Long-Run Drivers of Disability Insurance Rates[1]

John N. Friedman (Brown University and NBER)

Ithai Lurie (Treasury-Office of Tax Analysis)

Magne Mogstad (University of Chicago and NBER)

Raj Chetty (Stanford University and NBER)

Abstract

Understanding the causes of the rise in disability rolls lies at the heart of policies concerned with the interaction of working life, family well-being, and a country's social safety net. To explore the long-run drivers of disability insurance (DI) receipt, we use administrative tax data that allows us to link young adults (ages 24-34) to their parents. Our findings are threefold. First, DI receipt is strongly linked to the income of the recipient's parents, with rates for young adults from the poorest families roughly six times higher than those from the richest families. Second, children from low income families display sharply varying probabilities of receiving DI depending on the place where they grew up, while those from rich families show no similar differences. Suggestive evidence indicates that roughly 50% of these place-based differences are causal. Third, places where poor children grow up to have the highest rates of DI receipt tend to be "good" areas based on many standard characteristics, including lower inequality, lower segregation, higher school quality, and higher social capital.

1. Background and Literature

A striking pattern over the past few decades is the large and steady rise in participation rates in various sickness and disability related programs. Of particular interest is the rise in disability insurance (DI) receipt. This is in part because DI is the largest social insurance program in most industrialized countries, but also because it is usually an absorbing state: few individuals who go onto DI re-enter the work force at a later date. For example, over the past 50 years DI rolls have steadily risen from less than 1% to 6%

[1] This research was supported by the U.S. Social Security Administration through grant #1 DRC12000002-04 to the National Bureau of Economic Research as part of the SSA Disability Research Consortium. The findings and conclusions expressed are solely those of the author(s) and do not represent the views of SSA, the U.S. Department of Treasury, any other agency of the Federal Government, or the NBER.

of the adult population in the U.S. (Autor and Duggan, 2006, Burkhauser and Daly, 2012).[2] Prominent researchers have argued that such rises in disability insurance rolls are fiscally unsustainable (Autor and Duggan, 2006), especially as current DI recipients are younger and have longer life expectancies on average compared to previous cohorts of recipients.

Understanding the causes of the rise in disability rolls lies at the heart of policies concerned with the interaction of working life, family well-being, and a country's social safety net. To date, research has largely focused on describing non-medical factors correlated with the probability of claiming disability benefits, such as economic conditions, local allowance rates, and age. For instance, DI applications and awards spike during recessions and fall off during boom years (Black, Daniel and Sanders 2002, Autor and Duggan 2003), a pattern that held strongly as DI applications rose during the Great Recession (Mueller, Rothstein and von Wachter 2015). Less educated workers and older workers are also more likely to claim disability benefits (SSA 2014). There is also considerable variation in disability receipt across areas related to compositional differences in the population with respect to age, education, and industrial structure (Ruffing 2015).

While this research has been important in describing certain correlates of DI receipt, it has been limited in its ability to look at long-term factors that shift an individual's chances of DI receipt. Another limitation is that only a few existing studies try to distinguish between selection and causation in the factors that predict DI receipt.[3] Sorting out these scenarios is central to understand how economic conditions or government policies may affect disability rolls.

In this paper, we try to address these limitations, making two key contributions. First, we use U.S. administrative tax data to link young adults to their parents, and carefully describe the long-term predictors of DI receipt. In particular, the size and detailed nature of the data we are using allows us to describe the relationship between parents' income and the probability that the child participates in DI as young

[2] This trend is not specific to the U.S., as documented by OECD (2010). In the U.K., for example, DI rolls have steadily risen from 1% to 7% over the past 50 years.
[3] A notable exception is Dahl et al. (2014). They take advantage of random assignment of judges to DI applicant to show that DI receipt in one generation is causing DI participation in the next generation.

adult. Using our rich data, we characterize how these intergenerational relationships vary across areas within the U.S.

The geographic variation in the association between parents' income and children's DI participation could be driven by two very different sources. One possibility is that neighborhoods have causal effects on the chances an individual claims DI: that is, moving a given child to a different neighborhood would change her likelihood of participating in DI. Another possibility is that the observed geographic variation is due to systematic differences in the types of people living in each area, such as differences in demographic makeup or wealth. The second contribution of our paper is to test these explanations and identify the causal effects of neighborhoods by studying families who move across counties and exploiting differences in their children's ages when they move. This strategy has previously been used by Chetty and Hendren (2015) to study intergenerational income mobility.

2. Data

Our dataset is the universe of IRS administrative tax data from 1996-2014.[4] Our sample of potential DI claimants includes those born in the 1980-1990 cohorts. We measure DI receipt for young adults (ages 24-34) through the receipt of Form 1099-SSA, which the SSA files with the IRS for all DI payments. (Our data do not include SSI payments.) We cannot distinguish disabled workers from other claiming benefits (spouses, adult children, or dependents), but for individuals receiving SSDI payments at ages 24-34, just 2% of program recipients are spouses and dependents would be ineligible. Adult children are a greater concern, but our approach to study hazard rates (rather than the stock of DI recipients) minimizes this concern, since most adult children begin to receive benefits before age 24.

We then link young adults to their parents by finding the household that claims each child as a dependent for tax purposes. This procedure is especially effective for low-income children, whose parents often receive large tax credits as a result of filing;

[4] Raj Chetty and John N. Friedman accessed these data under contract TIRNO-16-E-00013 with Statistics of Income (SOI) Division of IRS.

altogether, previous work in these data has linked 95% of all children to a household in this way (Chetty et al. 2014).

We measure household income for the parents using adjusted gross income (AGI) from income tax returns, imputing this income from various information returns (including W-2s, 1099-SSA, and 1099-UI) for non-filers, using data from 1996-2000 (which is the earliest that we can observe parental income). We then rank parents' income against other households with children in the same cohort; this within-cohort ranking helps adjust for differences in the age of income measurement or in the calendar years at which income is measured. While these households may not include a child's biological parents, they do represent circumstances in which the child grew up (to simplify language we refer to such households as "parents"). We drop young adults whom we cannot link to their parents in this way. Including all 11 cohorts, this leaves us with a sample of 38.4 million young adults and 222.4 million individual-year observations.

Table I presents summary statistics for the key variables in our analysis. In Panel A, we present data at age 24, the only year when we have data for all 11 of our cohorts. The average DI rate in the full sample is 0.66%. Panel B presents the same statistics at age 34 (for cohort 1980 only). At that age, 2.0% of individuals receive SSDI payments. It is also worth noting that 2.5% of individuals at age 34 have received SSDI income at some point since age 24; thus, 20% of individuals ever receiving income from the program have left. This reflects (as least in part) a somewhat larger recovery rate for young adults; the comparable rate for disabled beneficiaries on average across the entire program is substantially lower. It is also possible that changing relationship to a beneficiary (e.g., divorced spouse) accounts for some of this, but the preponderance of disabled workers among beneficiaries at these ages implies that this should be a relatively small share of those leaving the program.

We can also calculate, for each individual in each year, whether they are covered by the SSDI program. SSA rules mandate that individuals work a minimum number of quarters of coverage (QCs) before applying to DI, where a worker earns one QC for each $1,260 (in 2016) of covered earnings up to a maximum of four QCs per year. (Despite the label "quarters," it does not actually matter when in the year workers earn this income; for example, a worker may earn all four credits in January even if she does not work in any other month.) For each worker in each year, we calculate the number of QCs earned by dividing the sum of Social Security Wages (W-2, Box 3) and Net Self-Employment Income (Schedule SE, Box 4 (Short Schedule) or Box 6 (Long Schedule)) by the annual QC amount.

We then compare an individual's accrued QCs to the minimum number required for eligibility. This minimum varies by age; individuals must have accumulated a minimum of 2*(Age – 21) QCs since the time they were 21 years old. For instance, a 27-year-old must have earned at least 12 QCs after turning 21. Once an individual is 31 or older in our sample, they must have earned a minimum of 20 QCs since age 21. Table I shows averages for this variable as well; at age 24, just 70.7% of individuals are eligible, but this fraction raises to 88.5% by age 34.

3. National Results

We begin our analysis by studying the relationship between DI rates and parental income nationally. Table I, Columns 2 and 3, repeat the basic summary statistics for individuals from the bottom and top quintiles of parent income, respectively. At age 24, 1.1% of individuals from bottom-quintile families receive benefits, as compared to just 0.3% of individuals from top-quintile families. At age 34, these numbers rise to 3.0% and 1.0%, respectively. These numbers represent the stock of individuals receiving DI benefits, however, which reflects individuals going onto or off of DI at all previous ages. To isolate behavior at each age, we instead calculate the net hazard rate at each age *a*, defined as

$$Hazard_a = \frac{DI_a - DI_{a-1}}{1 - DI_{a-1}}$$

where DI_a is the total fraction of individuals received DI benefits at age *a*. We refer to this as the "net" hazard because it reflects both new individuals who received DI benefits as well as individuals dropping out of the program (or having benefits withheld).

Figure 1 plots the net hazard rate for individuals from each percentile of the parents' income distribution. The straight line that fits the observed data best suggest that each 10-percentile increase in family income predicts a 0.014point drop in the net hazard rate of entering the DI program Non-parametrically, the data show that 20.1 of out 10,000 kids from the very poorest percentile of families go onto the program, as compared to just 4.2 of out 10,000 kids from the very richest percentile of families. As a result, the DI hazard rate is 4.8 times higher for those at the bottom than for those at the top.

Table II Column 1 replicates the best-fit line from Figure 1. Columns 2-4 show that this relationship is very stable across ages. Columns 5 and 6 then explore how much of this relationship is driven by the behavior of individuals whose parents also received DI benefits. Column 5 shows that the relationship is essentially unchanged among young adults whose parents did not receive DI themselves.

4. Geographic Variation in DI Rates

This section explores variation across place in the relationship between parental income and DI benefit receipt. To do so, we repeat the same relationship between parental income and DI receipt in young adulthood, but within each state and commuting zone (CZ). In each case, it is important to note that this is the location in which we believe the young adult grew up, defined as the earliest location in which we observe the child (typically when claimed as a dependent in 1996).

For some of the largest states, there is sufficient data to conduct this analysis non-parametrically. Figure 2 shows this analysis for two such states, California and Pennsylvania. For each group of five parent income percentiles, we calculate the net hazard rate for DI receipt. While young adults from rich families have very similar net hazard rates of DI receipt in each state, the net hazard rate for young adults from poor families is much higher in Pennsylvania than California. For young adults from the poorest families, the net hazard rate in Pennsylvania is roughly double (0.24%) that in California (0.12%). These state level relationships are also well summarized by the linear best-fit. The slope is roughly three times higher in Pennsylvania (0.19) than in California (0.06). To extend this analysis to other states, we estimate a separate linear best-fit between DI receipt and parental income percentile for each state. Because the differences in net hazard rates appears at the bottom of the parental income distribution, we then characterize each area by the predicted value for young adults from a 25th percentile family. Figure 2 demonstrates how these predicted values are constructed for Pennsylvania ($Pred_{25}$ = 0.184%) and California ($Pred_{25}$ = 0.109%). We then use the value of this predicted value to classify a state as "high" (top quartile) or "low" (bottom quartile). Figure 3 shows the average DI receipt to parental income gradient in high- and low-DI states. As we saw in California and Pennsylvania, both high- and low-DI states exhibit very similar net hazard rates for young adults from the richest families (0.05%), while the hazard rate for poor families is roughly twice as high in the top quartile states as in the bottom quartile states. Table III lists the state-specific slopes and $Pred_{25}$ for each state.

We also conduct this analysis at the CZ level. Figure 4 displays the predicted DI rate for each CZ on a heatmap, with darker (redder) colors denoting higher DI-rate places. Table 4 also lists the predicted values for each of the 100 largest CZs in the US. Many of the lowest-DI CZs are in California, along with three cities in (or bordering) Texas and New York City. The largest concentration of highest-DI CZs is in New England, including two CZs (Springfield, MA and Manchester, NH) with DI rates nearly 30% higher than even the other highest DI CZs.

To investigate whether the differences across areas shown in Figures 2 and 3 and Tables III and IV are causal, we study children who move from one CZ to another during childhood following Chetty and Hendren (2015). We run the following regression specification

$$DI_i = B'M_i\Delta_{odps} + B'_oM_i\bar{y}_{pos} + \alpha'M_i + B'_pM_ip + \psi'S_i + C'S_i\bar{y}_{pds} + C'_oS_i\bar{y}_{pos} \qquad (1)$$

where B is a vector of age-of-move-specific coefficients on the difference in predicted outcomes in the destination and origin location, B_o is a vector of age-of-move-specific coefficients on the predicted outcomes in the origin location, α is a vector of age-at-move fixed effects, B_p is a vector of coefficients on parent rank, ψ is a vector of birth cohort fixed effects, and C and C_o are vectors of coefficients on the predicted outcomes in the origin and destination interacted with birth cohort. M_i and S_i respectively indicate dummy variables for whether an individual is a "mover" or a "stayer," respectively, indicating which coefficients are identified by the two groups.

The key coefficients B compare the DI rates of children who move from one CZ to another at a given age to the DI rates of children who do not move. Table V displays the results from this regression. The age-specific coefficients in Column 1 are the extent to which these "movers" look like the "stayers" from the destination (as opposed to the origin) CZ. For instance, consider children who move from Boston (a very high DI-rate CZ) to New York (a very low-DI rate CZ) at age 8. The coefficient in Column 1 suggests that these children have DI rates that are a weighted average of the "stayers" in Boston in New York, with 75.8% of the weight from New York. As the children move at older ages (decreasing the exposure to New York), the weight on New York falls to 36.8% for children who move at age 22. This is consistent with a causal effect of place that is proportional to the exposure of children. After age 22, however, this weight does not decrease on average, and is almost unchanged from age 22 at age 32 (33.1%). Column 2 summarizes this pattern of coefficients by age in two numbers: the age-slope of the coefficients up through age 22, and then after age 22. The coefficient declines by a statistically significant 0.032 in each year up through age 22, after which the coefficient has a much smaller change by age (-0.016).

One concern with this research design is that families who move from one CZ to another when children are older may systematically differ from those who move when the kids are younger. In order to assess whether this source of bias is present in these results, we follow Chetty and Hendren (2015) in Column 3 and repeats the specification in Column 2 including family fixed effects. Intuitively, this assesses the effects of moving at different ages, comparing only between older and younger siblings within the same family. Up to age 23, the weight on the destination CZ falls by 0.024 for each extra year spent in the origin city; after age 23, there is no significant change. These coefficients suggest that differential moves by age are a small problem in Columns 1 and 2, but still a large fraction of the cross-sectional estimate of place effects on DI rates is causal. Extrapolating to earlier ages, the coefficient of 0.024 in Column 3 suggests that the entire causal effect of childhood exposure on DI rates is 23*0.024 = 0.561

(SE=0.108), which implies that roughly half of the differences in DI rates between place are causal.

5. DI Rates and Area Characteristics

In this section we explore what CZ-level characteristics predict high DI rates for children from poor families. For a wide range of covariates, we calculate the univariate Pearson correlation with the predicted DI rate at the 25th percentile of parental income, weighting by the total size for our eleven cohorts in each CZ. We calculate all characteristics from the 2000 US Census, unless otherwise indicated.[5] Table 6 contains the results.

Our first group of covariates contains measures of segregation, calculated using the Theil (1972) index of segregation across Census tracts within each CZ. Specifically, let ϕ_r denote the fraction of individuals of race or ethnicity *r* in a given CZ, with four groups: whites, blacks, Hispanics, and others. Let the entropy index $E = \sum \phi_r log_2 \frac{1}{\phi_r}$ measure the level of racial diversity in the CZ, with $E = 0$ when $\phi_r = 0$, and similarly measuring the level of racial diversity within each census tract *j* as $E_j = \sum \phi_{rj} log_2 \frac{1}{\phi_{rj}}$ where ϕ_{rj} denotes the fraction of individual in tract *j* from race *r*. Then we define the degree of racial segregation in a city as

$$H = \sum_j \left[\frac{pop_j}{pop_{total}} * \frac{E - E_j}{E}\right]$$

where pop_j denotes the total population of tract *j* and pop_{total} denotes the total population of the CZ. Intuitively, *H* measures the extent to which racial diversity in each Census tract mirrors racial diversity in the CZ as a whole. When $H = 1$, there is no racial diversity at all within Census tract; when $H = 0$, racial diversity in each tract is exactly the same as in the city as a whole. Table VI shows that DI rates are negatively correlated with racial segregation by this measure, but the correlation is not significant.

We also construct a measure of income segregation in each CZ. Specifically, following Reardon and Firebaugh (2002) and Reardon (2011), we construct a two-group Theil index *H(p)* to measure to extent to which individuals below national income

[5] We thank the authors of Chetty et al. 2014 for help with constructing CZ-level covariates.

percentile p are separated from individuals above income percentile p. We use the formula above, where for income segregation $E(p) = plog_2 \frac{1}{p} + (1-p)log_2 \frac{1}{1-p}$.We then define the overall level of income segregation in a CZ as

$$\text{income segregation} = 2\log(2) \int_p \; E(p)H(p)dp.$$

This measure is interpretable as a weighted average of *H(p)* across the income distribution, where the weights are larger in the middle of the income distribution where entropy is largest. Table VI shows that DI rates are significantly and negatively correlated with income segregation, so that less segregated cities have higher DI rates.

Second, we study different moments of the CZ-specific income distribution. We first correlate DI rates with mean household income; this statistic of income levels is almost entirely uncorrelated with DI rates. In contrast, we find that two different measures of income inequality – the fraction of income earned by the top 1%, and the Gini coefficient – are strongly negatively correlated with DI rates.

Third, we study measures of the quality of local education. Using both measures of inputs (student-to-teacher ratios) and outputs (test scores, high school dropout rate, and college graduate rate), CZs with higher quality education have higher DI rates. The correlations are strongest for measures of elementary school quality. Specifically, we find a strong and significant negative correlation between student-teacher ratios (based on data from the National Center for Education Statistics for the 1996-1997 school year) and DI rates. Similarly, we find a strong positive correlation between average grade 3-8 test scores (taken from the Global Report Card, which is based on National Assessment of Educational Progress (NAEP) scores). The correlations are still present, but somewhat weaker, for measures of the HS dropout rate (from the Global Report Card) and college graduation rate. Relatedly, we correlate DI rates with measures of social capital. Our measure of social capital is an index constructed by Rupasingha and Goetz (2008), which includes voter turnout rates, the fraction of people who return their Census form, and various measures of participation in community organizations. We find a strong positive correlation with DI rates, so that CZs with higher social capital have higher DI rates.

Finally, we correlate DI rates with a range of other CZ covariates. Chetty et al. (2014) find that the fraction of single mothers is the single most predictive characteristic for the degree of upward mobility in a CZ. We find no correlation between this variable and the DI rate. DI rates are negatively correlated with local tax rates (marginally) and tax progressivity (significantly), though DI rates are positively correlated with local EITC exposure. DI rates are positively correlated with a number of different aspects of the local labor force, including the local manufacturing share, the extent to which local industries have been exposed to trade competition from China, and the teenage labor force participation rate. CZs with lower out-migration (or in-migration) rates have higher DI rates, though there is no significant correlation with net migration rates. CZs with a large fraction of foreign-born residents have a very negative correlation with DI rates, while local health infrastructure (as measured by doctors or hospitals per capita) are not significantly correlated with DI rates.

Overall, the clear fact that emerges from this analysis is that CZs that generally appear "better" – for instance, with better schools, higher social capital, and lower income inequality – have higher DI rates. This is surprising in light of recent evidence showing that these characteristics correlate with higher rates of upward mobility and employment for children from poor families in such areas.

6. Conclusion

These results show that the circumstances of an individual's childhood, and not simply their current situation, play an important role in determining who receives disability insurance. Long-run forces also vary tremendously across areas in the US. These results suggest two areas for further research. First, what are the mechanisms by which childhood circumstances so powerfully affects DI receipt later in life? Second, are there similar long-run place-based effects on DI receipt at later ages?

References

Autor, David and Mark Duggan (2003) “The Rise in the Disability Rolls and the Decline in Unemployment”, The *Quarterly Journal of Economics*, 118(1): 157-206.

Autor, David and Mark Duggan (2006) “The growth in the social security disability rolls: A fiscal crisis unfolding.” *Journal of Economic Perspectives*, 20(3):71–96.

Black, Sandra and Paul Devereux (2011), “Recent Developments in Intergenerational Mobility”, *Handbook of Labor Economics*, Column 4, Part B, Chapter 16, 1315-1486.

Black, Dan, Kermit Daniel and Seth Sanders (2002) “The Impact of Economic Conditions on Participation in Disability Programs: Evidence from the Coal Boom and Bust”, *The American Economic Review*, 92(1): 27-50.

Bound, John (1991) “The Health and Earnings of Rejected Disability Insurance Applicants: Reply”, *The American Economic Review*, 81(5): 1427-1434.

Burkhauser, R. V. and Daly, M. C. (2012): “Social security disability insurance: Time for fundamental change”, *Journal of Policy Analysis and Management*.

Chetty, Raj, Nathaniel Hendren, Patrick Kline, and Emmanuel Saez (2014) “Where is the Land of Opportunity? The Geography of Intergenerational Mobility in the United States”, *The Quarterly Journal of Economics* 129(4): 1553-1623.

Chetty, Raj and Nathaniel Hendren (2015) “The Impacts of Neighborhoods on Intergenerational Mobility: Childhood Exposure Effects and County-Level Estimates”, Harvard University, mimeo.

Dahl, Gordon, Andreas Ravndal Kostol and Magne Mogstad (2014) “Family Welfare Cultures”, *The Quarterly Journal of Economics*, 129(4): 1711-1752.

Mueller, Andrea, Jesse Rothstein and Till von Wachter (2015), “Unemployment Insurance and Disability Insurance in the Great Recession”, NBER Working Paper No. 19672.

Reardon, Sean (2011), “Measures of Income Segregation,” *CEPA Working Papers*, Stanford University.

Reardon, Sean, and Glenn Firebaugh (2002), “Measures of Multigroup Segregation.” *Sociological Methodology*, 32(1), pp. 33-67.

Rupasingha, Anil and Stephan Goetz (2008), “US County-Level Social Capital Data, 1990-2005,” *The Northeast Regional Center for Rural Development*, Pennsylvania State University.

Ruffing, Kathy (2015). “Geographic Patterns of Disability Receipt Largely Reflects Economic and Demographic Factors.” *Center on Budget and Policy Priorities,* Policy Futures, January 15, 2015.

Social Security Administration (2014). *Annual Statistical Report on the Social Security Disability Insurance Program, 2013*.

Theil, Henri (1972). “Statistical decomposition analysis; with applications in the social and administrative sciences.” In *Studies in mathematical and managerial economics,* Amsterdam, New York: North-Holland Pub. Co.; American Elsevier Pub. Co. (No. 04; HA33, T4).

von Wachter, Till, Jae Song and Joyce Manchester (2011). “Trends in Employment and Earnings of Allowed and Rejected Applicants to the Social Security Disability Insurance Program." *The American Economic Review*, 101(7): 3308-29.

Figure 1: Net Hazard Rate of DI Receipt by Parental Income Percentile: Ages 24-34

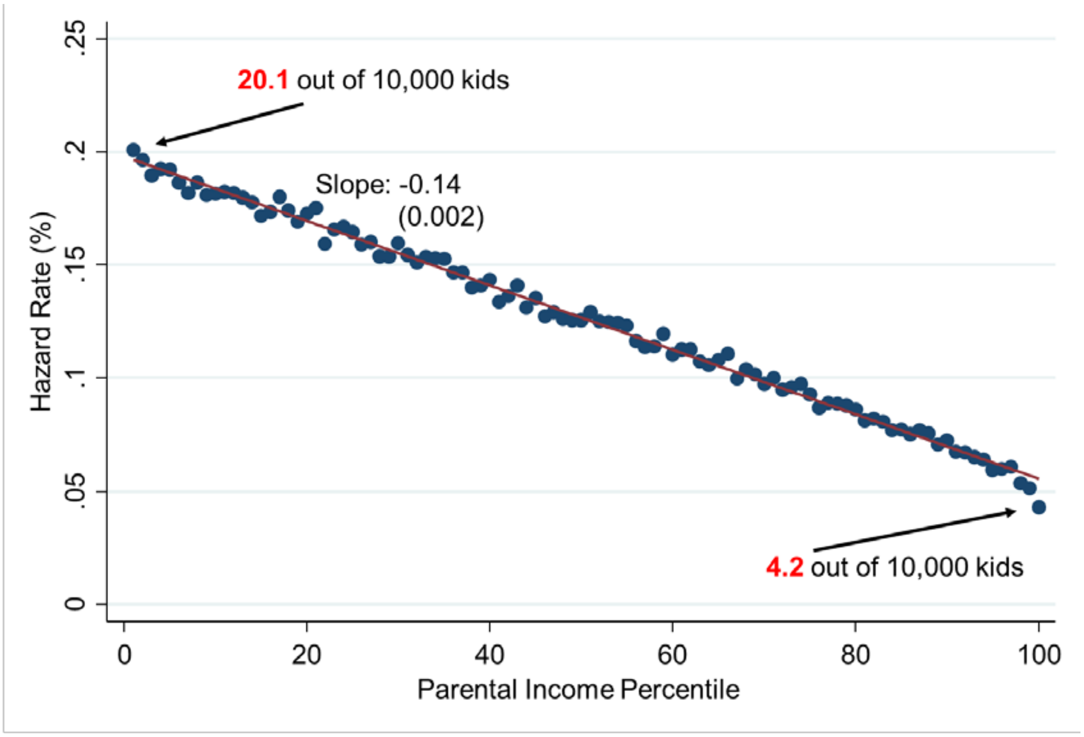

Figure 2: Net Hazard Rates of DI Receipt by Parental Income Percentile: California vs. Pennsylvania, Ages 24-34

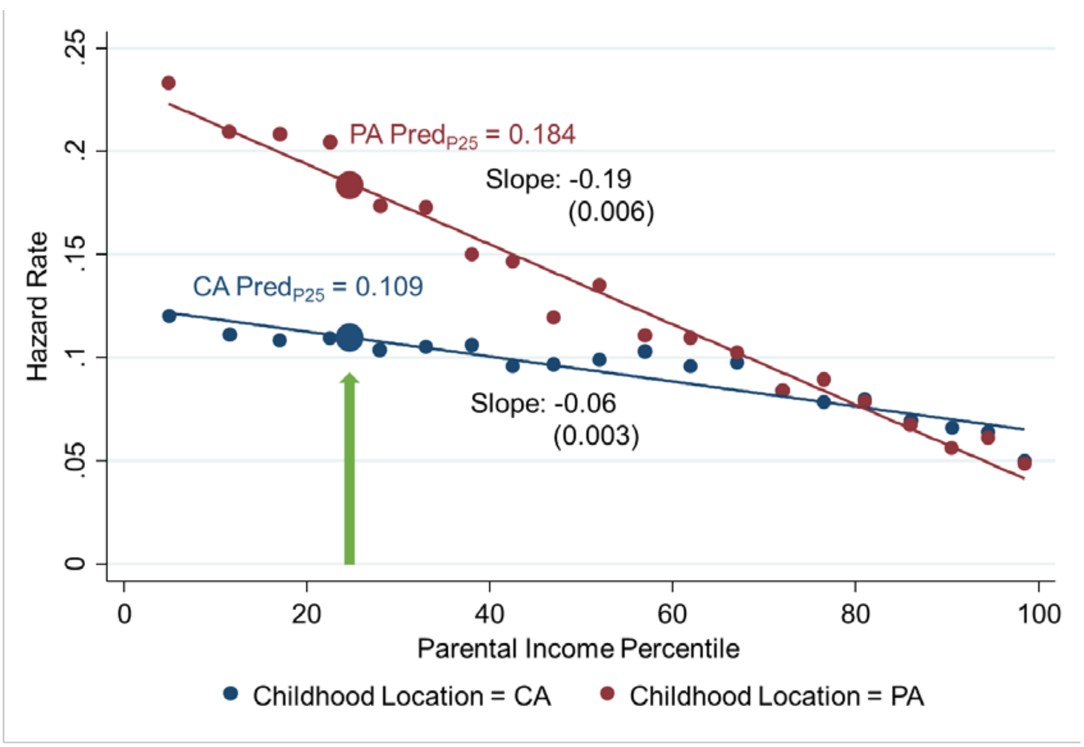

Figure 3: Hazard Rates of DI Receipt by Parental Income Percentile: Top vs. Bottom Quartile States

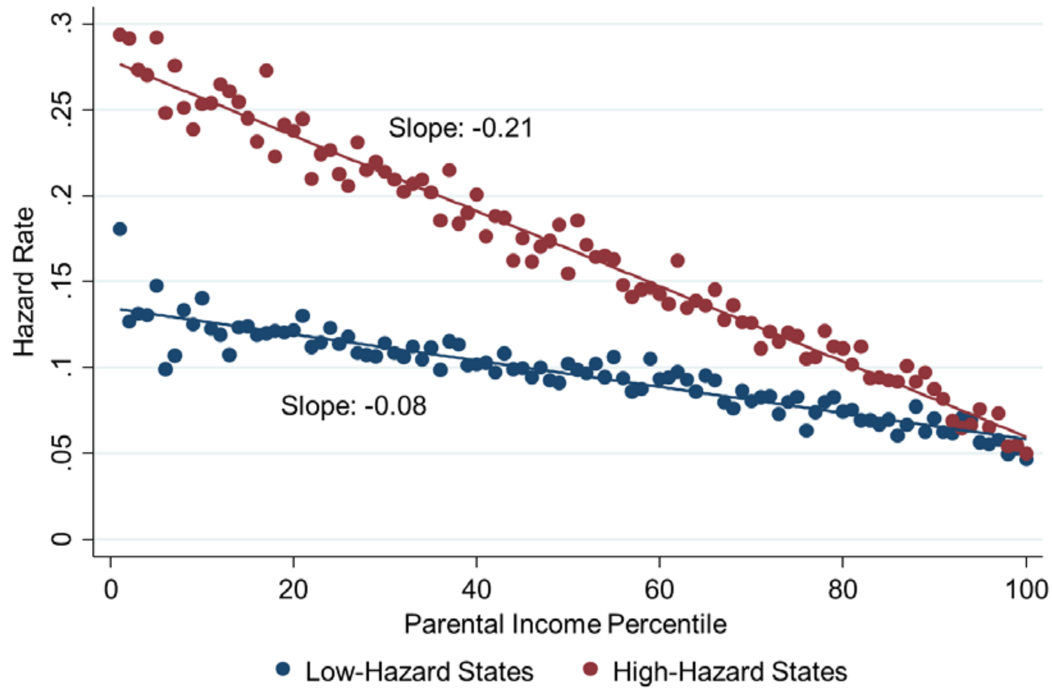

Figure 4: Predicted Rates of DI Receipt for 25th Percentile Households, by CZ

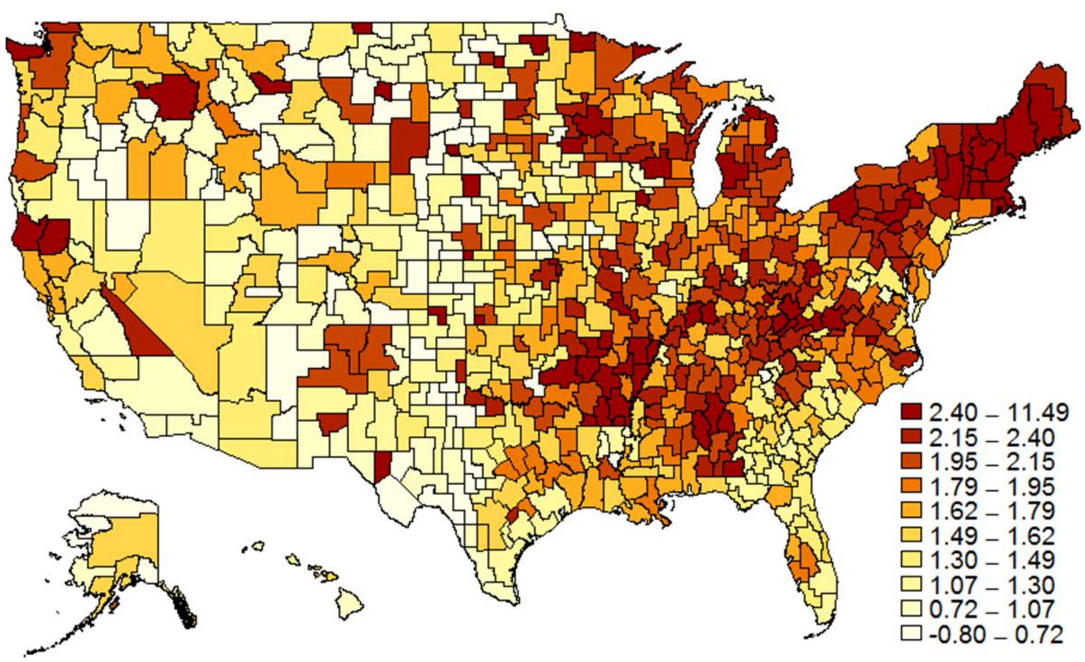

TABLE I
Summary Statistics

Income Group	All (1)	Bottom Quintile (2)	Top Quintile (3)
(A)			
Children at Age 24			
Percent Receiving SSDI	0.66	1.10	0.30
SSDI Eligibility Rate (%)	70.73	64.07	66.58
Sample Size	38,443,578	7,688,709	7,688,722
(B)			
Children at Age 34			
Percent Receiving SSDI	2.01	3.00	1.05
Percent Ever Receiving SSDI	2.51	3.88	1.27
SSDI Eligibility Rate (%)	88.49	81.11	92.32
Sample Size	3,012,424	602,484	602,486

Notes: This table presents summary statistics for SSDI benefit receipt and eligibility, as measured in the universe of U.S. tax records. When measured at age 24, the sample is all children born in the 1980-1990 cohorts who are matched to parents. When measured at age 34, the sample is all children born in the 1980 cohort and matched to parents. We measure SSDI benefit receipt with the presence of Form 1099-SSA from the SSDI trust fund; we measure eligibility as an indicator for whether a child has the minimum number of quarters of coverage (QCs), as measured from W-2 and Form SE records.

TABLE II
DI Harzard Rate by Parent Income Percentile

Dep. Var.:	DI Hazard Rate						
Sample:	Pooled Ages	Children at Age 24	Children at Age 28	Children at Age 32	Pooled Ages Conditional on Parents not on DI	High Hazard States	Low Hazard States
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Parent Income Rank	-0.142	-0.135	-0.156	-0.132	-0.153	-0.219	-0.076
	(0.0021)	(0.0046)	(0.0070)	(0.0088)	(0.0029)	(0.0040)	(0.0029)
Number of observations	183,961,160	34,539,595	19,927,933	6,247,396	36,593,632	28,187,555	32,936,227

Notes : This table presents regression estimates of the relationship between SSDI receipt and parental income. We run a weighted regression at the cell X year level, where the default definition of a cell is cohort X parental income percentile. The dependent variable is the net hazard rate of SSDI benefit receipt, defined as the change in the fraction of a cell receiving benefits from year *t-1* to year *t* , divided by the fraction in that cell not receiving benefits in year *t-1* . The independent variable is the national parental income rank in each cell, defined for each child's parents relative to the parents of all other children in the same birth cohort. In Column 5, we include only individuals for whom their parents did not receive SSDI benefits. In Columns 6 and 7, we define cells at the cohort X parental income percentile X state level and then split states into high- and low-DI states based on the predicted net DI hazard rate at the 25th percentile of the parental income distribution from a state-specific version of the regression in Column 1.

TABLE III
State-Specific Rank-Rank Slopes

	Rank-Rank Slope				Rank-Rank Slope		
	Coefficient (1)	Standard Error (2)	Predicted Hazard Rate at p25 (3)		Coefficient (4)	Standard Error (5)	Predicted Hazard Rate at p25 (6)
AK	-0.056	0.021	0.113	MT	-0.099	0.019	0.129
AL	-0.239	0.011	0.238	NC	-0.147	0.007	0.163
AR	-0.255	0.014	0.254	ND	-0.102	0.021	0.097
AZ	-0.073	0.007	0.115	NE	-0.123	0.017	0.125
CA	-0.060	0.004	0.110	NH	-0.483	0.032	0.409
CO	-0.107	0.008	0.135	NJ	-0.129	0.008	0.160
CT	-0.114	0.012	0.153	NM	-0.118	0.016	0.171
DC	-0.192	0.033	0.198	NV	-0.117	0.014	0.140
DE	-0.106	0.020	0.135	NY	-0.133	0.005	0.160
FL	-0.136	0.005	0.151	OH	-0.194	0.007	0.188
GA	-0.130	0.007	0.154	OK	-0.156	0.011	0.162
HI	-0.101	0.015	0.119	OR	-0.110	0.012	0.161
IA	-0.127	0.010	0.129	PA	-0.194	0.007	0.184
ID	-0.157	0.018	0.159	RI	-0.233	0.022	0.234
IL	-0.138	0.005	0.147	SC	-0.156	0.008	0.164
IN	-0.156	0.009	0.168	SD	-0.100	0.019	0.111
KS	-0.150	0.011	0.166	TN	-0.192	0.010	0.189
KY	-0.189	0.011	0.191	TX	-0.119	0.004	0.141
LA	-0.166	0.009	0.180	UT	-0.114	0.011	0.134
MA	-0.289	0.010	0.285	VA	-0.178	0.007	0.180
MD	-0.187	0.009	0.203	VT	-0.338	0.030	0.276
ME	-0.246	0.017	0.247	WA	-0.154	0.008	0.184
MI	-0.188	0.007	0.203	WI	-0.186	0.010	0.182
MN	-0.178	0.011	0.171	WV	-0.158	0.019	0.170
MO	-0.193	0.009	0.192	WY	-0.121	0.025	0.134
MS	-0.139	0.009	0.157				

Notes: This table presents regression estimates of the relationship between SSDI receipt and parental income from a state-specific version of the regression in Table 2, Column 1. We also show, for each state, the predicted net DI hazard rate at the 25th percentile of the parental income distribution based on that regression.

TABLE IV
CZ-Specific Rank-Rank Slopes

	Rank-Rank-Slope				Rank-Rank-Slope		
	Coefficient (1)	Standard Error (2)	Predicted Share (%) Receiving DI at p25 (3)		Coefficient (1)	Standard Error (2)	Predicted Share (%) Receiving DI at p25 (3)
Manchester	-0.413	-0.060	3.968	Kansas City	-0.105	-0.039	1.714
Springfield	-0.323	-0.061	3.849	South Bend	-0.133	-0.041	1.692
Portland	-0.188	-0.078	3.090	Mobile	-0.093	-0.058	1.688
Little Rock	-0.269	-0.068	3.030	Baton Rouge	-0.119	-0.056	1.676
Boston	-0.275	-0.037	2.877	Tampa	-0.052	-0.049	1.673
Providence	-0.230	-0.057	2.870	Jackson	-0.154	-0.092	1.653
Grand Rapids	-0.245	-0.049	2.690	San Francisco	-0.165	-0.029	1.637
Birmingham	-0.342	-0.082	2.645	Virginia Beach	-0.146	-0.046	1.631
Albany	-0.302	-0.060	2.618	Chicago	-0.116	-0.020	1.620
Minneapolis	-0.232	-0.044	2.542	Shreveport	-0.110	-0.050	1.618
Erie	-0.224	-0.085	2.524	San Antonio	-0.089	-0.036	1.597
Knoxville	-0.140	-0.074	2.364	Canton	-0.241	-0.049	1.591
Louisville	-0.095	-0.063	2.350	Sacramento	-0.190	-0.053	1.587
Allentown	-0.167	-0.065	2.333	Dallas	-0.155	-0.029	1.582
Syracuse	-0.264	-0.068	2.271	Oklahoma City	-0.081	-0.031	1.567
Harrisburg	-0.216	-0.040	2.270	Gary	-0.164	-0.057	1.557
Columbus	-0.290	-0.042	2.269	Nashville	-0.201	-0.048	1.545
Poughkeepsie	-0.097	-0.055	2.212	Las Vegas	-0.150	-0.047	1.540
Oshkosh	-0.083	-0.060	2.200	Peoria	-0.076	-0.052	1.527
Baltimore	-0.142	-0.035	2.199	Lafayette	-0.074	-0.043	1.511
Cincinnati	-0.232	-0.041	2.173	Portland	-0.057	-0.042	1.509
Toledo	-0.279	-0.060	2.153	Austin	-0.172	-0.070	1.504
Greenville	-0.273	-0.047	2.121	Aiken	-0.097	-0.052	1.497
Rockford	-0.087	-0.072	2.120	Eugene	-0.098	-0.038	1.487
Detroit	-0.160	-0.046	2.109	Washington DC	-0.127	-0.028	1.481
Pittsburgh	-0.202	-0.050	2.095	Columbia	-0.104	-0.044	1.463
Scranton	-0.213	-0.047	2.080	Newark	-0.086	-0.028	1.461
Albuquerque	-0.116	-0.057	2.079	Salt Lake City	-0.142	-0.038	1.442
Dayton	-0.304	-0.055	2.076	Phoenix	-0.047	-0.031	1.440
Reading	-0.180	-0.051	2.062	Orlando	-0.140	-0.035	1.437
Buffalo	-0.197	-0.028	2.061	Fort Worth	-0.213	-0.038	1.426
Richmond	-0.117	-0.052	2.055	Charlotte	-0.136	-0.037	1.407
Youngstown	-0.181	-0.046	2.010	Jacksonville	-0.056	-0.040	1.401
Omaha	-0.174	-0.041	2.006	Atlanta	-0.104	-0.028	1.363
Seattle	-0.139	-0.030	1.990	Florence	-0.222	-0.078	1.359
St. Louis	-0.153	-0.061	1.978	Tucson	-0.089	-0.041	1.310
Fort Wayne	-0.079	-0.074	1.942	Denver	-0.124	-0.029	1.300
Greensboro	-0.198	-0.041	1.938	Port St. Lucie	-0.113	-0.047	1.273
New Orleans	-0.113	-0.029	1.904	Honolulu	-0.105	-0.060	1.272
Bridgeport	-0.081	-0.045	1.900	Miami	-0.128	-0.030	1.253
Raleigh	-0.150	-0.044	1.895	New York	-0.094	-0.025	1.235
Milwaukee	-0.166	-0.030	1.860	Houston	-0.123	-0.021	1.198
Philadelphia	-0.159	-0.025	1.860	Modesto	-0.034	-0.053	1.158
Fayetteville	-0.111	-0.059	1.793	San Jose	-0.068	-0.029	1.132
Cleveland	-0.126	-0.028	1.789	Bakersfield	-0.137	-0.052	1.075
Indianapolis	-0.237	-0.060	1.776	San Diego	-0.071	-0.032	1.004
Spokane	-0.201	-0.067	1.762	Los Angeles	-0.029	-0.012	0.983
Toms River	-0.196	-0.046	1.747	El Paso	-0.071	-0.053	0.878
Memphis	-0.181	-0.044	1.724	Fresno	-0.079	-0.039	0.876
Tulsa	-0.121	-0.053	1.723	Brownsville	0.007	-0.052	0.845

Notes: This table presents regression estimates of the relationship between SSDI receipt (defined here as the fraction of individuals in a CZ X parental income percentile X cohort cell received SSDI benefits in a given year) and parental income. We also show, for each CZ, the predicted DI receipt rate at the 25th percentile of the parental income distribution based on that regression. We order CZs by this predicted rate.

Table V
Causal Effect of Childhool Location on DI

Coefficient on Predicted Rank in I Age of Child when Parents Move	Baseline (1)	Baseline (2)	Fam FE (3)
Age 8	0.758* -(0.099)		
Age 9	0.575* -(0.070)		
Age 10	0.552* -(0.054)		
Age 11	0.483* -(0.043)		
Age 12	0.65* -(0.036)		
Age 13	0.62* -(0.032)		
Age 14	0.687* -(0.028)		
Age 15	0.529* -(0.026)		
Age 16	0.569* -(0.024)		
Age 17	0.541* -(0.022)		
Age 18	0.443* -(0.022)		
Age 19	0.464* -(0.022)		
Age 20	0.446* -(0.022)		
Age 21	0.313* -(0.023)		
Age 22	0.368* -(0.024)		
Age 23	0.154* -(0.024)		
Age 24	0.375* -(0.024)		
Age 25	0.278* -(0.025)		
Age 26	0.297* -(0.026)		
Age 27	0.161* -(0.027)		
Age 28	0.218* -(0.029)		
Age 29	0.0738* -(0.030)		
Age 30	0.242* -(0.032)		
Age 31	0.292* -(0.036)		
Age 32	0.331* -(0.048)		
Exposure Slope (Age <= 23)		0.0322* -(0.002)	0.0244* -(0.005)
Exposure Slope (Age > 23)		0.0162* -(0.004)	-0.007 -(0.010)
Num of Obs.	12,737,392	12,737,392	12,737,392

Notes: This table presents regression estimates of the extent to which young adults who move from one CZ to another during childhood have DI rates that resemble young adults who spent their entire childhoods in either the destination or the origin CZ, based on equation (1) in the paper. In Column 1, the age-specific coefficients report the weight on the destination CZ (as opposed to the origin CZ) for young adults who moved at that specific age. In Column 2, we estimate a more parsimonious model in which we characterize the age-specific coefficients in Column 1 using two two parameters, a linear trend in age below and above age 23. In Column 3, we repeat the specification in Column 2 including family fixed effects. * denotes coefficients that are statistically significant at the 5% level.

TABLE VI

Correlates of Commuting Zone Characteristics with Predicted DI Rates at P25

	Dep. Var.:	Predicted DI Rates at P25	
Segregation	Racial Segregation Theil Index	-0.068	(0.082)
	Segregation of Poverty (<p25)	-0.199*	(0.078)
Income Distribution	Mean Household Income	-0.005	(0.086)
	Gini coefficient for Parent Income	-0.443*	(0.073)
	Top 1% Income Share for Parents	-0.303*	(0.084)
Education	Student Teacher Ratio	-0.408*	(0.091)
	Test Scores (Adj)	0.422*	(0.090)
	High School Dropout Rate (Adj.)	-0.126*	(0.056)
	College Graduation Rate (Adj.)	0.211*	(0.067)
Social Capital	Social Capital Index	0.481*	(0.074)
Other variables	Local Tax Rate	-0.151*	(0.074)
	State EITC Exposure	0.26*	(0.101)
	Tax Progressivity	-0.291*	(0.121)
	Manufacturing Share	-0.320*	(0.052)
	Chinese Import Growth	0.207*	(0.060)
	Teenage Labor Force Participation Rate	0.452*	(0.095)
	Migration Outflow	-0.361*	(0.043)
	Net Migration	-0.058	(0.106)
	Fraction Fraction Born	-0.562*	(0.058)
	Hospitals per capita	0.030	(0.066)
	Doctors per capita	0.064	(0.131)
	Fraction of Single Moms	0.032	(0.094)

Notes: This table presents univariate correlations between CZ-level characteristics and the CZ-specific predicted DI rate for young adults from the 25th percentile of the national parent income distribution. See Section 5 of the paper for a more detailed description of the covariates. * denotes correlations that are statistically significant at the 5% level.