CENTER *for* RETIREMENT RESEARCH *at* BOSTON COLLEGE

EXAMINING RACIAL INEQUITIES IN BOND IMPACTS

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Abstract

This paper reexamines impacts from the Benefit Offset National Demonstration (BOND) to explore previously unexamined racial differences in participant outcomes. It examines whether the impacts of BOND differed by participants' race/ethnicity and the extent to which community-level racial inequities in economic conditions are correlated with participant outcomes that were central to BOND's goals. It pairs Social Security Administration (SSA) data from the BOND evaluation on a sample of nearly 1 million Social Security Disability Insurance (SSDI) beneficiaries with multiple measures of racial inequalities in employment and economic conditions for beneficiaries' county of residence. Exploration of race differences using SSA data has been limited due to inconsistent collection of race/ethnic data. We overcome this issue by combining historical and contemporary sources of data to assign race/ethnicity to 99 percent of our sample.

The paper found that:

- In the absence of the BOND intervention, the highest levels of earnings and employment are observed among beneficiaries in the control group who are Black or non-Hispanic Asian. Beneficiaries who are White have the highest amount and months of benefits.
- BOND increased employment and the proportion with earnings above a programmatic threshold called the BOND Yearly Amount (BYA), SSDI payments, and SSDI months for beneficiaries of color. Increases in employment and earning above BYA were larger both for Black beneficiaries and all beneficiaries of color relative to White beneficiaries. While absolute values of impacts were small, impacts represent about a 5 percent increase in employment and a 12 to 14 percent increase in the proportion earning above BYA relative to the control group mean.
- Our results reveal mixed associations between area-level inequities and beneficiary outcomes. Racial parity in earnings and unemployment rates are associated with declines in employment-related outcomes for White beneficiaries and beneficiaries of color, whereas intergenerational mobility is uniformly associated with increases in employment-related outcomes for all beneficiaries.
- Combining multiple sources of SSA administrative data allowed us to identify or refine information on beneficiaries' race/ethnicity for 99 percent of the BOND sample.

The policy implications of the findings are:

- The impacts and benefits of SSA programs may differ depending on a beneficiary's racial or ethnic identity. Moreover, analyses of beneficiary experiences by race and ethnicity capture experiences only after acceptance to SSDI and may not account for differential application experiences or award rates by race.
- Inequalities in local economic and social conditions are often correlated with employment and benefit outcomes that are of interest to policymakers, though not always in a uniform way. Understanding local conditions may help inform efforts to tailor program implementation in consideration of the context in which they occur.
- Better collection and analysis of information on the race and ethnicity of beneficiaries would expand understanding of differential program experiences.

Introduction

Low employment rates for people with disabilities have prompted policymakers to consider changes to Social Security Disability Insurance (SSDI) program rules that might increase economic self-sufficiency and decrease reliance on SSDI benefits. Congress asked the Social Security Administration (SSA) to implement and evaluate the Benefit Offset National Demonstration (BOND) to analyze the effects on employment and earnings of replacing the sudden loss of SSDI cash benefits when earnings exceed the substantial gainful activity (SGA) threshold—which could act as a work disincentive—with a more gradual reduction in benefits.

An evaluation of BOND found evidence that the benefit offset policy increased the proportion of beneficiaries employed and the percentage with earnings above the annualized SGA threshold among a nationally representative sample over the five-year period 2011–2015, as well as in individual calendar years 2014 and 2015 (Gubits et al. 2018). Over the same five-year period, BOND did not impact total earnings, reflecting that while some beneficiaries increased earnings, others decreased earnings. Furthermore, BOND increased total SSDI benefits because the benefit savings from those induced to earn above annualized SGA was smaller than the windfall of benefits to beneficiaries who would have worked without the offset and would have received no benefits under current law.

The evaluation of BOND, like many SSA demonstration evaluations, did not consider differential experiences or impacts by race or ethnicity (von Wachter 2021). Such exploration is imperative to informing equitable practices and in alignment with SSA's 2022 Equity Action Plan and Executive Order 13985 on Advancing Racial Equity and Support for Underserved Communities Through the Federal Government. Analyzing race and ethnicity data allows us to identify—and ultimately work to address—any observed disparities. In this paper, we seek to expand the knowledge base regarding if, how, and why BOND impacts varied by race.

An investigation of racial disparities in BOND is particularly important given that the goal of BOND was to create incentives to encourage substantial employment but opportunities for work are not evenly distributed across race in the United States (Freyer et al. 2013). Black workers are less likely than White workers to be employed in a job consistent with their level of education (Williams and Wilson, 2019). The unemployment rate for American Indians and Alaska Native workers is nearly twice that of white workers (6.2 percent and 3.2 percent, respectively); unemployment rates for Native Hawaiians and other Pacific Islanders is 4.0

percent, and for Asian workers it is 2.8 percent (BLS 2022). Among people with disabilities, the jobless rates for Hispanic and Black people with disabilities are higher than the rates of White people with disabilities (Bureau of Labor Statistics, 2022).

Racial disparities in labor market outcomes and opportunities have been significantly influenced by a legacy of political, social, and institutional factors (Sites and Parks 2011). These structural forces may differentially affect demonstration employment outcomes (Hardy, Logan and Parman 2018). For example, labor market conditions have long been different for white workers relative to workers of color, irrespective of disability. For more than 50 years, the unemployment rate for Black workers typically remains twice as large as that of white workers (Wilson and Rogers 2016). While racial gaps in wage rates narrowed through the second half of the 20th century (Card and Kreuger), in 2020, Black men's average hourly inflation-adjusted wages are 22 percent lower than those of white men in 1979 (Rogers 2019). Among other reasons, discrimination in hiring practices, wage differentials, or racial occupational segregation may lead to differential opportunities for return-to-work opportunities for BOND participants of different racial and ethnic identities (Gaddis 2014; Wilson and Rogers 2016; Bayer and Charles 2016, Baert 2018). Moreover, racial residential segregation has been linked to greater employment inequalities in race by limiting access to employment and areas where job growth is most highly concentrated, a theory called the spatial mismatch hypothesis (Kain 1968, Turner 2008). Other pathways may include health pathways; for example, racial discrimination may lead to poorer health or more severe impairment types through stress or lower access to care (Williams 2018; Boen and Hummer 2019.) Further, evidence suggests that higher levels of racial/ethnic disparities in labor markets or schools can negatively affect all residents (Reardon, Fox, and Townsend 2015; Sheats et al. 2017; Hardy, Logan, and Parman 2018).

BOND participants of color live at the intersection of disability and race and are among our nation's most financially vulnerable (Goodman, Morris and Boston 2020). This paper examines (i) whether there are racial differences in program impacts for BOND on employment-related outcomes and SSDI benefits and (ii) whether outcomes associated with BOND's stated goals, namely increased employment and earnings and decreased SSDI benefits, differ if participants live in counties with greater economic racial inequality.

Background

SSDI is an income-replacement program for workers with disabilities and an essential safety net. To qualify for SSDI benefits, an applicant must have a sufficient work history in a job covered by Social Security and a long-lasting physical or mental impairment that creates an inability to work at a substantial level. This is captured by the concept of SGA and generally measured as monthly earnings below a programmatic threshold that is revised annually. In 2022, SGA is $1,350 for non-blind individuals and $2,260 for people who are statutorily blind. SSA paid SSDI benefits to over 9.5 million people in 2020 and the average monthly benefit payment was $1,277 (SSA 2021a).

Employment is a desirable outcome for many SSDI beneficiaries and from the perspective of SSA and policymakers. In 2015, 45 percent of SSDI beneficiaries reported having work-related goals or expectations (SSA 2018). SSA also encourages employment. Indeed, an SSA publication states that "One of Social Security's highest priorities is to support the efforts of beneficiaries with disabilities who want to work by developing policies and services to help them reach their employment goal" (SSA 2020). Congress's support of work among SSDI beneficiaries is evident in the passage of legislation such as the Ticket to Work and Work Incentives Improvement Act (SSA 1999), which expanded the availability of employment supports among other provisions designed to encourage employment.

For SSDI beneficiaries who do work, their earnings can affect entitlement to and the amount of benefits. Beneficiaries can test work with no effect to their benefits through the trial work period (TWP). The TWP consists of 9 months in a rolling 60-month window in which a beneficiary is permitted to have earnings above the monthly TWP threshold, which is $970 per month in 2022, without affecting benefit receipt for those months. Beneficiaries receive their unreduced monthly benefits for 9 such months with earnings above the TWP. If a beneficiary engages in SGA after the TWP, SSA deems that their eligibility for disability benefits has ceased due to work activity. SSA pays benefits in this month and the following two months—known as the grace period. For the first 36 months after TWP completion and after the grace period, if a beneficiary has earnings above the SGA threshold in any month, SSA withholds cash benefits for that month. SSA pays benefits for months in which earnings are below the SGA threshold. After this 36-month period, SSA terminates benefits if earnings exceed the SGA threshold. The suspension or termination of benefits for earnings above SGA after the TWP can create a disincentive to work and research has shown that some beneficiaries intentionally suppress earnings to maintain benefit receipt (Schimmel, Stapleton, and Song 2011).

The Benefit Offset National Demonstration

Recognizing the potential disincentives to employment that are inherent in current SSDI rules, Congress mandated the testing of a \$1 for \$2 benefit offset, which was tested as a randomized controlled trial, known as BOND. Instead of the complete loss of benefits for earnings above SGA, BOND treatment dictates that cash benefits are reduced by \$1 for every \$2 earned above the threshold. The result is that as earnings increase, total income (the sum of earnings and SSA benefits) increases. In contrast, under current rules, total income falls for earnings just above the SGA threshold. To facilitate the more complex benefit rules under BOND, there was an annual accounting period. That is, instead of comparing monthly earnings to the monthly SGA threshold, BOND rules compared annual earnings to an annual threshold that was 12 times SGA and known as the BOND yearly amount (BYA).

BOND was implemented in two simultaneous stages, both of which had control and treatment groups, following the randomized controlled trial design. Beneficiaries in the control were subject to the current law, rules, and processes – they did not observe any changes resulting from their assignment to the BOND control group. The Stage 1 treatment group included a representative sample of non-volunteers randomly assigned to BOND and notified of their assignment between May and August 2011. The goal of Stage 1 was to learn how a \$1 for \$2 benefit offset would affect the general SSDI population. Stage 2 included a smaller sample of recruited and informed consent volunteers, with the goal of studying how BOND would affect those most likely to use the offset. Treatment subjects who completed the TWP had a five-year participation period over which their benefits were subject to the \$1 for \$2 offset. Given the differences in national representation and sample size between the two stages, we focus our analysis on BOND Stage 1 participants.

BOND was fielded in 10 sites across the country. These 10 sites cover seven full states (Alabama, Arizona, Colorado, Maine, New Hampshire, Vermont, and Wyoming) and the District of Columbia. They also include notable portions of nine other states (California, Florida, Maryland, Massachusetts, Michigan, New York, Texas, Wisconsin, and Virginia), and smaller portions of two other states (Pennsylvania and West Virginia). The sites were selected to be national representative and to cover portions of eight of SSA's 10 regional offices and all or part of 10 of the 50 largest metropolitan areas in the county.

The predicted effects of BOND are ambiguous because incentives differ depending on what beneficiary earnings would be under current law. For beneficiaries who would earn below annualized SGA under current law, BOND is expected to increase employment and earnings and decrease SSDI benefits. However, for those who would earn above annualized SGA and hence would have received no benefit, BOND is expected to decrease earnings and increase SSDI benefits.

The evaluation of BOND established that there was no impact of BOND on total earnings in the evaluation period 2011–2015 (Gubits et al. 2018). However, as predicted, BOND increased the proportion of beneficiaries with any employment and the proportion with earnings above BYA over the five-year follow up period. For this group, there was a decrease in SSDI benefits: such beneficiaries received partial benefits rather than full benefits. There was also a decrease in the proportion with earnings above three times the annualized SGA threshold. For this group, there was an increase in SSDI benefits: such beneficiaries received partial benefits rather than no benefits. Collectively, the earnings changes offset each other to yield no significant change in total earnings. However, there was an increase in SSDI benefits (both total SSDI benefits and months with SSDI benefits). The increase in the share of beneficiaries induced to earn above BYA in BOND (who experienced decreased benefits) was not large enough to offset the windfall to beneficiaries who would not have received any benefits under current law (who experienced increased benefits in BOND).

Racial and Ethnic Disparities in Employment and SSDI Program Participation for People with Disabilities

In addition to long-standing gaps in employment between people with and without disabilities, racial and ethnic disparities in employment persistent within among people with disabilities. According to the Bureau of Labor Statistics (BLS), in 2021, the jobless rate for Black individuals with a disability and Hispanic individuals with a self-reported disability (15.1 percent and 13.3 percent, respectively) was higher than for White people with a self-reported disability (9.3 percent) or Asian people with a disability (9.5 percent) (BLS 2021). These statistics are paired with figures indicating that there is a higher prevalence of disability in people of color (Courtney-Long et al. 2017), due in part to environmental factors and barriers created by racism (Goyat et al. 2016). Combined with documented racial differences in labor market outcomes and opportunities, the relationship between disability and race in employment is one of overlapping identities that are both related to systemic inequality (Pokempner and Roberts, 2001; Goodman, Morris, and Boston 2020).

Participation in SSDI by race appears to mirror nationwide demographic trends, however there is evidence of historical differences in SSDI award rates by race. Specifically, 60 percent of those randomly assigned to BOND Stage 1, which was designed to be nationally representative, self-reported to be White non-Hispanic (Gubits et al. 2018), which is similar to the 62 percent among the broader population at the same point in time (Kaiser Family Foundation 2020). Although recent information is limited because of data limitations, historically there is documentation of racial differences in allowance rates. In the 30-year period between 1961 and 1991—when SSA somewhat consistently collected and analyzed race data (Martin 2016)—the acceptance rate of SSDI applications was lower for Black applicants than for White applicants, with the magnitude of the difference ranging from 4 and 13 percent (Government Accountability Office [GAO] 1992). For example, in 1988, 29 percent of Black applicants were allowed DI benefits as compared to 36 percent of White applicants. The causal mechanisms underlying observed differences are not well attributed. However, possible mechanisms cited by the GAO include differences in demographic characteristics, occupational history, impairment severity, availability of medical documentation, and bias in the determination process. More recent analyses of racial difference in awards have been hampered by methodological weakness and data quality challenges (GAO 2002).

The Role of Social Context and Area-Level Inequalities on Economic Outcomes

A growing literature has underscored the importance of social context as an important driver in explaining individual differences in health and economic outcomes. Building upon a literature on social determinants of health, this evidence suggests that an individual's outcomes are directly influenced by the social and economic conditions of their communities, and as such, that disparities in these conditions are a cause of individual-level disparities in health and financial well-being. This literature posits that area-level inequities are in part a reflection of long-standing structural racism through mutually reinforcing systems of housing, education, employment, earnings, credit, media, health care, and criminal justice (Adkins-Jackson et al. 2022; Bailey et al. 2017).

Recent work has advanced ways to operationalize and measure racial inequality and racial discrimination for the purposes of exploring its impacts on individual and population health and financial well-being (Krieger et al. 2016; Groos et al. 2018). These methods have been applied to build evidence that suggests that area-level structural inequities, including inequities in income, employment, and education have important consequences on a number of health outcomes including cardiovascular disease (Lukachko, Hatzenbuehler and Keyes, 2014), obesity (Bell, Kerr and Young 2019), infant mortality (Wallace et al. 2017; Siddiqi et al. 2016), self-rated health (Bell and Owens-Young 2020) and mental health (Lynch et al. 2021).

More recently, studies have examined the role of social context in explaining economic and employment outcomes as well. Racial disparities in employment and wages have long been documented across the United States (Pager and Shepherd 2008; Huffman and Cohen 2004). Differences between people of color and White populations in education, skills and work experience can explain part of this gap, but not all of it (Carr and Kutty 2008). Residential racial segregation, which creates differential access to jobs, employment segregation and racial discrimination in hiring practices and wages, contributes to racial disparities in economic and financial outcomes (Pager, Bonikowski, and Western 2009; Pager and Shepherd 2008; Turner 2008). These educational and labor market factors also explain differences in intergenerational mobility across race/ethnicity (Torche 2011). These structural inequalities can be compounded by the challenges of disability; evidence of labor market discrimination of people with disabilities is abundant (L'Horty et al. 2022; Ameri et al. 2018; Baldwin and Johnson 1994).

These community factors may influence race differences in BOND impacts in similar ways. As with all things, the effects of policy demonstrations are influenced by the contextual factors in which they take place. If labor market conditions for BOND participants differ across race, BOND participants of different racial identities may experience unequal benefits to the demonstrations intended impacts. For example, if unemployment or wage rates are higher for Black participants, opportunities to stay or return to work may be more difficult. Likewise, BOND participants in highly racially segregated communities may have differential barriers to accessing central employment hubs.

Given the historical difference in SSDI application acceptance rates and ongoing differences in labor market outcomes by race and ethnicity, one might expect to also observe differences in outcomes or impacts by race in BOND. For example, differences in the availability of work opportunities by race could affect beneficiaries' ability to take advantage of the offset. Given historical advantages, White SSDI applicants may have better probabilities of employment and may be able to benefit from BOND's intended benefits.

Our paper expands our understanding of BOND by estimating differences in key employment-related and benefits-related outcomes by race and ethnicity and BOND's impact on these outcomes. The evaluation of BOND included an analysis of seven subgroups—based on duration of SSDI receipt, concurrent receipt of SSI benefits, employment status before the demonstration, residence in a state with a Medicaid Buy-In program, age, primary impairment of a major affective disorder, and primary impairment of back disorder—but did not include race and ethnicity. A recent study examines impacts of BOND on benefits by race among Stage 2 BOND subjects, finding that there were larger average impacts on benefits among Black beneficiaries relative to White beneficiaries (Enayati et al. 2022). We expand on this study by examining impacts among the nationally representative sample of Stage 1 beneficiaries and considering employment-related outcomes in addition to benefit outcomes. Additionally, we analyze the role of structural racial inequities in these outcomes.

Data and Sample

Our analysis drew on data from multiple sources, including restricted-use BOND evaluation data and SSA data on race and ethnicity, as well as publicly available data on county characteristics. The SSA administrative data are only accessible by SSA staff or through other data use agreement.

Data on BOND Participants' Outcomes and Characteristics

We used data from the BOND evaluation to identify the sample of BOND participants and assignment to a BOND treatment or control group. This includes a representative sample of non-volunteers randomly assigned to BOND and notified of their assignment between May and August 2011. Our analysis sample included all 77,101 treatment subjects and 891,429 control subjects included in the final evaluation of BOND (Gubits et al. 2018). This represents 11 percent of the approximate 8.5 million disabled workers receiving SSDI in 2011.

We also used administrative data to measure key outcomes and for control variables used in estimating the impacts of BOND. These data were originally extracted from the Master Beneficiary Record for SSDI benefits-related data, the Supplemental Security Record for SSI-related data, and from the Master Earnings File for employment- and earnings-related data. BOND outcomes included: employment, annual earnings, earnings above BYA, amount of SSDI benefits due, and number of months with SSDI payments in 2014. We focused on outcomes in 2014, which was the third full year after BOND random assignment, to allow time for demonstration processes and understanding to be well established. This also follows precedent from the BOND Final Evaluation Report of focusing on 2014 for cost-benefit calculations (Gubits et al. 2018). Finally, we used these administrative sources to measure characteristics at or just before BOND random assignment including demographic characteristics, primary impairment, SSDI program participation, BOND eligibility factors, and employment status.

Data on BOND Participants' Race and Ethnicity

Our analysis drew on several SSA administrative data sources for race and ethnicity, as a consequence of changes in SSA's approach to collecting and recording these data. Starting in 1936, the application for a Social Security number collected limited race information: White, black, other (Martin 2016). The available race categories expanded in 1980 to include White, Black, Hispanic, Asian or Pacific Islander, American Indian or Alaskan Native, and unknown. Hence, for those born before 1980, the data reflects cruder categories of race than are currently used. An exception is that anyone who submitted a new application for a Social Security card in 1980 or after, for example because of a name change or lost card, may have reported more refined race and ethnicity information (Martin 2016).

Prior to 1987, SSA collected race and ethnicity data from individuals when they applied for an original or replacement Social Security card. Although providing race and ethnicity information to SSA was voluntary, the application form did not indicate the voluntary nature of the question and may have been interpreted as mandatory (Martin 2016). In 1987, SSA started to issue new Social Security numbers through enumeration at birth (EAB), which is administered by the states. The states do not provide information about newborns' race and ethnicity to SSA.

This process was implemented in 1987 as a pilot and was full implemented nationwide in 1997 (SSA 2021b). Since 2002, the Department of Homeland Security (DHS) has taken applications for Social Security numbers from persons applying for permanent residence through a process called enumeration at entry (EAE). DHS does not provide SSA with the race and ethnicity of applicants.

Historical race information is recorded in the Master Files of Social Security Number Holders and Applications (also known as the Numident). The availability of race data varies by birth year, reflecting the differences in data collection standards over time. To be eligible for BOND, beneficiaries must have been ages 20-59 as of May 2011, yielding a study cohort born between 1952 and 1991. Indeed, subsetting the BOND control group by birth year, we see 98.6 percent of those born before 1980 have race/ethnicity data in the Numident, compared to 97.1 percent of those born between January 1980 and December 1986, and 86.5 percent of those born in or after 1987 (Table 1).

Collection of race and ethnicity information also changed in response to a 1997 Office of Management and Budget (OMB) mandate establishing standard categories for race (Alaska Native, American Indian, Asian, Black/African American, Native Hawaiian, Other Pacific Islander, and White) and ethnicity (Hispanic/Latino or not Hispanic/Latino) and allowing for selection of multiple racial categories. Race data based on this more robust set of categories is recorded in the Race Ethnicity Collection System (RECS). RECS was implemented in 2009.

As a result of these changes, the quality of race data became inconsistent (Martin 2016; Martin and Murphy 2014). Recent research has largely avoided the use of SSA administrative data on race, which has led to a gap in understanding of experiences by race and ethnicity. In this study we acknowledge the data limitations and provide evidence using the available data.

We used a combination of the Numident and RECS data to create racial and ethnic subgroups. The Numident data were widely available: 98.2 percent of Stage 1 subjects had non-missing race data. This is likely a reflection of the study cohort birth years from 1952 to 1991 generally predating the implementation of the EAB and EAE processes. When available, we supplemented the Numident date with RECS, which were available for about 17 percent of our sample, with availability higher for those in more recent birth cohorts (Table 1).

When RECS data were available and only one race was reported, we used RECS as the source of race and ethnicity. When a RECS record indicated Hispanic ethnicity, we classified the beneficiary as Hispanic, overriding any recorded race information in the RECS (or Numident). This was done to create consistency with the Numident data, which considered Hispanic as a racial category. This approach yielded 98.4 percent with race data from Stage 1, with the same proportion from the treatment and control groups. Because we use the RECS data to assign ethnicity and override previously recorded race data, we also reassign a very small percentage of individuals to a different race/ethnicity category (0.09 percent of the treatment group and 0.10 percent of the control group).

Our final approach combining Numident and RECS yields five mutually-exclusive racial groups and one ethnicity group: White, Black, non-Hispanic Asian, non-Hispanic Native American, non-Hispanic participants of any other race, and Hispanic participants. This approach was necessary in order to create consistency in racial and ethnic grouping across the two data sources (RECS and Numident), but it is important to note that Hispanic beneficiaries who were born or immigrated to the United States before 1980 may have identified as white or black (rather than "other") in response to the limited categories available. In 1970, 4.5 percent of the U.S. population was Hispanic and in 1980 that had risen to 6.4 percent (Bureau of the Census, 1982). In addition, aggregating Hispanic ethnicity masks the heterogeneous racial makeup of this group.

To understand the extent to which data quality might affect our analysis, we compare the resulting race and ethnicity classification to self-reported survey data collected from a subset of BOND participants. Administrative data report a higher proportion of beneficiaries who are White and Black relative to the survey data (Appendix Table A1). This likely reflects the limited race and ethnicity categories used by SSA until 1980. The most notable difference between survey and administrative data is that the administrative data appear to underreport beneficiaries who identify as American Indian or Alaskan Native.

Although the administrative data that inform our analysis are imperfect, it is imperative to use available data to seek to better understand experiences and outcomes by race and ethnicity while acknowledging potential shortcomings. Indeed, the evolution of data quality versus the need to understand the role of race and ethnicity in SSA programs is apparent in the publication of administrative data-based statistics on race. The SSA Annual Statistical Supplement stopped producing administrative data-based statistics on race starting with the 2011 report but reinstituted their inclusion for 2022. However, results should be interpreted with the understanding that race data are imperfect, particularly for the American Indian or Alaskan Native race category because of small sample sizes. Because of this, many of our results compare outcomes for an aggregate category of beneficiaries of color relative to White beneficiaries.

Data on Social Context and Structural Inequities

To assess the role of contextual factors and economic and racial inequities in BOND impacts, we merged publicly-available county-level data to BOND participants' county of residence in 2014 through address information available in SSA's Disabled Beneficiary and Dependents Extract file. Matched geocoded information is available for all 968,530 BOND participants in the analysis sample (of whom 953,384 or 98.4 percent have race data available).

We considered five contextual factors measured at the county level: (i) differences in county-level average earnings by race/ethnicity (controlling for the average county-level earnings); (ii) differences in county-level unemployment by race/ethnicity (controlling for the overall county unemployment rate); (iii) intergenerational income mobility for residents of color (explained below); (iv) residential racial segregation; and (v) an index of concentration at the extremes (ICE) for racialized economic segregation. Difference in county-level earnings and county-level unemployment come from the American Community Survey and are calculated by subtracting the mean value of unemployment (or earnings) for non-White county residents from the mean value of white county residents. The intergenerational income mobility measures the likelihood that a child will have a higher income than their parents. Specifically, the measure comes from Opportunity Insights and measures the probability (0–100) that a household's income will rank above the mean for residents born to parents in the 25th percentile of the national income distribution. Residential racial segregation is measured using a dissimilarity index that measures the percentage of the Black population in a county that would have to move residences for each county to have the same percentage as the state. It ranges from 0 (full integration) to 1 (full segregation) and comes from the Robert Wood Johnson County Health Rankings. The ICE measures the concentration of high-income white populations relative to low-income Black residents in a county. As such, ICE measures economic racial segregation rather than physical residential racial segregation. Table 2 describes these measures in more detail.

These inequalities may represent barriers in labor market conditions that are posited to be, among other things, the consequence of historical policies and systems that excluded people of color from some labor market opportunities. These measures are generally accepted in existing literature and are intended to describe various aspects of potential economic or employment inequities in county residents of different race/ethnicities (Alvarez 2022; Owens-Young and Bell, 2020; Riley 2018; Krieger et al. 2016). To align the correct years of outcome and contextual factor, we used county-level data from or as close as possible to 2014.

Methods

BOND was designed as a randomized controlled trial to estimate the effects of the offset policy on earnings and benefit outcomes relative to current-law SSDI rules. In this analysis, we focused on three earnings-related outcomes: annual earnings, any employment, and earnings above BYA in 2014. We also estimated effects on two benefit outcomes: amount of SSDI benefits due and number of months with SSDI payments in 2014. To estimate impacts, we compared the treatment mean to the corresponding control group mean for a given outcome, controlling for differences in baseline characteristics available in SSA administrative data.[1] Results were also weighted for differences in assignment to BOND participation and are representative of the national beneficiary population. The impact estimates are "intent to treat estimates" measuring outcomes for all BOND subjects, regardless of their employment status or engagement with the demonstration. Additional details are available in Gubits et al. 2018.

We estimated the effects of BOND across racial and ethnic subgroups, following the approach to subgroup estimation used in the evaluation of BOND. That is, for each subgroup,

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[1] The full list of control variables includes demographic characteristics (age, age squared, gender, Spanish speaker, rural), primary impairment, SSDI program participation (SSDI duration of less than 18 months, SSDI duration of less than 36 months, years receiving SSDI, years receiving SSDI squared, monthly benefit amount, monthly benefit amount equals zero), average indexed monthly earnings (a measure of past earnings reflecting historic wage growth used by SSA to determine SSDI benefit), average indexed monthly earnings squared, average indexed monthly earnings equals zero, representative payee (who manages benefit payments on behalf of the beneficiary), SSI receipt, disabled adult child (DAC) beneficiary, dually entitled DAC beneficiary, disabled widow(er) beneficiary (DWB), dually entitled DWB, has auxiliary beneficiary (AUX) who is not a DAC or DWB), local conditions (the county 2010 employment rate for people with a disability, the county April 2011 unemployment rate, if missing employment rate for people with a disability, if disabled, if missing the 2010 unemployment rate/rural status), BOND eligibility factors (ineligible for Stage 2 of the BOND study for geographical reasons, and ineligible for Stage 2 for having a legal guardian who was not a representative payee), employment status (any employment in 2010, earnings in 2010), and several interaction terms (earnings × SSDI for less than 18 months, monthly benefit amount × average indexed monthly earnings, age × years receiving SSDI).

we use the impact estimation method used for the full sample and then we use t-tests to test for statistically significant differences between subgroups in impacts on outcomes in 2014.

Analysis of Structural Inequities

We used multilevel modeling techniques to assess the role of economic and employment inequities in explaining the differences in outcomes central to the BOND evaluation by participants' race and ethnicity. Drawing on standard multilevel approaches in which individuals are nested within counties, multilevel models allow us to simultaneously consider associations of both individual-level and county-level contextual factors—and the interdependencies therein—with outcomes.

We first tested for differences in the county contextual factors by participants' race/ethnicity, using t-tests and weighted by county population. We then focused our county-level analysis on the five primary BOND outcomes: employment, earnings over BYA, the number of months with SSDI payments, total earnings, and the average SSDI payment in 2014. We stratified each model by race, pooling all beneficiaries of color into one sample. We do so to simplify the large number of results we have, given the multiple measures of area-level inequality and BOND outcomes. Models based on individual race/ethnicity category are similar and available upon request. We used the analytical sample for which county-level data were available: 961,560 of the 968,530 observations (645,375 White beneficiaries and 316,185 beneficiaries of color).[2] We fit all models in SAS using the PROC MIXED or PROC GLIMMIX commands and standardized all county-level factors and control variables. We assessed model goodness-of-fit with the AIC and BIC statistics and likelihood-ratio tests.

To test the association of area-level inequities with participant outcomes, we employed a multilevel model with a random intercept on county that included the county-level measure of inequity (Level 2) and individual-level race/ethnicity information (Level 1), adjusting for individual-level control variables.

Our model followed the specification in equation 1:

$$y_i = \alpha + \beta_1 s_i + \beta_2 r_i + \gamma_1 w_j + b_{j[i]} + \varepsilon_i \quad (1)$$

$$b_j \sim N(0, \tau^2)$$

[2] As described in more detail below, in some counties, data were not available for residents of color because of small sample sizes. In those cases, BOND participants residing in those counties were dropped from the analysis.

where, for individual i in county j, y_i = BOND outcomes for individual i (earnings, employment, earning over BYA, months with SSDI payments in 2014, total earnings, and/or SSDI payments), s_i represents a vector of individual-level covariates identical to what was used in the BOND evaluation's impact analysis,[3] r_i denotes the race/ethnicity category of individual i,[4] w_j denotes the county-level factor of interest,[5] and $b_{j[i]}$ *and* ε_i represent error terms for levels 2 and 1, respectively. All models are assumed to follow a normal distribution.

These models examine individual-level and area-level factors in conjunction with and in relation to each other. Notably, we can examine if there is an association between area-level inequities and BOND participants' employment and benefit outcomes. For each one of our five BOND outcomes, we ran a separate set of models testing each of the five county-level measure separately, stratified by White beneficiaries and beneficiaries of color. As such, we ran 20 different multilevel models—two different models for each of the county-level measures, one for White beneficiaries and one for beneficiaries of color. For each of the five outcomes, this resulted in a total of 100 models. We did not include a model with multiple contextual factors for two reasons. First, we wanted to simplify interpretation of our models by identifying the unique effects of the identified contextual factor. Second, there were high levels of collinearity between contextual factors.

We also conducted sensitivity analyses, limiting our sample to participants residing in counties in which there are at least 50 participants, following guidelines in the literature for minimum thresholds for sample sizes (Ali et al. 2019). We see no notable difference in results from our sensitivity analysis.

Results

Table 3 displays the characteristics of the BOND sample. There are no statistically significant differences between treatment and control group members in most characteristics. BOND subjects are fairly evenly split between men and women, with a slightly higher share of

[3] We did not include the standard BOND evaluation covariate for county April 2011 unemployment rate as a control variable, because it is highly collinear to all of the county-level measures we modeled.
[4] We do not control for race in the stratified model of the White sample.
[5] Two of our measures of racial inequality included both levels and differences: (1) unemployment rate and differences in the unemployment rate and (2) earnings and earnings gap. In the model with the unemployment-related measures of racial inequality, we did not include the standard BOND evaluation covariate for county April 2011 unemployment rate as a control variable.

men, and have a mean age of 48 years. The two most common primary impairment types are mental disorders and back or other musculoskeletal problems. The average amount of time in which BOND participants were receiving SSDI participation before random assignment is 8 years and 4 months, and the average monthly payment of SSDI benefits is $996 (in 2014 dollars). The majority of BOND participants are only receiving SSDI, but 18 percent are concurrently receiving SSDI and SSI. BOND was administered in 10 states; the largest shares of BOND subject were residing in western New York state, followed by the Detroit area, the state of Alabama, and Arizona and southeastern California.[6]

The distribution of race and ethnicity is quite similar across treatment and control groups. There is no statistically significant difference in the proportion of treatment and control reporting nearly every race and ethnicity category. The exception is that the treatment group has 0.1 percent more beneficiaries who are Hispanic compared to the control group (Table 3), which is a 1.5 percent higher rate relative to the 7.2 percent of beneficiaries in the control group. Although this difference is statistically different, it does not appear to be a meaningful difference. Moreover, the distribution between White beneficiaries versus beneficiaries of color is not statistically significant (p-value 0.972 not shown in Table 3).

Across both the treatment and control groups, one percent or less of the sample identified as any of the three remaining categories: non-Hispanic Asian, American Indian or Alaskan Native, or another unspecified race. We might expect Hispanic, non-Hispanic Asian, and non-Hispanic American Indian or Alaskan Native beneficiaries to be undercounted given that these groups were not offered as race or ethnicity choices on SSA forms until 1980. Indeed, when we compare self-reported race from a survey administered to a subset of BOND participants (less than 4 percent of beneficiaries assigned to BOND), we see that the administrative data yields higher proportions of White and Black beneficiaries and lower proportions of non-Hispanic Alaskan Native or American Indian and Hispanic beneficiaries (Appendix Table A1).

[6] To support the national representativeness of the results, the sites were randomly selected from 53 SSA Area Offices.

BOND Impacts by Race and Ethnicity

For context in interpreting differential impacts by race, we present mean outcomes and impacts by race and ethnicity in Table 4.[7] In absence of the BOND intervention, Black beneficiaries have the highest average level of employment and average earnings are highest among beneficiaries in the control group who are non-Hispanic Asian. Beneficiaries who are White have the highest average SSDI payment amount and months of SSDI benefit receipt.

Non-Hispanic Native American or American Indian beneficiaries have the lowest levels of earnings, employment, SSDI months, and SSDI payments. These results should be interpreted with caution given that administrative data appear to notably underreport the proportion of Non-Hispanic Native American or American Indian beneficiaries relative to survey data. However, a previous study finds that Native American or American Indian have lower benefit amounts relative to other Social Security beneficiaries (Smith-Kaprosy et al. 2012).

When analyzing differences in BOND impacts by race/ethnicity subgroup (Table 4), we find positive[8] impacts on employment and in the proportion earning above BYA for Black beneficiaries and for a combined group of all beneficiaries of color. These impacts represent about a 5 percent increase in employment and a 12 to 14 percent increase in the proportion earning above BYA relative to the control group mean. The absolute impacts of 0.41 and 0.47 for the proportion earning above BYA are also notable relative to a historical program goal. The Ticket to Work and Work Incentives Improvement Act of 1999, which sought to encourage work, noted considerable program benefits if 0.50 of beneficiaries were to sustain earnings above BYA.

We also observe statistically significant increases in SSDI payments and SSDI months for every racial group except one (Table 4). There is no statistically significant impact of BOND on SSDI payments or months for non-Hispanic Native Americans. The lack of impacts could reflect the small sample size for this group and also warrants general caution in interpretation given underreporting relative to survey data.

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[7] We do not report estimates for the group of "All other races" because the small sample size makes for unstable estimates and the composition of "other" race is difficult to define and interpret. We do include this group in the aggregate category of all beneficiaries of color.

[8] Unless otherwise, we only discuss impacts and differences in impacts that are significantly different from 0 at the $p \leq 0.10$ level using a t-test.

We also test whether differences in impacts across the race/ethnicity groups are statistically significant (Table 4). BOND caused a larger increase on employment, earnings above BYA, and the number of months of SSDI receipt for Black beneficiaries than for White beneficiaries. This relationship also held when comparing all beneficiaries of color to their White counterparts. The only other observed difference across race/ethnicity was observed for non-Hispanic Asian beneficiaries, wherein the impact of BOND on the number of months of SSDI receipt is more than twice as large for non-Hispanic Asian beneficiaries as the impact for their White counterparts. Importantly, there are no statistically significant differences in the size of impacts across race/ethnicity for earnings and SSDI payments.

Differential impacts across racial and ethnic subgroups were identified only within outcomes for which there was a statistically significant impact for the entire BOND sample. The lack of subgroup impacts for total earnings aligns with the finding from the BOND evaluation that BOND did not increase earnings for the full BOND sample (Gubits et al., 2018).

The Role of Structural Inequities

There is substantial geographic variation in levels of employment and financial racial inequality our BOND analytical sample. Figure 1 displays the values of all five racial inequality contexts across U.S. counties in which there are at least 10 BOND participants residing in 2014.[9,10] The Index of Concentration at the Extremes (ICE) index is the measure with the strongest geographic pattern, with lower levels of ICE concentrated across the South, southern Texas, and parts of the Southwest. Intergenerational income mobility is mostly positive except in parts of the Northeast, Colorado, and Michigan. There is more racial parity in earnings and unemployment in parts of Colorado, Wyoming, and New Mexico, and counties with the highest levels of racial residential segregation are largely concentrated in the Northeast, Pennsylvania, Ohio, Arizona, and Wyoming.

Before examining the results of the models, we describe patterns of county-level measures by participant race and ethnicity. We find important differences in county-level inequality for beneficiaries of different races (Table 5). In particular, on average, Black beneficiaries tend to live in counties with the highest levels of unemployment, the largest

[9] SSA data disclosure rules do not permit us to report on data with less than 10 individuals.
[10] As a sensitivity analysis, we re-ran the models on counties with at least 50 residents, following Ali et al. 2019, and find similar results.

differences in unemployment rates between White and residents of color, the largest racial gaps in intergenerational mobility, and the highest levels of racial residential segregation. Hispanic beneficiaries tend to live in counties with the lowest average earnings and the largest differences in earnings across racial groups. With two exceptions,[11] differences in county-level inequalities are statistically significant across all pairwise combinations of race/ethnicity.

As described in more detail above, we modeled all five BOND outcomes on each of the five contextual factors, controlling for individual and county characteristics and stratifying by race. In order to streamline the large number of results, we pooled all beneficiaries of color (which includes all beneficiaries who are Black, non-Hispanic Asian, non-Hispanic Native American, non-Hispanic beneficiaries of "other race," and all Hispanic beneficiaries) into one category.[12]

We find some suggestive evidence of significant effects of area-level inequalities on participants' outcomes, but with mixed results. Table 6 provides a summary of these results. The table summarizes the predicted direction of the outcome (column) based on the direction of the county-level factor (row) for White beneficiaries and beneficiaries of color separately. The plus (+) and minus (−) signs represent the direction of the outcome as the factor increases; the plus sign implies the value of the outcome goes up (for example, higher percentage employed) and the minus sign implies the value goes down (for example, fewer months of SSDI receipt). We display more detailed results for all five outcomes in Tables 7–11, for both White and beneficiaries of color. Because employment and earnings above BYA are binary variables, results for those models are displayed as odds ratios; all other models are linear models. All measures of county-level inequality are standardized with a mean of zero.

Taken together, results suggest that some forms of inequality have varied associations with employment-related and SSDI outcomes, while others do not, and that the significance and direction of these associations sometimes differ by race and ethnicity. Results show that racial parity in earnings and unemployment rates at the county level is associated with declines in employment-related outcomes for White and beneficiaries of color, whereas intergenerational

[11] The difference in residential racial segregation between Asian and Hispanic beneficiaries and Asian and Native American beneficiaries was not statistically significant.

[12] We acknowledge that aggregating all non-White beneficiaries in this analysis hides important potential differences in relationships across racialized groups. The authors did perform disaggregated analysis and found similar relationships, so decided to aggregate for the sake of streamlining the large set of results and simplifying interpretation. Disaggregated results are available from the authors upon request.

mobility is uniformly associated with increases in employment-related outcomes for both groups. Lower residential segregation is associated with worse employment-related outcomes for White and positive (or neutral) outcomes for beneficiaries of color. Finally, lower concentration of high-income White residents relative to low-income residents of color is associated with a mix of both increases and decreases in employment-related outcomes for both race/ethnicity groups. As expected, associations with county-level inequalities and benefit-related outcomes generally move in the opposite direction of associations with employment-related outcomes, with a few exceptions.

Racial Gaps in Average Earnings

Greater racial inequality in earnings may potentially be associated with differential BOND impacts. If earnings for White residents are much larger than earnings for non-White residents, this may reflect lower average wage rates or employment opportunities for people of color. This in turn might impact BOND outcomes, as the positive impacts of the demonstration might be dampened by lower wages or employment for beneficiaries of color. As such, we expect that larger gaps in earnings may lead to less beneficial impacts of BOND for Black, Hispanic, American Indian and Native Alaskan participants. Residing in counties with larger earnings gaps in which residents of color have average earnings that are lower than White residents' average earnings is associated with a higher likelihood of employment, earnings above BYA, and higher earnings as well as fewer months of SSDI receipt and lower SSDI payments for White beneficiaries. Counter to our hypothesis, we observe that larger racial earning gaps are also associated with higher likelihood of employment and earnings above BYA and a lower number of months of SSDI receipt. There were no associations between racial earnings gaps and SSDI payments and employment for beneficiaries of color.

We confirmed that the model is producing results in expected directions when estimating the association between average county earnings and employment-related and benefits outcomes. Indeed, we find that higher average county earnings are associated with increased employment, earnings, and earnings above BYA and lower SSDI benefit amounts and months of benefit receipt for both White residents and residents of color.

Difference in Unemployment Rates by Race

Counties with larger racial gaps in unemployment rates imply that a greater share of residents of color are unemployment relative to white residents. This gap could represent a greater available labor supply of residents of color, or it could suggest fewer employment opportunities for residents of color. As such, the hypothesized direction of impacts on BOND are ambiguous. Our findings show that residing in counties in which the unemployment rate for residents of color is lower than the White unemployment rate is associated with higher likelihood of employment for both White residents and residents of color. In other words, larger racial unemployment gaps are associated with better BOND employment outcomes for both white and nonwhite beneficiaries of color. Specifically, a one standard deviation decrease in the differences in unemployment rates between White residents and residents of color is associated with a 5.3 percent decrease in employment for White residents and an 8.1 percent decrease in employment for residents of color (OR = 0.947 for White beneficiaries, OR = 0.919 for beneficiaries of color). It is also associated with shorter periods of SSDI receipt for White beneficiaries. There are no significant relationships between unemployment gaps with most other outcomes.

We also confirmed that, as expected, a higher county unemployment rate is associated with worse employment, earnings, and SSDI outcomes and less reliance on SSDI benefits for all sample members. This helps reassure us that our model is working as intended.

Intergenerational Income Mobility

A county with greater intergenerational income mobility for residents of color is likely to have more avenues for upward mobility, including greater employment opportunities and higher financial returns to education and employment. As such, we might expect that BOND beneficiaries of color living counties with greater intergenerational income mobility may experience more positive benefits of the intended BOND impacts. Indeed, we observe that higher upward intergenerational income mobility for residents of color in a county is associated with better employment, earnings and SSDI outcomes for both White and nonwhite beneficiaries. Intergenerational mobility for residents of color is measured as the probability (from 0 to 1) that a county resident of color will have an income at or above the mean county income given that their parents' income was at the national 25th percentile (Chetty et al. 2020).

A higher value of this measure represents greater upward income mobility for county residents of color. For White residents, a one standard deviation increase in upward intergenerational income mobility is associated with a 10 percent increase in the likelihood of employment, a 16.2 percent increase in the likelihood of earning above BYA, a $124 average increase in earnings, a decrease of 0.044 months in SSDI receipt, and a $48 decrease in average SSDI payments. For residents of color, a one standard deviation in upward intergenerational income mobility is associated with a smaller but still positive increase in the likelihood of employment (1.9 percent), a 12.3 percent increase in the likelihood of earning above BYA, a $73 increase in earnings, a decrease of 0.053 months in SSDI receipt, and a $50 decrease in average SSDI payments.

Racial Residential Segregation

Counties with high levels of residential racial segregation have been shown to have a concentration of residents of color living away from central financial areas and employment hubs (cite). As such, we might expect that the impact of BOND in highly segregated counties might differentially benefit White beneficiaries relative to beneficiaries of color. Indeed, we found that higher levels of racial segregation are associated with higher employment rates for White residents (OR = 1.031) but lower employment rates for residents of color (OR = 0.955). However, counter to our hypothesis, higher levels of racial residential segregation are associated with greater likelihood of SSDI receipt for both White residents and residents of color. Finally, racial residential segregation is positively associated with the likelihood of earning above BYA and average earnings for White beneficiaries. Racial residential segregation is not associated with SSDI payments.

Index of Concentration of Extremes, Racialized Economic Segregation

Area-level inequities as measured by the index of concentration of extremes have different associations with employment and DI receipt for White and residents of color. Higher concentrations of White residents with high incomes are associated with better employment outcomes but higher SSDI receipt for White beneficiaries and the reverse for beneficiaries of color. Higher values of ICE are associated with lower likelihood of earning above BYA but higher average earnings for both race/ethnicity categories. Likewise, higher values of ICE are associated with higher SSDI payments for White beneficiaries but lower SSDI payments for beneficiaries of color.

Discussion

In this paper, we reexamined impacts from BOND to explore racial differences in outcomes. We examined whether race differences in program impacts exist and the extent to which community-level racial inequities in economic and employment conditions are associated with employment and benefit outcomes. To do so, we linked multiple county-level measures of employment-related racial inequities to geocoded addresses of BOND participants and used multilevel models to explore the role of structural racial inequities in program-related outcomes.

In the absence of the BOND intervention, the highest levels of earnings and employment are observed among beneficiaries in the control group who are Black or Asian. Native American beneficiaries also have the lowest levels of SSDI months and payments, whereas beneficiaries who are White have the highest amount and months of benefits.

We find small but statistically significant differences in the impacts of BOND on employment, earnings above BYA, and months of SSDI receipt between White beneficiaries and beneficiaries of color. Specifically, when compared to White beneficiaries, both (i) an aggregated sample of all beneficiaries of color and (ii) Black beneficiaries have slightly larger and more positive impacts of BOND on employment, earnings above BYA, and the number of months of SSDI receipt, though differences are small. There are no statistically significant differences in the size of impacts across race/ethnicity for earnings and for SSDI payments.

These findings highlight the complex relationship between race, employment, and SSDI program participation. Our results revealed higher levels of employment and earnings for Black beneficiaries in the control group, which is consistent with findings in previous research (Mamun, O'Leary, Wittenburg and Gregory 2011; Ben-Shalom and Mamun 2015; Mamun et al. 2011; Patnaik et al. forthcoming). However, national averages indicate that Black individuals have lower levels of employment and earnings (Kijakazi, Smith and Runes 2019). Given the evidence of disparities in the labor market between Black and White workers, this finding is counter to expectations based on existing literature. Further investigation could explore potential reasons for this unexpected finding, including differences in labor market dynamics such as occupational segregation or other factors that may result in this counterintuitive finding.

Evidence from other programs serving people with disabilities (not limited to SSDI beneficiaries), such as vocational rehabilitation programs, suggest employment outcomes are worse for beneficiaries of color relative to those for White beneficiaries (Olney and Kennedy 2002; LeBlanc and Smart 2007; Glynn and Schaller 2017; Rumrill et al. 2017). This may create differential incentives across racial groups and could lead to selection into other programs serving people with disabilities including SSDI. More studies like this one are needed to build a more conclusive understanding of the potential for differential effects of demonstrations by race and ethnicity.

Our results also suggest the role of social context in some employment and SSDI benefit outcomes. We find a mixed pattern of associations wherein different measures of inequality have varied effects on BOND outcomes and the effects also vary by race. Results show that residing in counties in which average earnings and unemployment rates are more favorable for residents of color than for White residents is associated with worse employment-related outcomes for all beneficiaries. This finding ran counter to our hypothesized direction and to a large body of evidence suggesting that inequality is associated with poorer economic outcomes for people of color. Future work may further explore these relationships. It is possible that the unexpected direction of the associations may be due to statistical confounding; in other words, counties with greater levels of inequality also have other characteristics that are associated with unfavorable economic conditions that hamper the intended effects of BOND. In contrast, intergenerational mobility is uniformly associated with better employment-related outcomes for both racial groups. Associations between residential segregation and racialized economic segregation are mixed and vary by race. Collectively, lower rates of racial economic inequality are associated with mixed employment-related and benefits outcomes for SSDI beneficiaries.

An additional strength of our study lies in the use of segregation measures, such as the index of concentration of extremes, which allow for a more holistic design at capturing the inequities in employment and SSDI benefit outcomes. And, although residential segregation has been shown to be associated with economic and educational outcomes (Carr and Kutty 2008), the ICE measure that captures racialized economic segregation is a novel approach at capturing racial and economic privilege versus disadvantage (Krieger et al. 2015, Krieger et al. 2016; Larrabee Sonderland et al. 2022).

This study extends the current literature—which points to the role of geographic context (namely, state of residence) in return-to-work and employment outcomes for SSDI beneficiaries (Stapleton, Livermore and Roche 2009; Ben-Shalom and Mamun 2015; Mamun et al. 2011) but that falls short of examining inequities within these contexts—by exploring both individual and contextual level associations to SSA-funded program outcomes. Although there is little evidence examining the role of structural and social racial inequities specifically in relation to SSA program-related outcomes, the findings in this paper speaks to a broad and growing literature providing evidence that community-level racial inequalities and systemic racism contribute to disparities in health and employment outcomes (Jones 2000; Smedley 2007; Bailey et al. 2017; Riley 2018; Bell and Owens-Young 2020). Still, our findings present mixed results on this topic and further research on this topic could help better clarify these relationships.

Although the findings in the paper represent an important contribution to the literature, they are not without limitations. First, the racial categories used in the analysis are limited to what is defined in the SSA administrative data sources. As such, we categorize beneficiaries either by ethnicity (Hispanic) or by race (non-Hispanic racial category), despite that beneficiaries might prefer to self-identify using both ethnicity and race. This masks the large racial heterogeneity within Hispanic ethnicity. Likewise, in our multilevel models, we aggregate all people of color together for statistical power, which masks important heterogeneity in these populations. As such, we lose the potential to measure differences within race and ethnicity, which encompass people who have distinct historical and social experiences in the United States. In particular, our analysis of BOND impacts revealed that Native Americans have different outcomes than other people of color. Second, we cannot determine the extent to which our chosen measures of inequality might reflect structural racism. Literature suggests that these measures capture the likely consequence of a history of systemic racism (Bell et al. 2019). Moreover, our findings related to the role of social inequalities are all associational and therefore we cannot make any causal claims about the role of systemic racism in our findings. Therefore, there are important considerations with regards to interpretations. Specifically, inequalities in counties do not *determine* outcomes; rather, they highlight complex historical, geographic and social relationships between race and economic and social outcomes in the United States. For example, associations between higher levels of inequality and better outcomes for White beneficiaries may reflect historical social structures that benefited some race/ethnicity groups over others. Finally, this paper did not involve direct input of communities through community participatory research methods such as focus groups or community advisors. Future work could build upon these findings to examine potential mechanisms informed by direct community input.

Taken together, these findings provide a basis for further exploring differential impacts of SSA programs by race and their potential correlates. Importantly, this project attempts to go beyond describing statistics on racial disparities in outcomes to examine the potential role in structural inequities in explaining those disparities. In doing so, we hope the findings can highlight structural forces that contribute to racial disparities in return to work and inform future SSA efforts to tailor program implementation in consideration of the context in which they occur.

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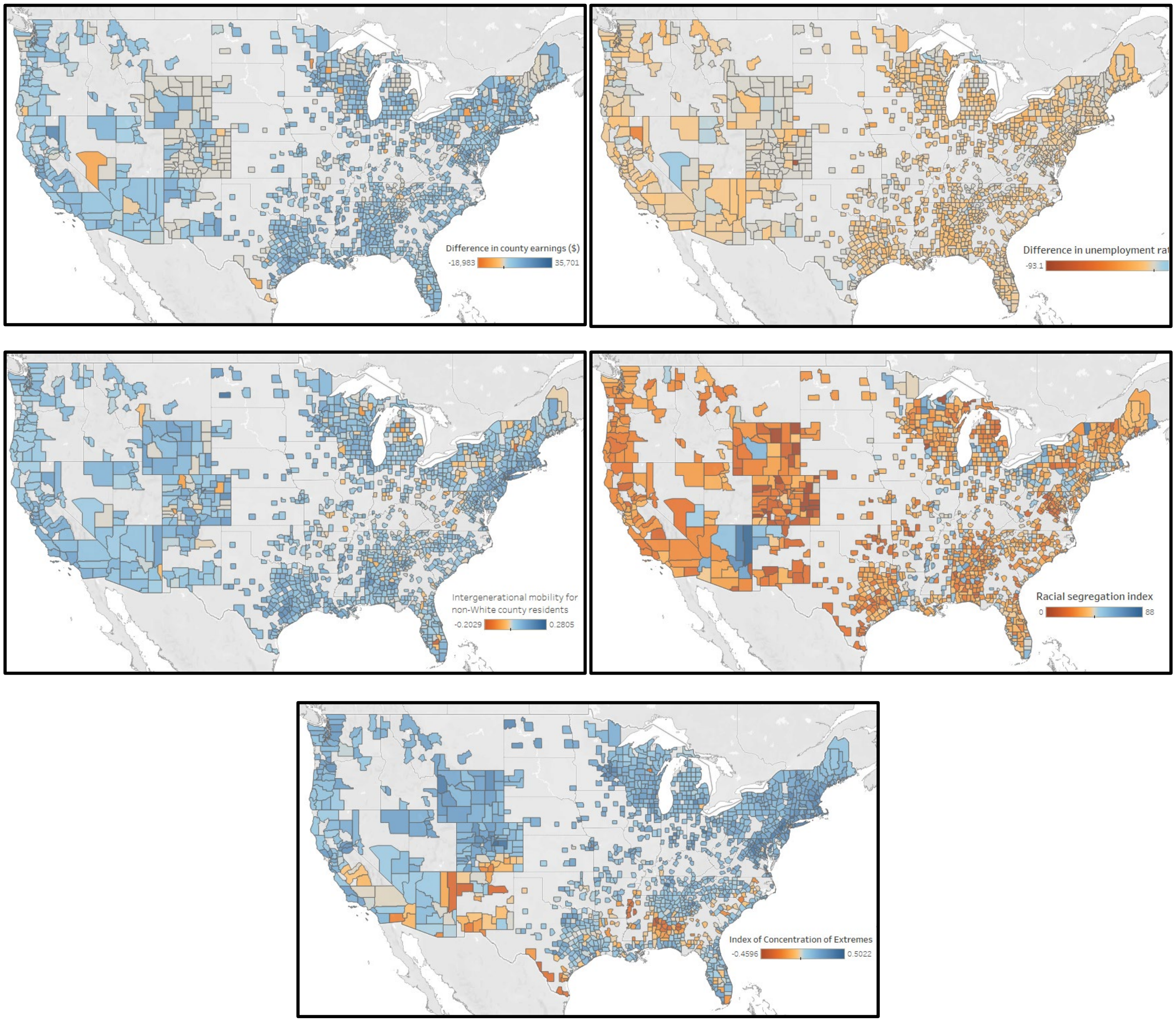
Figure 1. *Maps Displaying Inequality Measures by Race/Ethnicity (White Residents Relative to Residents of Color) for BOND Residents' Counties*



Notes: For all measures, positive values are depicted in blue, and smaller or negative values are depicted in orange. Positive county earnings indicate average earnings for White residents exceed those for residents of color. Positive county unemployment rates indicate unemployment rates are lower for residents of color than for White residents. Higher levels of intergenerational mobility indicate a higher probability that a county resident of color's household income will rank above the county average when born to parents in the 25th percentile of the national income distribution. Higher levels of racial segregation indicate that a higher percentage of the non-White residents would need to move to be geographically distributed like White residents. Positive values of the index of concentration of extremes indicates a high concentration of high-income White residents. The maps are limited to counties with at least 10 BOND beneficiary residents.

Sources: American Community Survey 2010–2014 Five-Year Data Profile, Opportunity Insights (Harvard University), Robert Wood Johnson County Health Rankings (2014), Public Health Disparities Geocoding Project (Harvard University).

Table 1. *Summaries of Race/Ethnicity Data Available for BOND Participants, by Data Source and Participant Birthdate*

	All BOND Control Subjects	Born 1/1/1937 - 12/31/1979	Born 1/1/1980 - 12/31/1986	Born on or after 1/1/1987
N	891,429	812,869	58,088	20,472
Race/ethnicity data available in Numident	98.2%	98.6%	97.1%	86.5%
Race/ethnicity data available in RECS	16.7%	16.0%	23.5%	24.4%
Race/ethnicity data available in Numident or RECS	98.4%	98.7%	97.5%	89.0%

Table 2. *Description of County-Level Measures of Racial Inequality Used in Analysis*

No.	Contextual factor	Source	Description
1.	Earnings gap	ACS, 2010–2014 Five-Year Data Profile	Average earnings for White residents minus average earnings for all county residents of color.
2.	Difference in unemployment rate	ACS, 2010–2014 Five-Year Data Profile	Average unemployment rate for White residents minus the average unemployment rate for all residents of color.
3.	Intergenerational income mobility for residents of color	Harvard University Opportunity Insights, from ACS 2010–2014	This measure is the probability (0–100) that a household's income will rank above the mean for residents born to parents in the 25th percentile of the national income distribution. We use a measure for all county residents of color.
4.	Racial residential segregation	Robert Wood Johnson County Health Rankings	This Dissimilarity Index measures how non-White residents are geographically distributed differently relative to White residents. It has a value between 0 and 100 that represents the percentage of non-White residents that would need to move in order to be distributed like White residents.
5.	Index of concentration of extremes, racialized economic segregation (ICE)	Harvard University Public Health Disparities Geocoding Project, using ACS 2014–2018 Five-Year Data Profile	This ICE Index measures the relative concentration of income by race. It measures the concentration of White residents that have high incomes compared to the concentration of residents of color that have low incomes. It has a value between −1 and 1, wherein values closer to −1 means a higher concentration of lower-income county residents of color and values closer to 1 implies a higher concentration of high-income White residents.

Table 3. *Characteristics of BOND Subjects at Random Assignment (Percentage, Unless Otherwise Noted)*

	Treatment Group Mean	Control Group Mean	Difference	*p*-value
Number of Beneficiaries	77,101	891,429		
Gender				
				0.992
Male	51.6	51.6	0	
Female	48.4	48.4	0	-
Age				
				0.848
20-29 years	6.5	6.4	0.1	
30-39 years	13.2	13.1	0.1	
40-44 years	10.7	10.9	-0.2	
45-49 years	16.9	16.7	0.2	
50-54 years	23.4	23.6	-0.2	
55-59 years	29.3	29.3	0	
Mean age (years)	47.6	47.7	0	0.576
Primary Impairment				
				0.278
Neoplasms	2.6	2.6	0	
Mental Disorders	31.2	30.9	0.3	
Back or Other Musculoskeletal	22.8	23.2	0.3	
Nervous System Disorders	7.2	7.3	-0.1	
Circulator System Disorders	5.8	5.9	0	
Genitourinary System Disorders	1.8	1.8	0	
Injuries	4.3	4.2	0.1	
Respiratory	1.9	2	-0.1	
Severe Visual Impairments	1.9	2	-0.1	
Digestive system	1.6	1.5	0.1	
Other impairments	18.6	18.5	0.1	
Length of SSDI receipt				
Short duration (36 months or less)	30.2	30.1	0.1	0.321
Number of Months Received SSDI	100.8	100.7	0.1	0.724
Benefit Amount and Status				
Monthly SSDI Benefits ($)	997	995.8	1.2	0.733
SSDI Only	81.8	82	-0.2	0.424
Concurrent Beneficiary	18.2	18	0.2	-
Disabled adult child	12.9	12.7	0.2	0.592
Disabled widow beneficiary	1.7	1.7	0	0.555

Dually-entitled disabled adult child	2.3	2.3	0	0.993
Dually-entitled disabled widow Beneficiary	0.9	0.9	0	0.217
Payee is other than self	18.3	18.5	-0.2	0.507
Site				
Alabama	11.5	11.5	0	
Arizona/Southeast California	11.5	11.5	0	
Colorado/Wyoming	5.8	5.8	0	
DC Metro	8.3	8.3	0	
Greater Detroit	12.5	12.5	0	
Greater Houston	9.6	9.6	0	
Northern New England	3.9	3.9	0	
South Florida	11.4	11.4	0	
Western New York	15.3	15.3	0	
Wisconsin	10.2	10.2	0	
Race and Ethnicity				
White	65.8	65.7	0.0	0.828
Black	23.0	23.1	-0.1	0.131
Asian (non-Hispanic)	1.1	1.1	0.0	0.538
American Indian or Alaskan Native (non-Hispanic)	0.6	0.6	0.0	0.877
Other race (non-Hispanic)	0.6	0.6	0.0	0.469
Hispanic	7.3	7.2	0.1	0.037
Missing/Unknown	1.6	1.6	0.0	0.312

Notes: p-values are associated with pairwise t-tests for binary variables and chi-squared tests for categorical variables. All dollar amounts are in 2014 dollars. SSDI= Social Security Disability Insurance.
Source: Authors' tabulation of SSA administrative data sources. Data are weighted. P-values represent significance tests for chi-squared or pairwise t-tests (in the case of race and ethnicity).

Table 4. *Impact Estimates on BOND Employment Outcomes, by Race/Ethnicity*

BOND outcome	White		Black		Hispanic		Non-Hispanic Asian		Non-Hispanic Native American		All Beneficiaries of Color	
	Control group mean	Impact	Control group mean	Impact	Control group mean	Impact	Control group mean	Impact	Control group mean	Impact	Control group mean	Impact
Employment (%)	12.36	0.11	14.95	0.75**†††	11.81	0.58	12.77	0.21	11.46	-0.33	14.03	0.65**††
Earnings ($)	1,306	-0.98	1,541	86.83	1,416	30.19	1,894	-42.34	1,037	-216.29	1,513	65.99
Earnings over BYA (%)	2.35	0.11	3.45	0.47**††	3.16	0.21	3.60	-0.20	2.19	0.09	3.35	0.41**††
SSDI months	10.42	0.17***	10.2	0.25***††	10.34	0.27***	10.16	0.50***†††	10.15	0.38	10.23	0.26***†††
SSDI Payment Due ($)	11,784	144***	10,160	256***	9,812	162**	9,992	399*	9,116	274.50	10,086	210***
N (control group)	593,863		195,581		68,101		8,854		5,642		283,631	
N (treatment group)		51,512		16,559		6,056		813		488		24,378

Note: This table shows the observed means for the control group and the regression-adjusted impact estimates of BOND. The adjusted mean for the treatment group can be calculated by adding the impact estimate to the observed mean for the control group. All outcomes are weighted using BOND weights to represent the entire SSDI beneficiary population at the time of random assignment. All dollar amounts are measured in 2014 dollars. */**/*** Impact estimate is significantly different from zero (p-value is less than .10/.05/.01) using a two-tailed t-test. †/††/††† Impact estimate is significantly different from estimate for White (p-value is less than .10/.05/.01) using a two-tailed t-test. BYA= BOND Yearly Amount.
Source: Authors' analysis of SSA administrative data sources.

Table 5. *Weighted Means of County-Level Measures of Inequality by Race/Ethnicity*

	White	Black	Non-Hispanic Asian	Non-Hispanic Native American	Hispanic	Non-Hispanic Other Race	*p*-value
Unemployment Rate (county average, %)	8.94	10.56	8.70	8.21	8.10	8.55	<.0001
Unemployment Rate Inequalities (white-nonwhite)	-5.98	-6.74	-5.71	-5.83	-5.04	-5.73	<.0001
Earnings (county average, $)	29,953	29,253	30,625	30,119	28,994	29,964	<.0001
Earnings Inequality (white-nonwhite, $)	9,198	10,960	11,509	8,703	12,053	10,341	<.0001
Index of Concentration of Extremes	0.140	0.040	0.147	0.100	0.041	0.101	<.0001
Intergenerational mobility for residents of color	0.067	0.092	0.089	0.071	0.088	0.083	<.0001
Residential segregation (0-100)	44.69	53.31	42.83	39.62	42.70	42.79	<.0001

Note: This table shows the weighted mean value of a county measure for BOND residents in each race/ethnicity group. Values are weighted by the share of BOND residents in each county. All dollar amounts are measured in 2014 dollars. The p-value signifies the probability that the values are different across two or more race/ethnicity categories using an adjusted Wald test.
Source: Authors' analysis of publicly-available data sources described in Table 1.

Table 6. *Summary of Predicted Association Between County-Level Inequalities and Key Outcomes, by Race*

	Key outcomes tested in BOND									
	Employment (%)		Earnings Above BYA (%)		Earnings ($)		Months of SSDI receipt		SSDI payments ($)	
County-level contextual factor	White	Residents of color	White	Residents of color	White	Residents of color	White	Residents of color	White	Residents of color
Larger gap in earnings	+	**N.S.**	+	+	+	+	−	−	−	**N.S.**
Unemployment rate for residents of color is equal to or below White unemployment rate	−	−	**N.S**	**N.S.**	**N.S.**	**N.S.**	−	−	**N.S.**	**N.S.**
Higher intergenerational mobility	+	+	+	+	+	+	−	−	−	−
Lower residential segregation	−	+	−	**N.S.**	−	**N.S.**	−	−	**N.S**	**N.S.**
ICE: lower concentration of high-income White residents	−	+	+	+	−	−	−	+	−	+

Notes: This table summarizes the predicted direction of the BOND outcome (column) based on the direction of the county-level factor (row) for White beneficiaries and beneficiaries of color. Separate models are run for each of the five county-level variables. Beneficiaries of color are the pooled sample of Black, non-Hispanic Asian, Non-Hispanic Other race, and Hispanic beneficiaries. We pool this sample to have enough statistical power to estimate effects. The plus (+) and minus (−) signs represent the direction of the BOND outcome; + implies the values goes up (e.g., higher percent employed), and the minus sign implies the value of the outcome goes down (e.g., fewer months of SSDI receipt). N.S. = Estimate is not statistically significant at the $p \leq 0.10$ level.
Source: Author’s analysis of SSA administrative data and publicly available county data.

Table 7. *Estimated Association Between County-Level Inequalities and Employment for White Beneficiaries and Beneficiaries of Color (Odds Ratios)*

	White beneficiaries		Beneficiaries of color	
	Association	*p*-value	Association	*p*-value
Difference in average county-level earnings	1.014	0.016	0.992	0.358
Difference in county unemployment rate	0.951	<.0001	0.941	.0004
Intergenerational mobility	1.102	<.0001	1.019	0.038
Residential segregation	1.031	<.0001	0.955	<.0001
Index of Concentration of Extremes	1.193	<.0001	0.902	<.0001
N	645,375		316,185	

Notes: This table shows the results of a series of multilevel logit models that analyze the association between BOND employment and each county-level measure listed in the subhead of the table. "Beneficiaries of color" refers to the pooled group of beneficiaries who are Black, non-Hispanic Asia, Native American, non-Hispanic other race, and Hispanic individuals of all races. Results for White beneficiaries and beneficiaries of color are run separately as stratified models. Coefficients represent odds ratios. All county-level variables are standardized. P-values represent the probability that the estimated coefficient is significantly different from zero using a two-tailed t-test. All outcomes are weighted using BOND weights. All dollar amounts are measured in 2014 dollars.

Source: Authors' analysis of SSA administrative and public data sources.

Table 8. *Estimated Association Between County-Level Inequalities and Earnings Over BYA for White Beneficiaries and All Beneficiaries of Color (Odds Ratios)*

	White beneficiaries		Beneficiaries of color	
	Association	*p*-value	Association	*p*-value
Difference in average county-level earnings	1.067	<.0001	1.042	0.002
Difference in county unemployment rate	0.999	0.970	0.987	0.441
Intergenerational mobility	1.162	<.0001	1.123	<.0001
Residential segregation	1.047	<.0001	1.020	0.109
Index of Concentration of Extremes	0.955	<.0001	0.943	0.001
N	645,375		316,185	

Notes: This table shows the results of a multilevel logit models that analyze the association between the probability of earnings over BYA and each county-level measure listed in the subhead of the table. "Beneficiaries of color" refers to the pooled group of beneficiaries who are Black, non-Hispanic Asia, Native American, non-Hispanic other race, and Hispanic individuals of all races. Results for White beneficiaries and beneficiaries of color are run separately as stratified models. Coefficients represent odds ratios. County-level variables are standardized. P-values represent the probability that the estimated coefficient is significantly different from zero using a two-tailed t-test. All outcomes are weighted using BOND weights. All dollar amounts are measured in 2014 dollars. BYA=BOND Yield Amount.

Source: Authors' analysis of SSA administrative and public data sources.

Table 9. *Estimated Association Between County-Level Inequalities and Annual Earnings for White Beneficiaries and Beneficiaries of Color ($)*

	White beneficiaries		Beneficiaries of color	
	Association	*p*-value	Association	*p*-value
Difference in average county-level earnings	56.87	<.0001	42.58	0.001
Difference in county unemployment rate	-8.51	0.471	-15.42	0.538
Intergenerational mobility	123.95	<.0001	73.16	<.0001
Residential segregation	29.34	<.0001	-6.10	0.541
Index of Concentration of Extremes	79.62	<.0001	110.00	<.0001
N	645,375		316,185	

Notes: This table shows the results of a series of multilevel logit models that analyze the association between the number of months of SSDI receipt and each county-level measure listed in the subhead of the table and includes individual and county-level covariates. "Beneficiaries of color" refers to the pooled group of beneficiaries who are Black, non-Hispanic Asia, Native American, non-Hispanic other race, and Hispanic individuals of all races. Results for White beneficiaries and beneficiaries of color are run separately as stratified models. All county-level variables are standardized. P-values represent the probability that the estimated coefficient is significantly different from zero using a two-tailed t-test. All outcomes are weighted using BOND weights. All dollar amounts are measured in 2014 dollars.
Source: Authors' analysis of SSA administrative and public data sources.

Table 10. *Estimated Association Between County-Level Inequalities and Number of Months Receiving SSDI for White Beneficiaries and Beneficiaries of Color*

	White beneficiaries		Beneficiaries of color	
	Association	*p*-value	Association	*p*-value
Difference in average county-level earnings	-0.026	<.0001	-0.023	0.011
Difference in county unemployment rate	-0.036	<.0001	-0.037	0.051
Intergenerational mobility	-0.044	<.0001	-0.053	<.0001
Residential segregation	0.017	0.001	0.019	0.011
Index of Concentration of Extremes	0.042	<.0001	-0.060	<.0001
N	645,375		316,185	

Notes: This table shows the results of a series of multilevel logit models that analyze the association between the number of months of SSDI receipt and each county-level measure listed in the subhead of the table and includes individual and county-level covariates. "Beneficiaries of color" refers to the pooled group of beneficiaries who are Black, non-Hispanic Asia, Native American, non-Hispanic other race, and Hispanic individuals of all races. Results for White beneficiaries and beneficiaries of color are run separately as stratified models. All county-level variables are standardized. P-values represent the probability that the estimated coefficient is significantly different from zero using a two-tailed t-test. All outcomes are weighted using BOND weights. All dollar amounts are measured in 2014 dollars.
Source: Authors' analysis of SSA administrative and public data sources.

Table 11. *Estimated Association Between County-Level Inequalities and Total SSDI Payments ($) for White Beneficiaries and Beneficiaries of Color*

	White beneficiaries		Beneficiaries of color	
	Association	*p*-value	Association	*p*-value
Difference in average county-level earnings	-35.77	<.0001	-13.99	0.130
Difference in county unemployment rate	-12.73	0.191	-7.67	0.683
Intergenerational mobility	-48.15	<.0001	-49.60	<.0001
Residential segregation	8.46	0.152	-0.41	0.957
Index of Concentration of Extremes	27.96	0.000	-31.15	0.000
N	645,375		316,185	

Notes: This table shows the results of a series of multilevel logit models that analyze the association between the number of months of SSDI receipt and each county-level measure listed in the subhead of the table and includes individual and county-level covariates. "Beneficiaries of color" refers to the pooled group of beneficiaries who are Black, non-Hispanic Asia, Native American, non-Hispanic other race, and Hispanic individuals of all races. Results for White beneficiaries and beneficiaries of color are run separately as stratified models. All county-level variables are standardized. P-values represent the probability that the estimated coefficient is significantly different from zero using a two-tailed t-test. All outcomes are weighted using BOND weights. All dollar amounts are measured in 2014 dollars.
Source: Authors' analysis of SSA administrative and public data sources.

Appendix Table A1. *Comparison of Survey and Administrative Race and Ethnicity Data for BOND Control Group Subjects*

	Administrative Data	BOND Survey	Difference	*p*-value
Race and Ethnicity				
				<.0001
White	65.3	59.3	6.0	
Black	22.5	19.6	2.9	
Asian (non-Hispanic)	1.1	1.2	0.0	
American Indian or Alaskan Native (non-Hispanic)	1.0	2.5	-1.5	
Other race (non-Hispanic)	0.2	4.1	-3.8	
Hispanic	7.9	10.1	-2.2	
Missing/Unknown	2.0	3.3	-1.3	

Notes: Samples are weighted and include 2,819 Stage 1 control group subjects (0.3 percent of all 891,429 Stage 1 control group subjects). Weighted, they represent 5,885,938 beneficiaries.
Source: Authors' analysis of the BOND Stage 1 36-Month Survey and SSA administrative data sources.

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