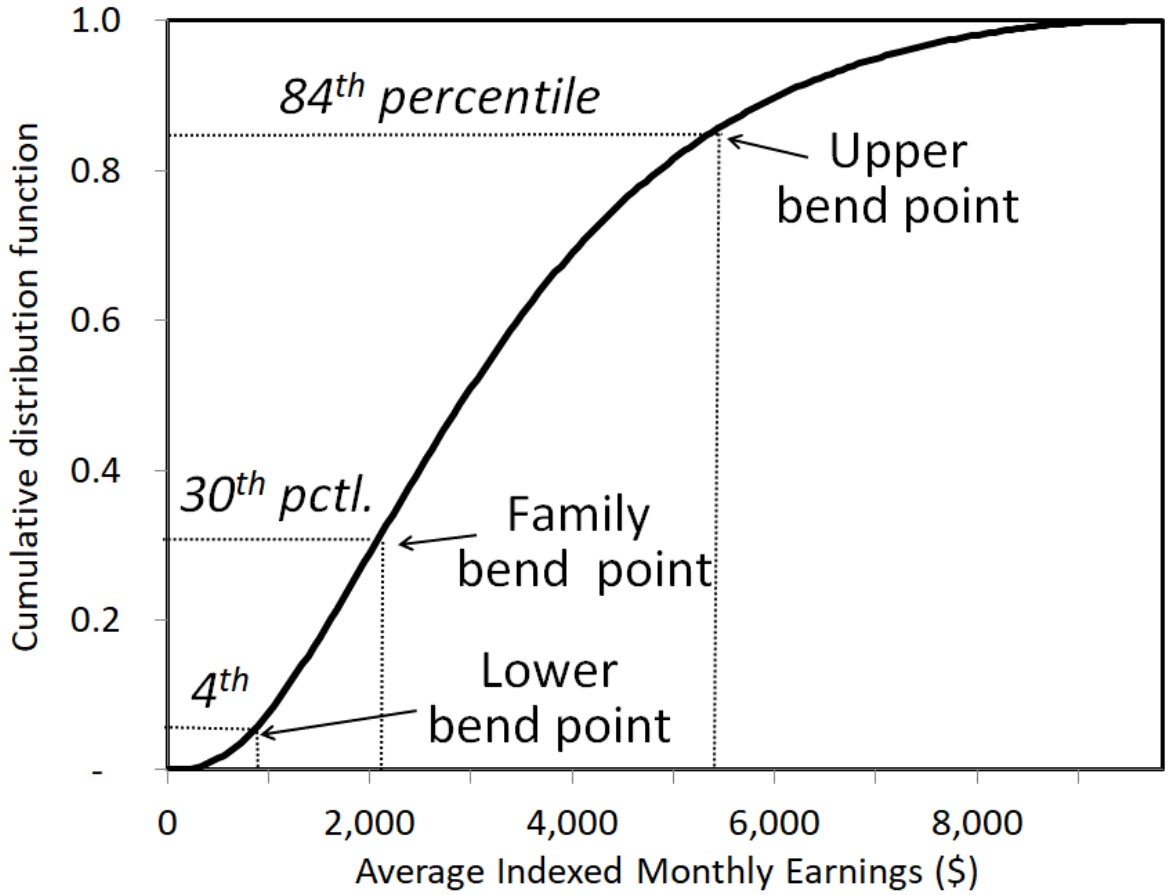


Figure A2 Cumulative distribution function of the Average Indexed Monthly Earnings of Disability Insurance beneficiaries in sample



Notes: This figure shows the distribution of Average Indexed Monthly Earnings within the sample relative to the three bend points. See the text for sample restrictions and Table A2 for the characteristics of this full sample.

Table A1 How the lower BP interacts with the individual SSI federal benefit rate, 1997-2009

Year	Lower BP		SSI federal benefit rate	AIME above lower BP where PIA=SSI rate	
	AIME	PIA		Nominal $	2020 $
1997	455	410	481	224.70	365.47
1998	477	429	492	194.41	309.71
1999	505	455	498	135.63	213.29
2000	531	478	510	101.41	155.58
2001	561	505	528	72.85	107.99
2002	592	533	542	28.58	41.29
2003	606	545	550	12.91	18.40
2004	612	551	561	32.10	44.80
2005	627	564	576	37.26	50.63
2006	656	590	600	29.52	38.54
2007	680	612	620	23.88	30.18
2008	711	640	634	-6.67	-8.24
2009	744	670	671	3.31	3.87

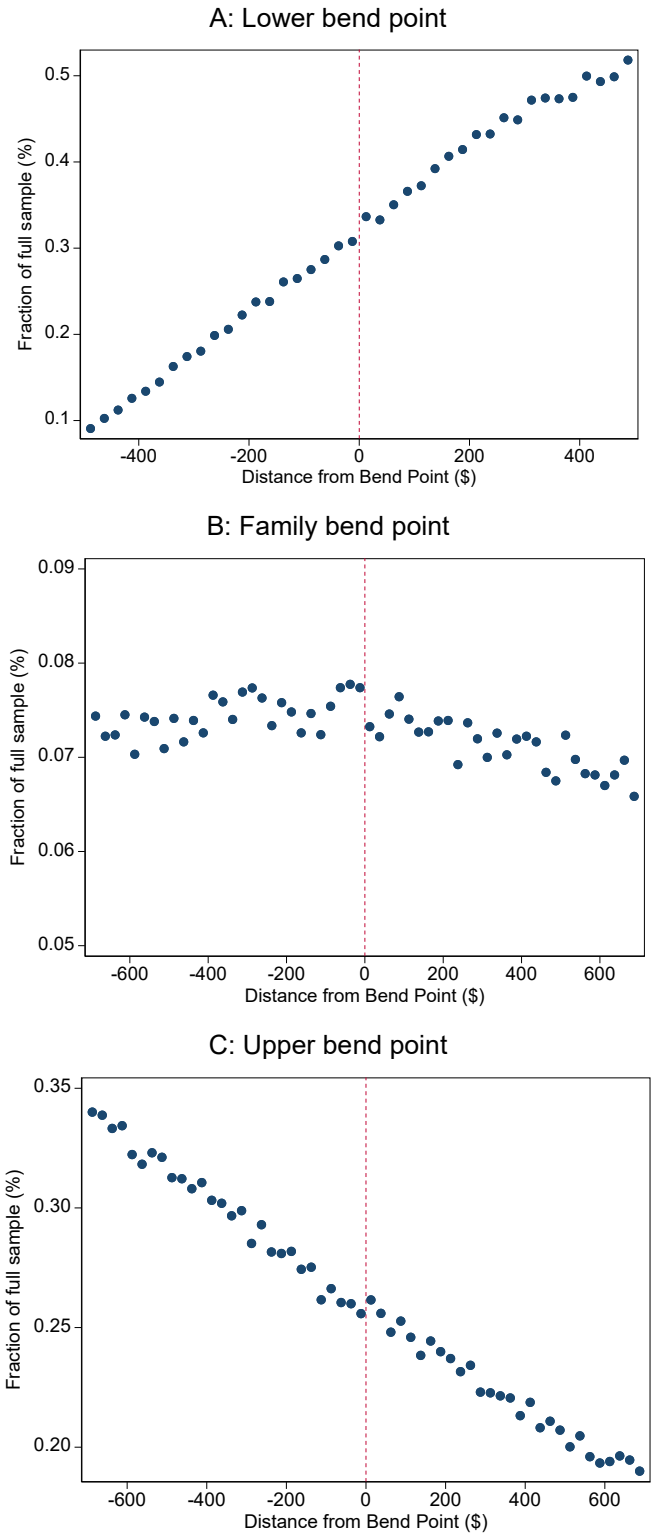
Notes: From SSA (2021a, 2021c) and authors' calculations.

Table A2 Summary statistics for the estimation samples

	Lower BP		Family BP		Upper BP		Full sample	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Demographic information								
Age when applying for DI (years)	46.5	9.64	41.1	8.20	50.5	7.27	48.6	8.61
Fraction male	0.293	0.455	0.504	0.500	0.711	0.453	0.531	0.499
Fraction black	0.135	0.341	0.162	0.368	0.124	0.330	0.135	0.341
Program information								
Primary Insurance Amount (PIA)	$897	$189	$1,234	$217	$1,993	$201	$1,507	$532
- Annualized PIA	$10,760	$2,273	$14,808	$2,604	$23,916	$2,412	$18,084	$6,384
Fraction w. dependent payments	0.100	0.300	1.00	0.00	0.121	0.326	0.118	0.323
Family payments	$929	$237	$1,817	$391	$2,112	$382	$1,598	$623
- Annualized family payments	$11,147	$2840	$21,804	$4,692	$25,344	$4,584	$19,176	$7,476
Fraction awarded DI via a hearing (after an initial denial)	0.321	0.467	0.221	0.415	0.250	0.433	0.283	0.450
Fraction by disability type:								
Musculoskeletal conditions	0.303	0.460	0.216	0.412	0.293	0.455	0.297	0.457
Mental disorders	0.241	0.428	0.291	0.454	0.168	0.374	0.201	0.401
Cancers	0.101	0.301	0.124	0.329	0.129	0.335	0.116	0.320
Cardiovascular conditions	0.079	0.270	0.076	0.266	0.123	0.329	0.103	0.304
Other disabilities	0.276	0.447	0.293	0.455	0.287	0.452	0.283	0.450
Annual mortality rates								
1st year after entry	0.060	0.238	0.067	0.250	0.080	0.271	0.070	0.256
2nd year after entry	0.035	0.183	0.034	0.181	0.044	0.206	0.039	0.194
3rd year after entry	0.026	0.160	0.022	0.148	0.034	0.182	0.026	0.159
4th year after entry	0.023	0.149	0.018	0.135	0.030	0.169	0.020	0.142
Observations	1,042,286		241,597		930,133		3,648,988	

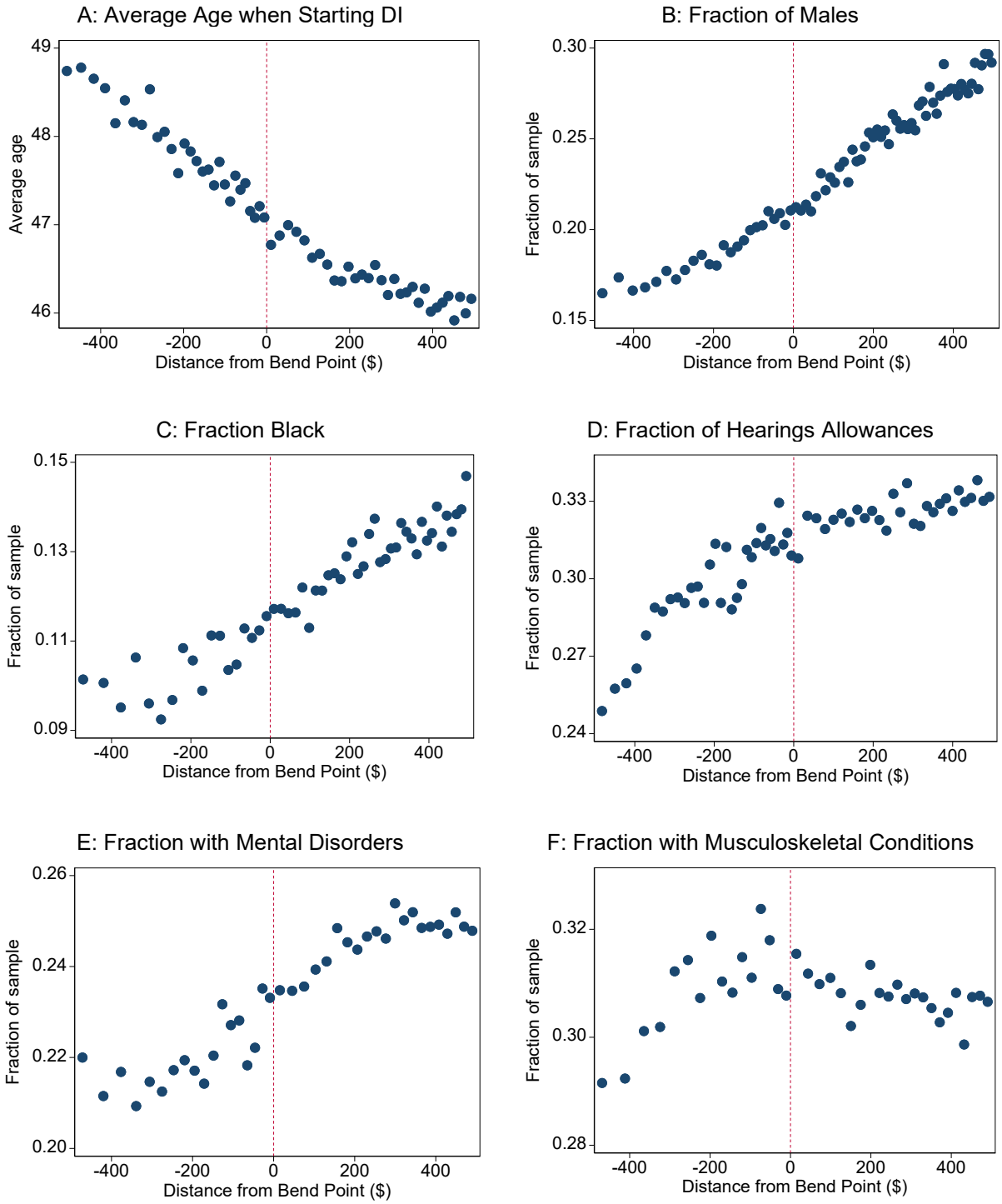
Notes: "SD" denotes the standard deviation. All of the estimation samples include DI beneficiaries with an AIME value within $1,200 of each bend point. At the family BP, we restrict the sample to beneficiaries who have dependent payments that start at the same time as their own.

Figure B1 Smoothness of density



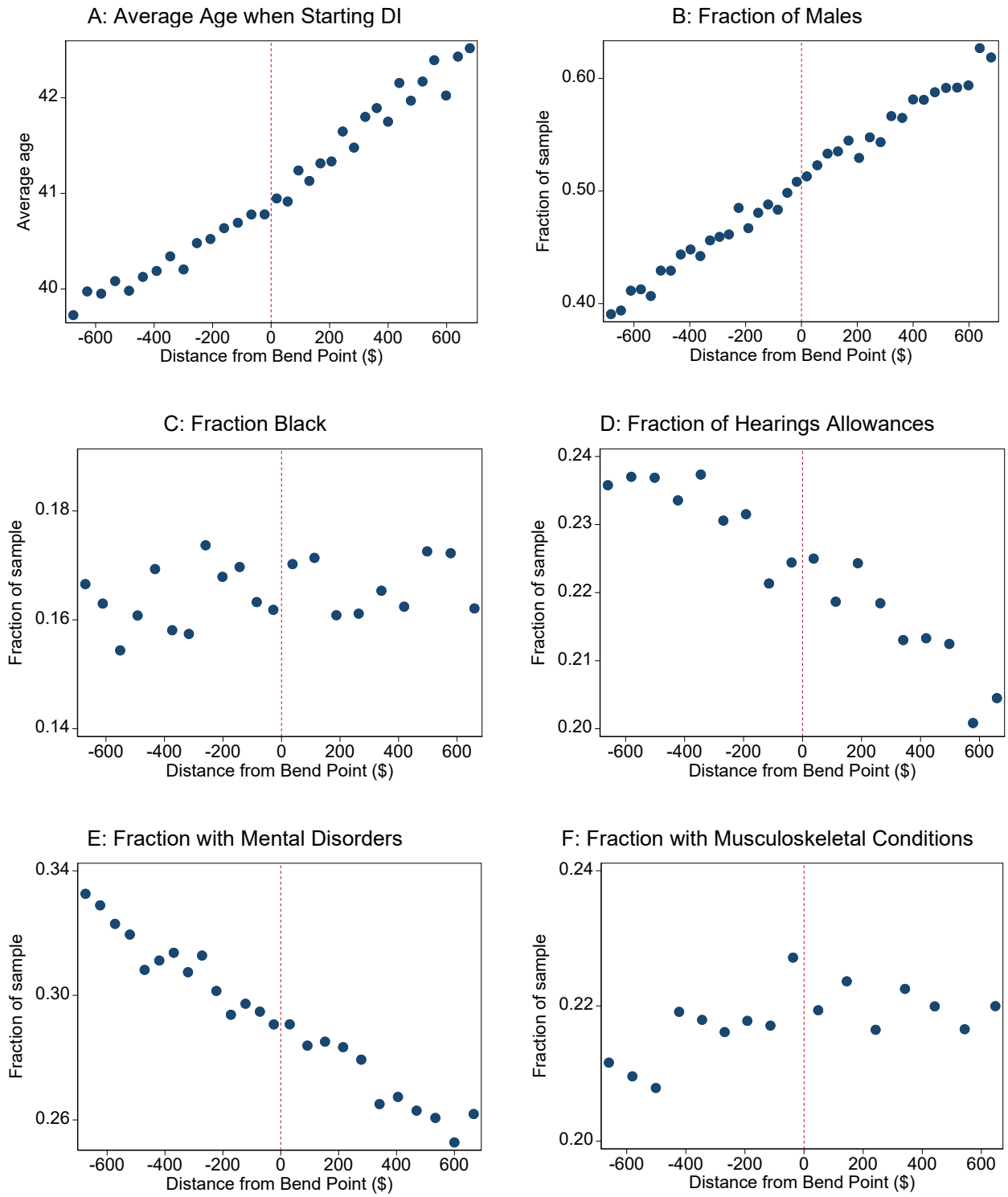
Notes: The figure shows the distribution of initial AIME around each bend point. We use (equally spaced) $25 bins, and the figure shows the percent of the sample in each bin.

Figure B2 Distribution of covariates around the lower bend point



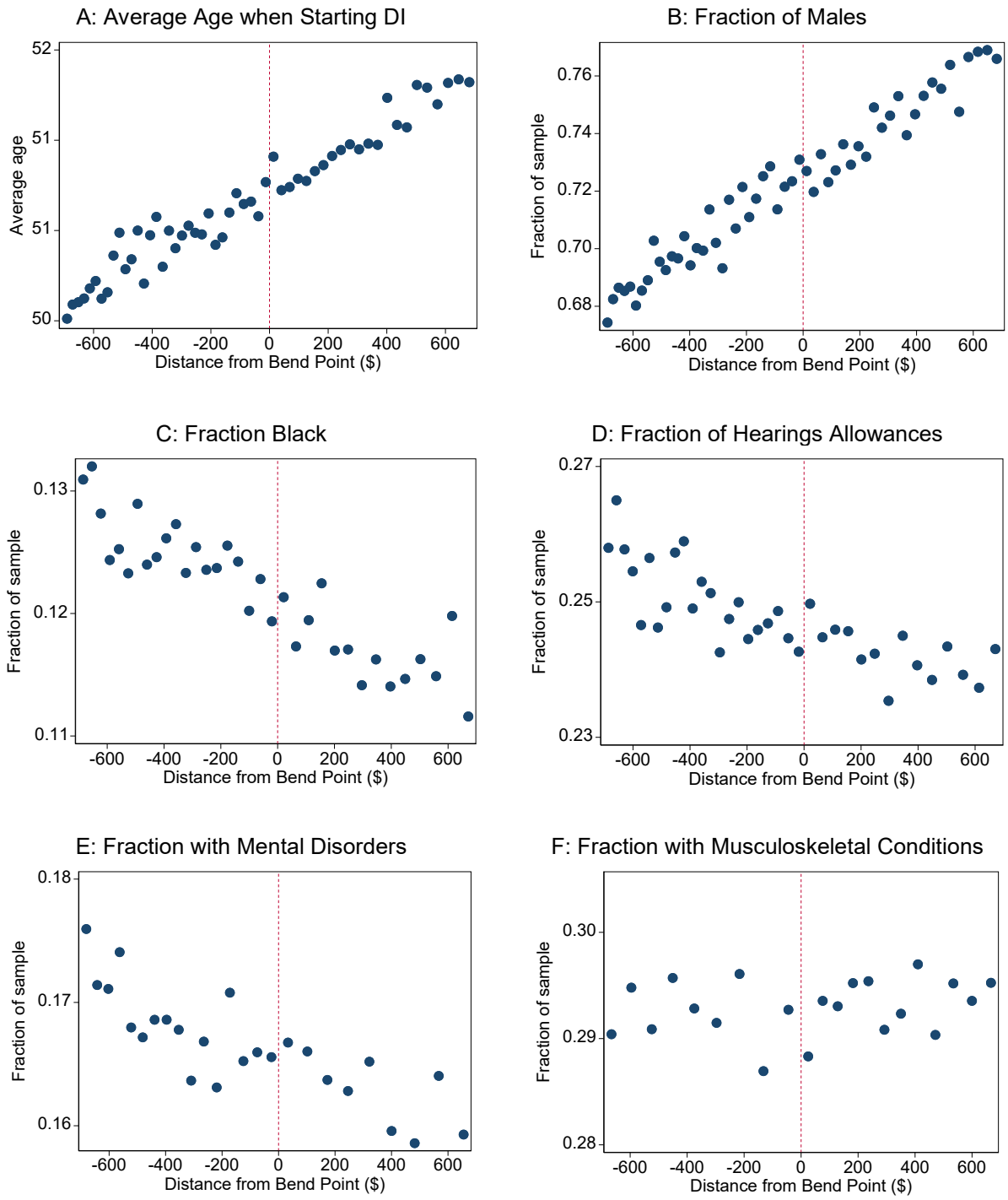
Notes: This figure shows the averages of predetermined covariates as a function of distance from the lower bend point. Bin numbers and widths are chosen using the IMSE-optimal quantile-spaced selector of Calonico et al. (2015).

Figure B3 Distribution of covariates around family bend point



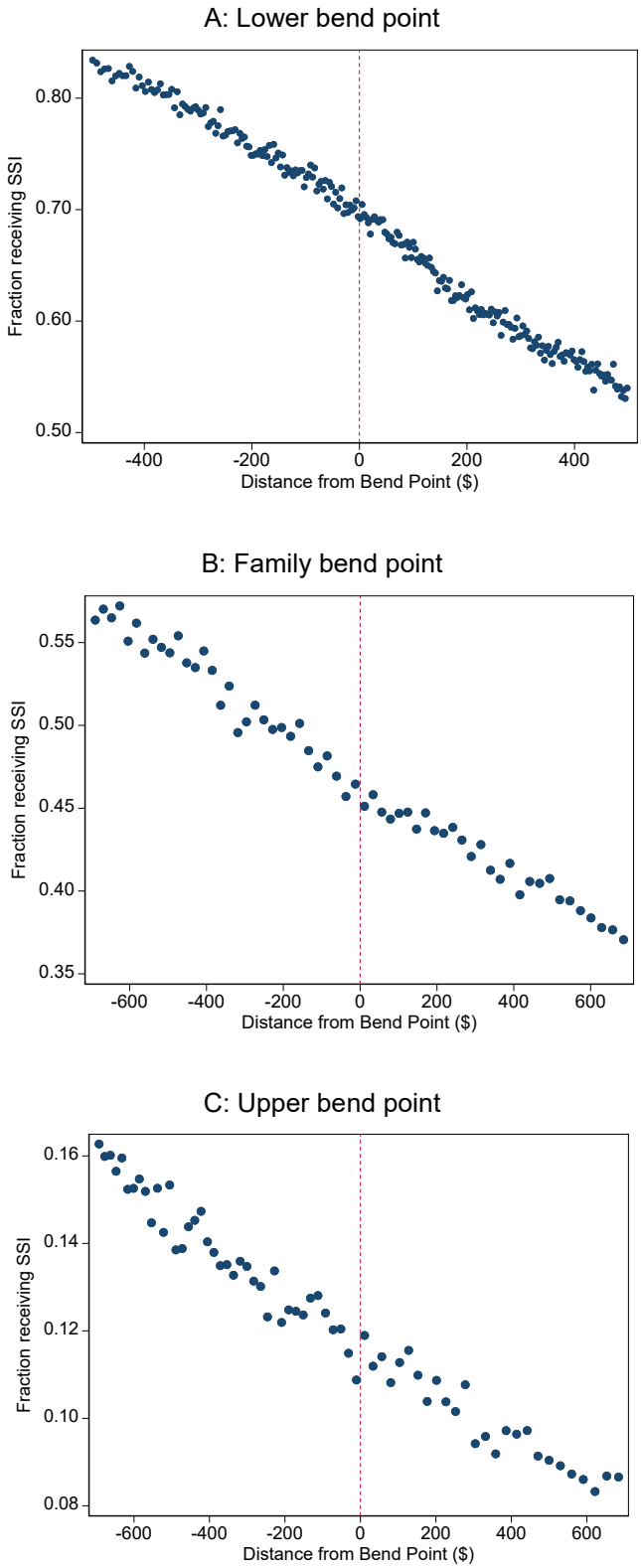
Notes: This figure shows the averages of predetermined covariates as a function of distance from the family bend point. Bin numbers and widths are chosen using the IMSE-optimal quantile-spaced selector of Calonico et al. (2015).

Figure B4 Distribution of covariates around the upper bend point



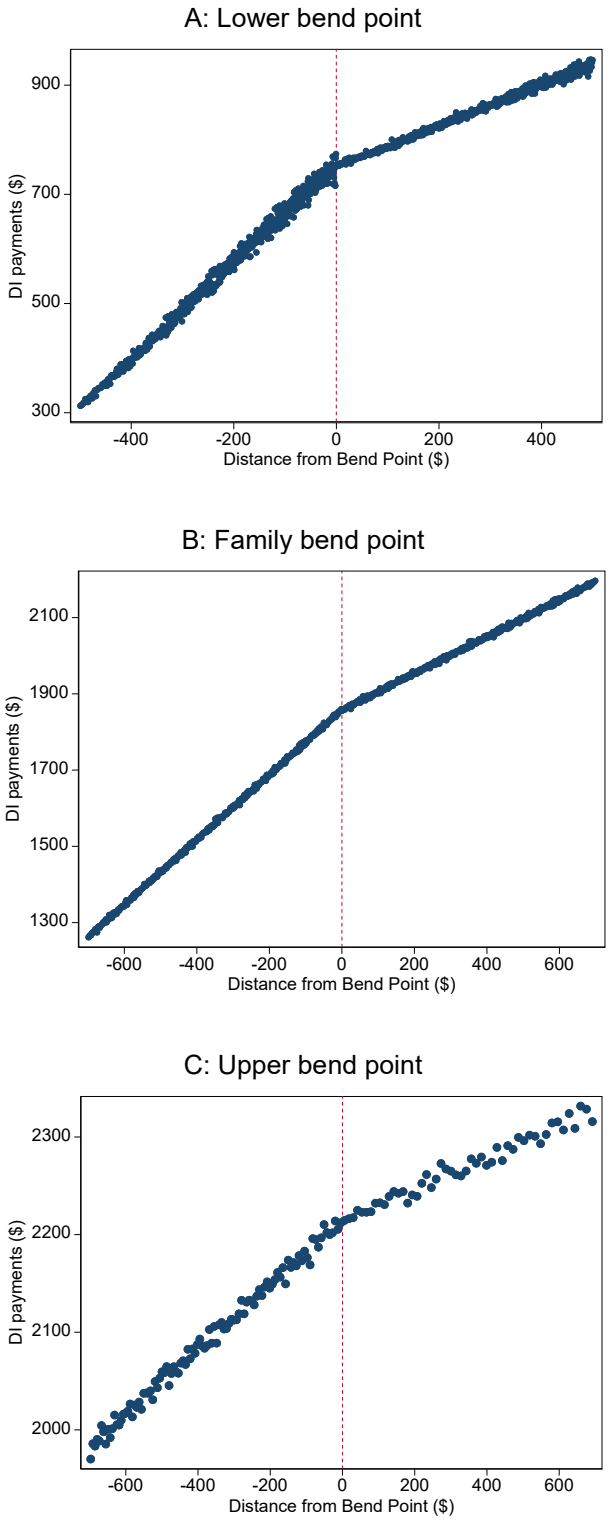
Notes: This figure shows the distributions of predetermined covariates as a function of distance from the upper bend point. Bin numbers and widths are chosen using the IMSE-optimal quantile-spaced selector of Calonico et al. (2015).

Figure B5 Fraction of DI beneficiaries who received SSI [removed from sample]



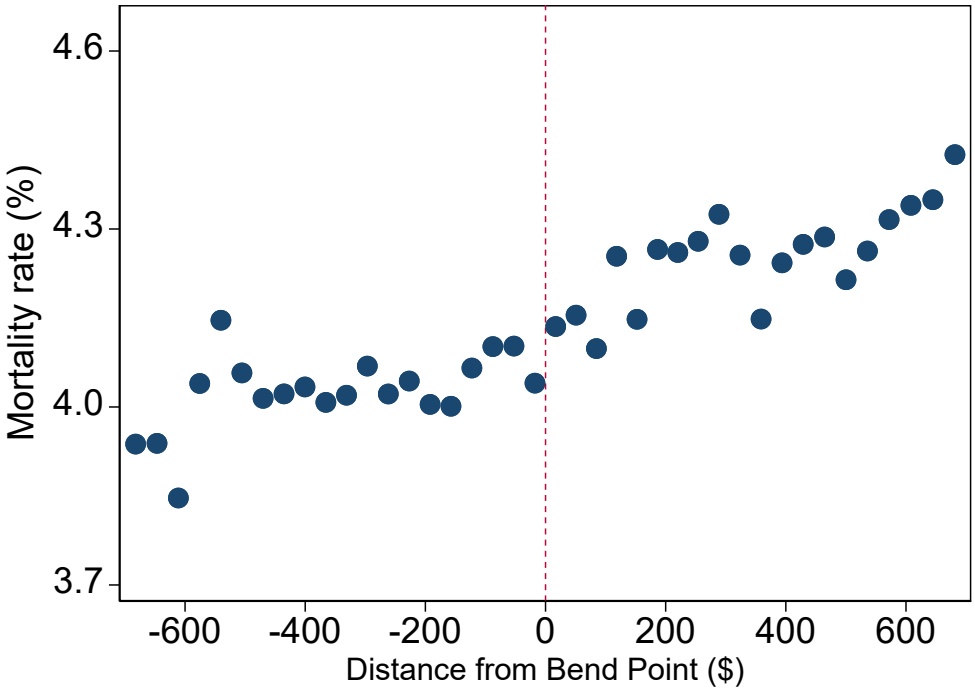
Notes: This figure shows the fraction as a function of distance from each bend point. Bin numbers and widths are chosen using the IMSE-optimal quantile-spaced selector of Calonico et al. (2015).

Figure B6 Actual DI payments around the bend points



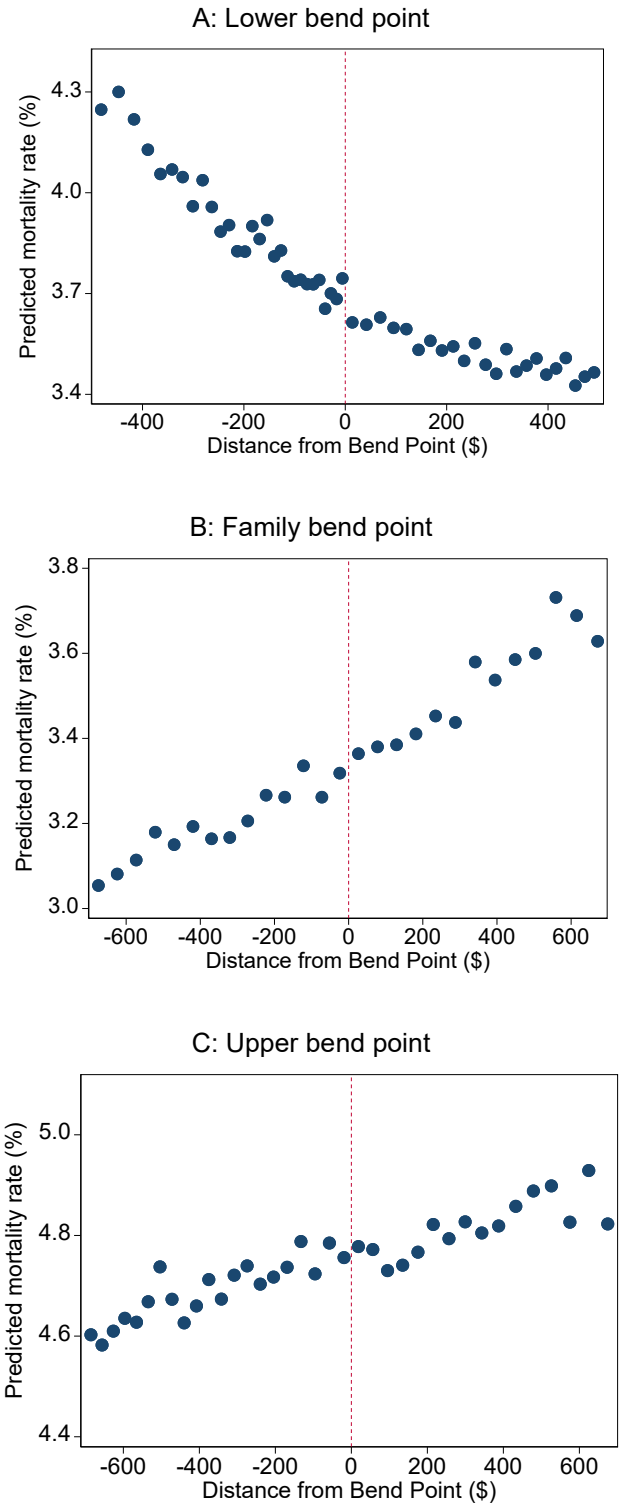
Notes: The figure shows DI payments (as measured in our data) as a function of AIME. It includes dependent payments. Bin numbers and widths are chosen using the IMSE-optimal quantile-spaced selector of Calonico et al. (2015). The figure shows that the effective marginal replacement rates change at the bend points similar to those indicated by the formulas translating AIME to PIA.

Figure B7 Placebo mortality rates for beneficiaries without dependents around the family bend point



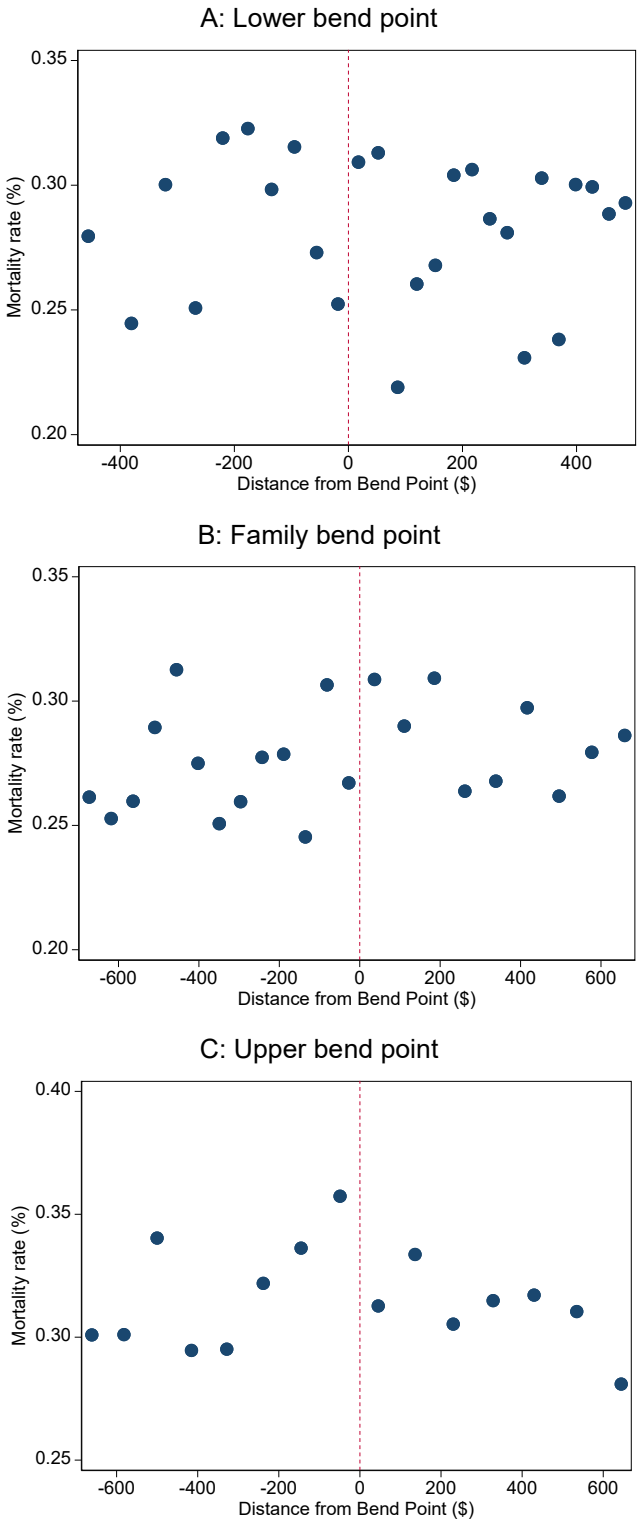
Notes: The figure shows the mortality rates as a function of AIME for the first four years for the sample of DI beneficiaries without dependents, for which we expect disability insurance payment to have no effect. Bin numbers and widths are chosen using the IMSE-optimal quantile-spaced selector of Calonico et al. (2015).

Figure B8 Predicted mortality rates for beneficiaries based on available covariates



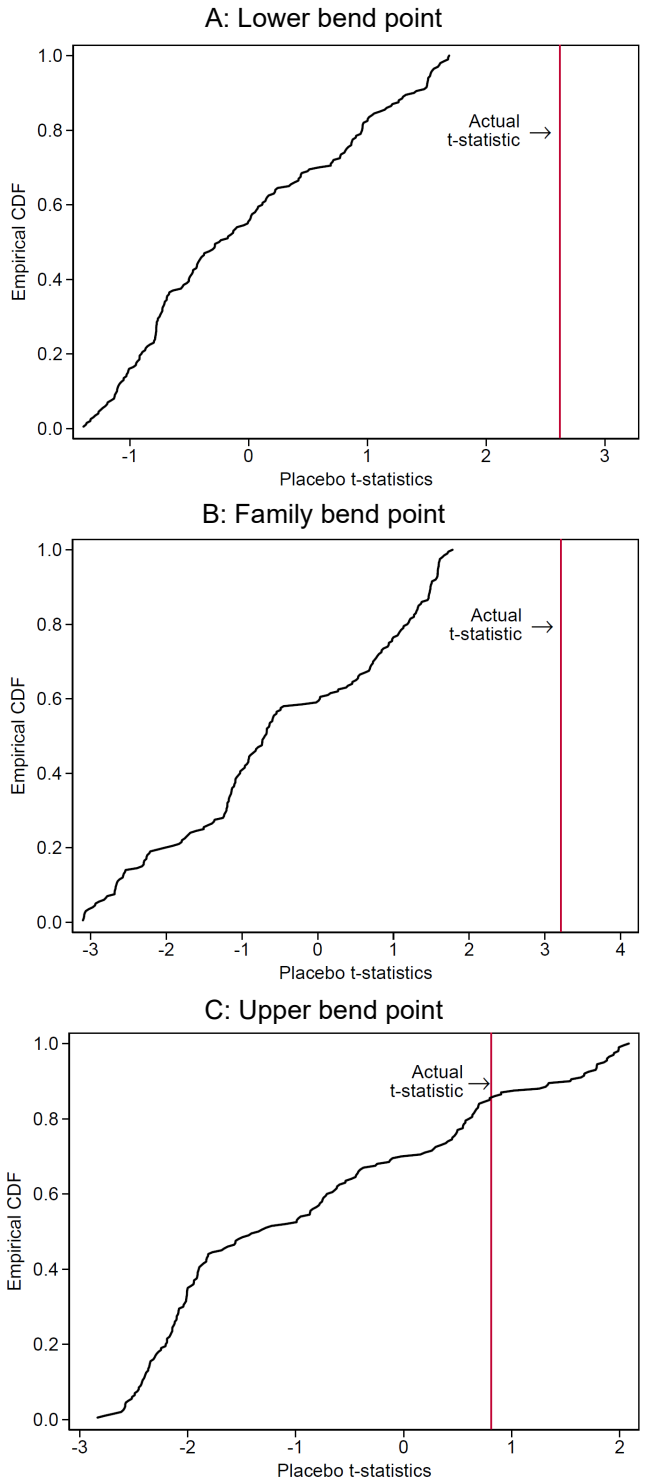
Notes: The figure show predicted mortality rates for the main samples based on the available covariates: age; sex; race; hearings allowed; has mental disorder; and has musculoskeletal condition. Annual mortality rates in the first four years after going on DI are presented. Bin numbers and widths are chosen using the IMSE-optimal quantile-spaced selector of Calonico et al. (2015).

Figure B9 Placebo mortality rates for non-beneficiaries



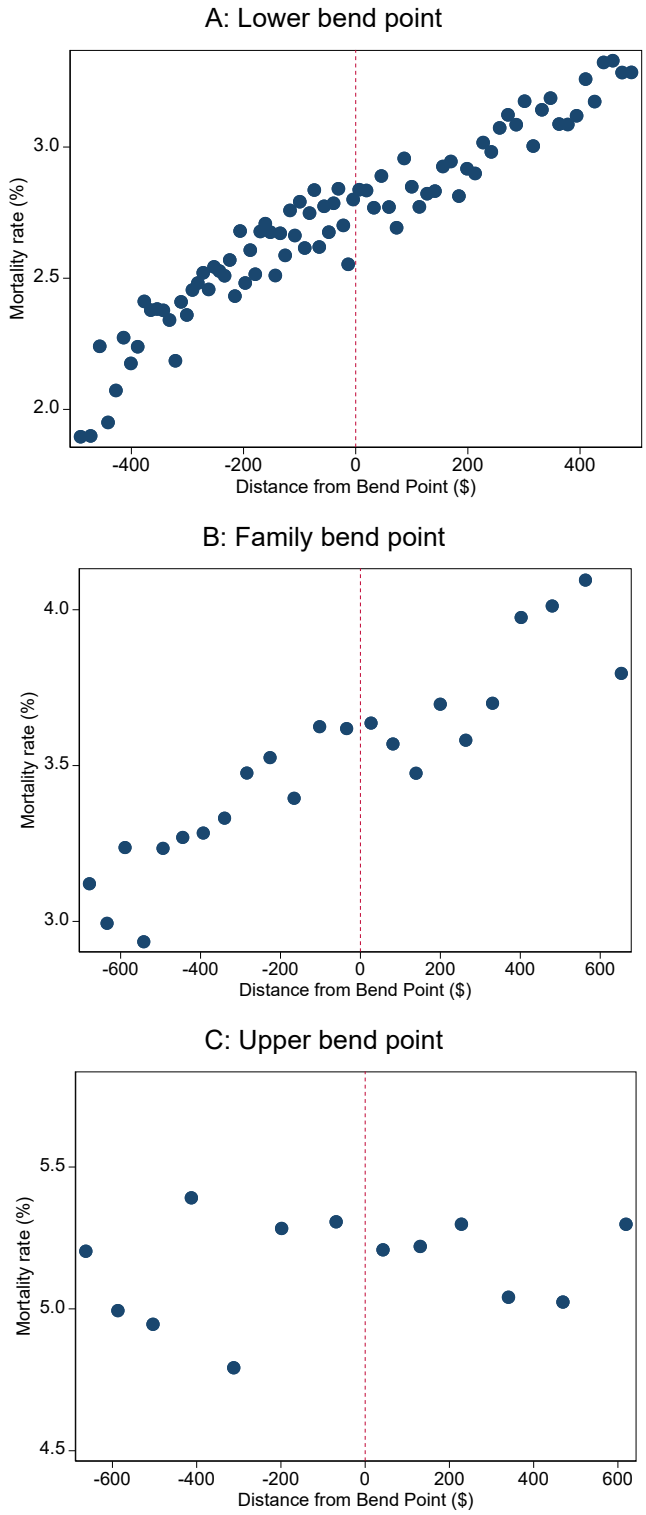
Notes: The figure shows that we find no noticeable changes in slope in placebo samples of non-beneficiaries that are constructed from the Continuous Work History Sample One Percent File. Bin numbers and widths are chosen using the IMSE-optimal quantile-spaced selector of Calonico et al. (2015).

Figure B10 Mortality estimates for placebo kink locations



Notes: This figure plots the results of the Ganong and Jäger (2018) permutation test. At each bend point, we draw 200 placebo thresholds and estimate local linear regressions with quadratic bias correction using data that does not include the true policy threshold. For these placebo regressions, we use the same bandwidths as in the main specifications without covariates from Table 1. We plot the cumulative distributions of the placebo robust t-statistics, with the vertical line indicating the robust t-statistic for the main estimate.

Figure B11 Mortality rates for DI/SSI beneficiaries after the DI waiting period



Notes: The figure shows the mean annual mortality rates as a function of AIME around the bend points in the first four years of receiving DI payments. Some beneficiaries around the lower BP continue to receive SSI after the DI waiting period (to top up DI payments). Bin numbers and widths are chosen using the IMSE-optimal quantile-spaced selector of Calonico et al. (2015).

Table B1 Testing for kinks in the densities at the bend points

	p-value of density kink		
Polynomial order	Lower bend point	Family bend point	Upper bend point
	(1)	(2)	(3)
1	0.884	0.000	0.001
2	0.963	0.590	0.812
3	0.287	0.152	0.213

Notes: The table contains the *p*-values of density tests from fitting polynomials of order 1, 2, and 3 on both sides of each bend point. Following Card et al. (2012), we test for a kink via the minimum chi-squared method (e.g., Lindsay and Qu, 2003). We use the bandwidths for the main treatment effect estimates without covariates (i.e., those from columns (1) and (2) of Table 1). The exact bin width is determined as the closest number to $25 such that it ensures an integer number of bins within the bandwidth.

Table B2 Estimated kinks in beneficiary characteristics

	Age at DI filing	Male	Black	Hearings allowed	Mental disorders	Musculo. conditions	Fraction on SSI [excluded]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Lower bend point							
Estimated kink	19.87	0.683	-0.239	-0.532	-1.198	1.009	-1.025
(Std. error)	(15.94)	(0.447)	(0.614)	(1.031)	(1.985)	(1.652)	(0.913)
Bandwidth	486.80	217.14	309.49	252.40	431.04	1199.89	333.57
Observations	450,577	204,055	290,512	237,274	401,253	1,042,286	998,041
Mean at bend point (p.p./years)	47.1	21.1	12.0	31.2	23.6	29.7	70.4
Family bend point							
Estimated kink	22.68	0.617	-1.579	-0.077	-0.278	0.054	-1.089
(Std. error)	(21.98)	(1.453)	(1.066)	(0.442)	(1.772)	(0.609)	(1.646)
Bandwidth	987.71	503.82	383.62	759.92	664.30	1199.97	266.01
Observations	204,127	108,180	82,983	160,597	241,597	241,597	109,104
Mean at bend point (p.p./years)	40.8	52.4	16.5	19.7	28.0	22.2	45.9
Upper bend point							
Estimated kink	6.62	0.284	0.233	0.232	0.726	-0.148	-0.545
(Std. error)	(18.94)	(0.587)	(0.393)	(2.258)	(0.567)	(0.454)	(0.763)
Bandwidth	319.46	597.87	1199.89	892.44	726.00	870.75	413.30
Observations	240,625	452,336	930,133	682,258	551,256	665,047	353,894
Mean at bend point (p.p./years)	50.9	73.0	12.1	22.9	16.5	28.0	11.2

Notes: p.p.= percentage points. The table contains coefficients and standard errors showing the estimated kinks in beneficiary characteristics at each bend point. Age is measured in years [column (1)], while the other outcomes are reported in percentage points. We use a local linear RKD specification with quadratic bias correction and robust standard errors; see the text for more details. We report the means for beneficiaries at AIME values from $10 below the bend point to the bend point itself. The results show there are not statistically significant kinks in the predetermined kinks in relation to the bend points.

Table B3 Placebo estimates

	Lower bend point	Family bend point	Upper bend point
	(1)	(2)	(3)
DI beneficiaries without dependents			
Mortality change per $1,000 DI (p.p.)	--	-0.005	--
		(0.098)	
Bandwidth		983.77	
Observations		1,050,561	
Mean at bend point (p.p.)		4.14	
DI beneficiaries' predicted mortality based on predetermined covariates			
Mortality change per $1,000 DI (p.p.)	0.001	-0.053	-0.022
	(0.097)	(0.032)	(0.048)
Bandwidth	248.34	1,199.97	680.22
Observations	233,326	769,401	515,746
Mean at bend point (p.p.)	3.75	3.32	4.76
Non-beneficiaries			
Mortality change per $1,000 DI (p.p.)	0.099	-0.029	-0.237
	(0.092)	(0.031)	(0.159)
Bandwidth	198.66	631.17	413.98
Observations	84,483	345,974	98,941
Mean at bend point (p.p.)	0.268	0.281	0.335

Notes: p.p.=percentage points. The table shows placebo estimates of increasing annual DI payments by $1,000 on the mortality rate of different groups. The top panel shows the results from using DI beneficiaries without dependents, which is only a placebo test at the family bend point. The middle panel shows results using predicted mortality rates for the main samples based on the available covariates: age; sex; race; hearings allowed; has mental disorder; and has musculoskeletal condition. The bottom panel shows the results for placebo samples of non-beneficiaries that are constructed from the Continuous Work History Sample One Percent File. We use a local linear RKD specification with quadratic bias correction covariates and robust standard errors; see the text for more details. We control for predetermined covariates except for the results in the middle panel, which uses mortality predicted by the predetermined covariates. The results show that we find no noticeable changes in slope in the various placebo samples.

Table B4 Heterogeneity in the mortality effects at the upper bend point

		Full sample		DDS examiner awardees only	
Category	Subgroup	Estimate (p.p.) (1)	Mean (p.p.) (2)	Estimate (p.p.) (3)	Mean (p.p.) (4)
How DI awarded	DDS examiner awardees (a)	0.107	6.00	--	
		(0.152)			
	Hearings level awardees (b)	-0.164	1.28	--	
		(0.253)			
	p-value: (a)=(b)	0.36			
Sex	Females (c)	0.102	4.55	-0.003	5.68
		(0.33)		(0.369)	
	Males (d)	0.082	5.06	0.208	6.12
		(0.198)		(0.233)	
	p-value: (c)=(d)	0.96		0.63	
Race	Non-black (e)	0.118	4.93	0.222	6.02
		(0.17)		(0.261)	
	Black (f)	-0.178	4.89	-0.610	5.88
		(0.186)		(0.694)	
	p-value: (e)=(f)	0.24		0.26	
Age at filing	Age < 45 yrs. (g)	-0.209	3.16	-0.182	4.41
		(0.188)		(0.683)	
	Age ≥ 45 yrs. (h)	-0.071	5.30	-0.067	6.30
		(0.084)		(0.151)	
	p-value: (g)=(h)	0.50		0.87	
Year started on DI	1997-2005 (i)	-0.222	5.26	-0.235	6.32
		(0.162)		(0.137)	
	2006-2009 (j)	0.055	4.41	1.824	5.52
		(0.142)		(0.911)	
	p-value: (i)=(j)	0.20		0.03	
Primary disability	Mental (k)	-0.703	1.52	-0.802	1.63
		(0.547)		(0.49)	
	Musculoskeletal (l)	0.111	1.34	0.025	1.77
		(0.187)		(0.251)	
	Cancers (m)	0.337	18.90	0.821	19.41
		(0.362)		(0.821)	
	Cardiovascular (n)	-0.406	4.28	0.232	4.75
		(1.043)		(0.589)	
	All other disabilities (o)	0.244	8.75	0.067	9.94
		(0.714)		(0.312)	
	p-value: (k)=…=(o)	0.41		0.44	
Time on DI	Years 1 & 2 (p)	0.318	6.59	0.127	8.08
		(0.257)		(0.184)	
	Years 3 & 4 (q)	0.035	3.25	-0.086	3.93
		(0.362)		(0.583)	
	p-value: (p)=(q)	0.52		0.73	

Notes: The table shows group-specific estimates of increasing annual DI payments by $1,000 on the mortality rate. We use a local linear RKD specification with quadratic bias correction, predetermined covariates and robust standard errors; see the text for more details. We report the mean annual mortality rates for beneficiaries from $10 of AIME below the bend point to the bend point itself. Columns (3)-(4) are the results for those awarded DI by Disability Determination Services (DDS) examiners.

Appendix Table B5 Effect of DI payments on earnings

	MSE-optimal bandwidths			Bandwidths used in Gelber,Moore & Strand (2017)		
	Local linear (1)	+ Bias correction (2)	+ Covariate adjustment (3)	Local linear (4)	+ Bias correction (5)	+ Covariate adjustment (6)
Lower bend point						
Change per $1 of DI	0.051	-0.049	-1.126	-0.012	0.046	0.030
	(0.106)	(0.363)	(0.820)	(0.158)	(0.219)	(0.219)
Bandwidth	117.45	117.45	199.71	600	600	600
Effective no. of observations	109,681	109,681	187419	548,218	548,218	548,218
Family bend point						
Change per $1 of DI	0.081	0.144	0.164			
	(0.055)	(0.100)	(0.099)			
Bandwidth	512.84	512.84	509.82			
Observations	110,088	110,088	109,435			
Upper bend point						
Change per $1 of DI	-0.223	-0.173	-0.390	-0.242	-0.261	-0.374
	(0.113)	(0.221)	(0.203)	(0.028)	(0.068)	(0.099)
Bandwidth	550.05	550.05	682.41	1500	1500	1500
Observations	323,314	323,314	402,044	918,598	918,598	918,598

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 (2017). The estimates differ very slightly from those in Gelber, Moore, and Strand, due to a slightly different sample selection criteria and different empirical approach, and the family bend point was not used. The mean annual earnings for beneficiaries at AIME values from $10 below the bend point to the bend point itself is $1,244 at the lower BP, $1,507 at the family BP, and $2,912 at the upper BP.

Table B6 Combined effect of DI payments plus earnings on mortality rates

	Lower bend point (1)	Family bend point (2)	Upper bend point (3)
First-stage estimates (DI/SSI pay change per $1 AIME)	-0.508	-0.414	-0.150
	(0.007)	(0.003)	(0.012)
Mortality change per $1,000 DI (p.p.) (a)	-0.338	-0.181	-0.057
	(0.114)	(0.069)	(0.105)
Bandwidth	235.58	529.44	705.28
Observations	221,422	113,585	535,044

Notes: p.p. = percentage points. The table shows estimates using the sum of DI income plus beneficiaries' W-2 earnings to estimate the income changes at each bend point. We use a local linear RKD specification with quadratic bias correction, predetermined covariates and robust standard errors; see the text for more details.

Table B7 Estimates using DI/SSI beneficiaries after the DI waiting period

	Lower bend point (1)	Family bend point (2)	Upper bend point (3)
First-stage estimates (DI/SSI pay change per $1 AIME)	0.0010	-0.367	-0.161
	(0.0015)	(0.001)	(0.006)
Mortality change per $1,000 DI (p.p.) (a)	-0.415	-0.054	0.140
	(1.913)	(0.106)	(0.320)
Bandwidth	165.29	600.32	1199.96
Observations	194,826	134,288	166,435
Mean at bend point (p.p.)	3.96	3.62	5.29
p-value: coefficient (a) equals estimate for main sample [from Table 1, column (3)]	0.97	0.12	0.60

Notes: p.p.=percentage points. The table shows estimates for SSI/DI beneficiaries after the DI waiting period, who are excluded from our main estimation samples. We use a local linear RKD specification with quadratic bias correction, predetermined covariates and robust standard errors; see the text for more details.