Geographic Differences in Disability Insurance Rates[1]

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Abstract

Although much research has explored the rise in disability insurance (DI) receipt, there has been much less work explaining the large geographic differences in DI rates across cities and states. We explore the drivers of this heterogeneity using administrative tax data that allows us to link young adults (ages 24-34) to their parents. Our findings are threefold. First, 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. We study children who move between cities to show that roughly 30% of these place-based differences are causal. Second, we show that kids' outcomes for DI receipt and income exhibit an "aggregation reversal," in that they correlate negatively at the individual level but positively at the CZ level. 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. State level tax policies are also predictive of DI rates; states with more generous EITCs, lower tax rates, and less progressive tax rate structures, each tend to have higher DI rates. Third, we show that a substantial fraction of the geographic variation in DI rates can be explained by local labor market conditions, and by cities' heterogeneous sensitivity in DI rates to those underlying economic conditions.

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1. Introduction 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% 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.

[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.

In this paper, we try to address these limitations by focusing on both temporal and geographic differences in disability insurance receipt rates. We make three key contributions. First, 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. Following the method of Chetty and Hendren (2017), we study children who move between cities to show that roughly 30% of these place-based differences are causal. Second, we show that kids' outcomes for DI receipt and income exhibit an "aggregation reversal," in that they correlate negatively at the individual level but positively at the CZ level. 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. State level tax policies are also predictive of DI rates; states with more generous EITCs, lower tax rates, and less progressive tax rate structures, each tend to have higher DI rates. Third, we show that a substantial fraction of the geographic variation in DI rates can be explained by local labor market conditions, and by cities' heterogeneous sensitivity in DI rates to those underlying economic conditions.

The remainder of this paper proceeds as follows. Section 2 describes our data. Section 3 presents basic facts about the dependence of the DI rates of children on the income of their parents. Section 4 estimates geographic differences in DI rates, both as observed in the raw data and also as causal effects from the movers design. Section 5 presents evidence of the "aggregation reversal" between DI and income outcomes for children from local areas. Section 6 analyzes the importance of local economic conditions in the differences in DI rates across place. Section 7 concludes.

2. Data

Our dataset is the universe of IRS administrative tax data from 1996-2015.[4] Our sample of potential DI claimants includes those born in the 1980-1992 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

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

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. Our analysis of the data indicated an implausibly large number of individuals receiving DI payments for just a single year; we therefore recode these observations, which are likely some form of technical filing, so that we only "count" DI spells in which individuals receive DI payments in at least two consecutive calendar years.

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; 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 13 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 $1,300 (in 2017) 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

a. Observational Estimates

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.

b. Place Effects vs. Place-Based Sorting

An obvious concern with the above estimates is the potential for bias from sorting. If poor households in one CZ differ from those in another CZ – for instance, perhaps the parents in poor households in Pennsylvania are less educated than those in California, even conditional on income – the differences in eventual DI rates might reflect the direct impact of these other differences on DI rates rather than the causal effect of place, per se.

In this subsection, we address this concern in two steps using variation in location from the timing of moves, for children who move from one CZ to another during childhood (following Chetty and Hendren 2017). To flesh out the logic behind this empirical design, consider children whose families move from Boston (a very high DI-rate CZ) to New York (a very low-DI rate CZ) at some point during childhood. Those children who move at a young age spend more time in New York, compared to those children who make this move at an older age. To the extent that the differences in DI rates between New York and Boston reflect the causal effect of exposure to these respective places while growing up – and assuming that these difference children are similar on other dimensions, despite the differential age at move – then children who move to New York earlier in life should have lower DI rates in adulthood. Importantly, this approach conditions on DI rates in both the origin and destination cities, and so the identification derives entirely from the *timing* of the move, rather than the choice of cities themselves.

We conduct this analysis using two related approaches. First, we assess the effects of exposure: do children who spent more time in locations with higher average DI rates have higher DI rates themselves, conditional on the origin and destination of their move. Second, we use the same variation to directly estimate the causal effect of place, which we then combine with the observational estimate to form the optimal prediction of the causal effects of place. These two approaches offer contrasting strengths and weaknesses and are thus complementary modes of analysis. The first approach maximizes the power of our empirical design by projecting the causal effects of place (which comprise many parameters) onto the single dimension of average DI rates in reach place. The second approach estimates the 590 separate place effects, albeit at a significant reduction in power.

i. Causal Effects of Exposure

Our first approach runs 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. Figure 5 presents results from this regression by plotting the age-of-move-specific exposure coefficients, that is the extent to which children who move at age *a* look like the permanent residents from the destination (as opposed to the origin) CZ. Continuing the example from above, consider children who move from Boston to New York. The left-most coefficient dot in Figure 5 suggests that children who make this move at age 10 have DI rates that are a weighted average of the "stayers" in Boston in New York, with 53% 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 just 23% for children who move at age 23. This is consistent with a causal effect of place that is proportional to the exposure of children. After age 23, however, this weight does not decrease significantly, so that it remains almost unchanged from age 23 to age 34 (8%). We summarize this pattern of coefficients by age in two numbers: the age-slope of the coefficients up through age 23, and then after age 23. The coefficient declines by a statistically significant 0.034 in each year up through age 23, after which the coefficient has a much smaller and statistically insignificant change by age (-0.010).

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 (2017) and repeat 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. In Friedman, Chetty, Mogstad, and Lurie (2016), we show that these regressions generate similar results.

ii. Causal Estimates of Place Effects

Our second approach uses the same variation in the timing of move to directly estimate the causal effect of place. We do so in a two-step procedure. First, for each origin-destination pair, we separately estimate the following simplified version equation (1):

$$DI_i = \alpha_{od} + E_{od} * A_i + E'_{od} * A_i * p_i + f_{od}(s_i, p_i) \qquad (2)$$

where A_i is age of move from origin city o to destination city d, E_{od} and E'_{od} combine to produce the city-pair-specific estimate exposure (that potentially varies by parental income), and $f_{od}(s_i, p_i)$ represents a flexible control for a children's year of birth s_i and parent income percentile p_i. We interact the exposure coefficient with parental income percentile, because the evidence in Section 4a suggests that place effects may be stronger for poor children than for rich ones; we then use the coefficient that would be implied for children at the 25th percentile of the parental income distribution. Second, we regress the set of city-pair-specific estimates E_{od} on a matrix of origin and destination fixed effects to obtain a single causal effect of exposure for each location. We rescale these parameters to have mean 0, so that one can interpret each estimate as the causal effect of each city, relative to the average place in the U.S.. Denote the rescaled estimates of the causal effect of each city c on DI rates for children from households at the 25th percentile of the parents income distribution as $\hat{\beta}_c$, with standard error $\widehat{se}_c$.

Figure 6 presents a scatterplot of the estimates from this procedure, for each CZ, against the raw DI rates at the 25th parental income percentile (as estimated in Section 4a). We highlight in blue and label cities with populations over 2.5 million. As suggested by the results in sub-section 4bi, the causal place effects are correlated with the raw observed DI rates; moving from the 25th to the 75th percentile of raw DI rates increases the causal effect by 0.00543. Note that these effects are scaled as the increase in DI rates per year of exposure; as a result, the difference of 0.00543 would imply a causal effect of 0.125 if a child grew up entirely in 25th percentile vs. a 75th percentile city. There are also important differences between the observational estimates and the causal estimates. For instance, children from Cleveland and Philadephia have similar DI rates in young adulthood (roughly 2.6% for children with parents at the 25th percentile), yet the causal estimates suggest that Cleveland in fact has a substantially positive impact on children's DI rates relative to the average city, while Philadephia does not.

It is also clear that there is substantial variation in these local estimates, as shown by the confidence interval bars in even the largest cities. While we cannot of course know the exact magnitude of estimation error in any given case, we can assess its overall influence on the estimated magnitude of the causal place effects by distinguishing between the underlying variance of the true causal effects and the variation driven by the estimation error. We do this using the estimated standard errors for each causal effect. We calculate the total noise variance as the average of the standard errors squared, and then subtract this from the total variance of the estimated causal place effects. We estimate that the standard deviation of the underlying true causal effects is 0.0288. A one SD increase in the place effect, over the 23 years of childhood, would imply an increase in the DI rate at age 26 of 0.663, which is 30.8% of the SD of observed DI rates across cities. One can also see the importance of the causal effect of place by calculating the noise-corrected correlation between the true causal effect and the raw observed DI rates from above, which is 0.473. This analysis suggests that the causal effect of childhood location is an important determinant of geographic dispersion of DI rates.

We can also use the correlation between observed DI rates and the causally estimated place effects to optimally predict the causal effects in each place following Bayesian signal extraction methods. At the broadest level, consider estimating the value of some underlying value x_i using a noisy observation of that value, denoted as $\hat{x}_i$. Suppose that the prior distribution for the value of x_i is normally distributed with a mean of μ_x and variance σ_x^2, and the noisy observation is determined as the true underlying value plus a random mean-zero shock that has variance σ_ε^2. In this setting, the optimal prediction of x_i given the noisy observation is

$$E[x_i|\hat{x}_i] = \frac{\sigma_x^2}{\sigma_x^2+\sigma_\varepsilon^2}\hat{x}_i + \left(1 - \frac{\sigma_x^2}{\sigma_x^2+\sigma_\varepsilon^2}\right)\mu_x \qquad (3)$$

which is intuitively a weighted average between the prior mean and the noisy observation, with the weights dependent on the signal-to-noise ratio of the observation.

We implement this estimator in our setting in two steps. First, we estimate the signal-to-noise ratio for the causal estimates by combining the true underlying variance of the causal effects (as estimated above) with a CZ-specific noise variance, estimated as the square of the standard error on the causal effect estimate. Intuitively, this places a higher weight on the observation, relative to the prior, in cities with a more precise estimate. Second, we allow the prior expectation μ_x to vary across cities, as predicted by a regression of the noisy causal estimates on the raw DI rates (as shown in Figure 6). Our optimal predictions of the causal effects in each CZ are thus calculated as

$$\tilde{\beta}_c = E\left[\beta_c | \hat{\beta}_c\right] = \frac{\sigma_\beta^2}{\sigma_\beta^2 + \widehat{se}_c^2} \hat{\beta}_c + \left(1 - \frac{\sigma_\beta^2}{\sigma_\beta^2 + \widehat{se}_c^2}\right) DI_c \qquad (4)$$

where DI_c denotes the observed DI rate in each city at age 26, σ_β^2 is the true variance of underlying causal effects β_c, and $\tilde{\beta}_c$ represents the optimal prediction given both the observed DI rates and the noisy causal estimate.

Column 3 in Table IV presents the optimal predictions for each of the largest 100 cities. To repeat from above, these causal estimates represent the effect of a single year of exposure as a child to a particular area. So for instance, growing up entirely in Springfield, MA – which has the highest predicted causal effect of the largest cities – would increase DI rates at age 26 by 23*0.07 = 1.61%, more than a tripling of the national average DI rate at that age. Table IV also shows the observational and raw causal estimates for each of these cities. For the largest cities, there are sufficient data so that the weight on the raw causal effect (relative to the prediction based on the observational estimate) is relatively high, for instance at 0.713 for New York City; in contrast, for smaller cities (even in the top 100 nationally) the weight on the raw causal estimate is much lower, for instance at 0.0788 for Madison, WA.

5. DI Place Effects and Area Characteristics

The analysis in Section 4 shows that growing up in some areas of the country causes significantly greater incidence of Disability Insurance claiming in young adulthood. In this section we explore what CZ-level characteristics predict high DI rates for children from poor families.

a. CZ Characteristics for DI Effects

For a wide range of covariates, we calculate the univariate Pearson correlation with the optimal predicted causal effect on DI at the 25th percentile of parental income, weighting by the precision of the causal estimates. 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.

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 percentile *p* are separated from individuals above income percentile *p*. We use the formula

[5] We thank the authors of Chetty et al. 2014 for help with constructing CZ-level covariates, and in most cases we follow their method for the precise construction of these vairables.

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. Cities in with less inequality produce children who are more likely to receive DI in young adulthood.

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 about half the magnitude, for measures of the HS dropout rate (from the Global Report Card) and college graduation rate.

We also 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. Across all variables (other than the fraction foreign born, which is somewhat of a mechanical relationship due to eligibility for DI), social capital is the single strongest correlate of the causal effect of place on DI rates.

We also correlate the causal effect of place on DI rates with state and local tax policies. We estimate local tax rates using data on tax revenue by county from the U.S. Census Bureau's 1992 Census of Government county-level summaries, by calculating the mean per-household tax revenue for counties in each CZ, divided by nominal household income in these CZs. We measure state income tax progressivity as the difference between the top state income tax rate and the state income tax rate for individuals with taxable income of $20,000 in 2008 based on data from the Tax Foundation. We calculate state EITC exposure as the mean EITC rate for the years 1980-2001, setting the rate to zero for state-year pairs where there was no state EITC.[6] States with lower tax burdens and less progressive tax systems tend to cause higher DI rates. Intuitively one can see these differences between California, which has a relatively high tax burden and a highly progressive tax system, yet very low DI rates, and New Hampshire, which has low tax burden from a flat tax system (since there is no income tax) yet very high DI rates. States with larger EITCs tend to cause higher DI rates.

Finally, we correlate DI rates with a range of other CZ covariates. 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, though this relationship is likely driven partly by the mechanically lower eligibility rates for foreign born residents, since workers must have a minimum number of covered quarters in order to apply for disability insurance.

Figure 8 displays the correlations between these characteristics and both the causal estimates (as in Table VI) and observational estimates. The difference between these two correlations represents the nature of selection into place, as in effects DI rates. For instance, the observational estimates suggest that household income correlates negatively with DI rates, but this is in fact driven by selection; instead the causal estimates of the place effects correlate positively with household income.

[6] We obtain data on State EITC rates by year from Hotz and Scholz (2003). Note that Wisconsin's state EITC rate depends on the number of children in a household; we use the rate for households with two children.

b. Relationship to Place Effects on Income

The analysis in Section 5a suggest a counterintuitive relationship between the characteristics of cities and the causal effect on DI rates. In particular, it seems 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 from Chetty and Hendren (2017) showing that these characteristics correlate with higher rates of upward mobility and employment for children from poor families in such areas.

To quantify this relationship, we compare the characteristics that predict DI rates in adulthood with those that predict high incomes in adulthood. Specifically, we calculate the same precision-weighted univariate correlations between each of the CZ-level characteristics in Table VI with the optimal forecast of the causal effects of place on income, as estimated in Chetty and Hendren (2017) (constructed similarly to our measure in Section IVbii). Figure IX presents a scatterplot of these coefficients, where each dot presents the correlation of the DI causal effects (y-axis) and income causal effects (x-axis) for a single characteristic. There is a clear positive relationship. For instance, characteristics such as share married and share middle class strongly correlate with both higher DI rates and higher income; characteristics such as inequality (as measured by the Gini coefficient) and crime rates correlate strongly with lower DI rates and lower incomes.

Going beyond place-specific characteristics, we can also directly compare the causal effects on DI rates and income for each of the 591 CZs for which we have sufficient data. As above, we subtract out the estimation error from the variance so that we present estimates of the "signal" correlation between the underlying effects. The resulting signal correlation is 0.0665.

The analysis in this sub-section makes it clear that the causal effects of exposure to different cities tends to increase or decrease income and DI receipt together. Since the incidence of disability insurance receipt and college-going or income earned are strongly negatively correlated at the individual level, this is an example of what Glaeser and Sacerdote (2007) calls an "aggregation reversal." Glaeser and Sacerdote focus on peer effects as the drivers of aggregation reversals. This is a plausible explanation in our setting;

specifically, if high income individuals cause their peers to be more likely to claim disability – for instance due to an increased desire to find help for those coworkers or friends who need it – that would generate our results. It is also possible that places increase both the mean and variance of income for children from poor families. It remains for future work to explore the causes of this reversal.

6. Economic Conditions and Geographic Differences in DI Rates

Our analysis thus far has focused on the long-term effects of childhood exposure to different places on DI rates in young adulthood. Another plausible driver of geographic differences is local economic differences, and in this section, we try to quantify the contribution of local labor market factors to the geographical variation in DI rates. The movitation for focusing on local labor market condition is the countercyclical movement of DI awards (and applications) observed at the national level (Black, Daniel, and Sanders, 2002; Mueller Rothstein, and von Wachter, 2016).

Figure 10 illustrate how DI award rates vary over the business cycle (as measured by national unemployment rates) in our data. The hazard rates to DI tend increase sharply in periods when unemployment rates rise. By comparison, the DI hazard rates decline modestly during periods in which the unemployment rates fall. One potential explanation for the countercyclical movement of DI is that individuals with weak labor market attachment who would work in good economic conditions instead, when times are bad, apply for DI.

Our analysis is centered on two types of local labor market factors. The first is variation in local labor market conditions, as measured by local unemployment rates. Some areas may have higher DI rates than others because of differences in the salaries and availability of jobs. The second factor is the responsiveness of individuals in different areas to local labor market conditions. Some areas may have more individuals at the margin of program entry (e.g. due to less human capital and work experience), and as a consequence, the DI hazard rates in these areas may be more sensitive to the business cycle.

a. Framework

To quantify the contribution of these two factors to the geographical variation in DI rates, we consider the following model for SSDI entry hazard rates at the commuting zone level:

$$DI_{azt} = \beta_{0at} + \beta_{1azt}UE_{zt} + \beta_{2az} + \epsilon_{azt} \qquad (5)$$

where DI_{azt} is a measure of hazard rate for DI among the cohort of age *a* in calendar year *t* and commuting zone *z*, and UE_{zt} denotes the local unemployment rate in commuting zone *z* and year *t* derived from the county-level annual averages reported by in the BLS Local Area Unemployment Statistics. We estimate parameters of this model using data on annual US cohorts born in 1980 and later, at ages 22 and older, up to the year 2013. We weigh observations of a cohort at age *a* in commuting zone *z* and calendar year *t* by its person count in all the following estimation procedures. To address the potential for delayed effects of unemployment on DI entry hazard rates, we also re-estimate equation (5) as a distributed lag model, including lagged measures of local unemployment from the two previous years. We report coefficient estimates from the main model and distributed lag model in Tables 9 and 10 respectively.

The model can be used to decompose the variation in DI_{azt} into three components: the national age-specific time trends (β_{0at}), heterogeneity attributable to local labor market conditions ($\beta_{1at}UE_{zt}$), and heterogeneity orthogonal to local labor market conditions (β_{2az}). Since we are interesting in heterogeneity in DI rates across commuting zones, we remove the age-specific time trends (β_{0at}) which are invariant across commuting zones. We then consider the variance decomposition on the remaining components of the right hand side of equation (5):

$$Var(\beta_{1az}UE_{zt} + \beta_{2az} + \epsilon_{azt}) = \underbrace{E[Var(\beta_{1az}UE_{zt} + \beta_{2az} + \epsilon_{azt}|z)]}_{mean\ variance\ within\ CZs} +$$

$$\underbrace{Var(E[\beta_{1az}UE_{zt}|z] + E[\beta_{2az}|z])}_{variance\ in\ means\ across\ CZs} \qquad (6)$$

We first show how much overall variation in DI hazard rates that can be attributed to heterogeneity in means across commuting zones (the second term of Equation 6). Then, we decompose the heterogeneity in means across commuting zones into its components: heterogeneity attributable to local labor markets, and heterogeneity orthogonal to local labor markets. Lastly, we drill further into the heterogeneity attributable to local labor markets, and evaluate the relative importance of differences in local labor market conditions versus heterogeneity in the responsiveness to these conditions. All results from this decomposition procedure are reported in Table 7. We repeat the same procedures in a distributed lag model with 2 lagged terms on unemployment in Table 8, reaching qualitatively similar conclusions across the board.

b. Importance of Local Labor Markets

The standard deviation in DI uptake after removing aggregate time trends is about 0.066 percentage points in probability of enrolling in DI, relative to a raw average DI hazard rate of 0.1428 percentage points. About 70 percent of this is attributable to heterogeneity within commuting zones and across ages (the first term of Equation 6), and the remaining 30 percent attributable to variation across commuting zones (the second term of Equation 6). Consistent with our previous finding that geographic heterogeneity at the state level matters only for individuals from lower parental income quintiles, the share of overall heterogeneity coming from differences across commuting zones is declining in parental income quintile and nearly vanishes altogether in the top quintile.

That 30 percent of variation across commuting zones decomposes into its components as follows:

$$Var(E[\beta_{1az}UE_{zt}|z] + E[\beta_{2az}|z]) = \underbrace{Var(E[\beta_{1az}UE_{zt}|z])}_{variation\ due\ to\ local\ labor\ markets} + \underbrace{Var(E[\beta_{2az}|z])}_{variation\ unexplained\ by\ local\ labor\ markets} + \underbrace{2Cov(E[\beta_{1az}UE_{zt}|z], E[\beta_{2az}|z])}_{covariance\ term} \quad (7)$$

where variation due to local labor markets (the first term of Equation 7) is equal to about 160 percent of the overall variation across commuting zones, and variation unexplained by local labor markets is about 180 percent of that same value. These relatively large component variations must imply a strong and negative covariance between the two components, which we see in the data. In particular, we estimate that the covariance component accounts for -240 percent of the total variation between commuting zones, implying a correlation coefficient of about -0.7.

c. Decomposing the Contribution of Local Labor Markets

To study the relative importance of variation in local labor market conditions versus heterogeneity in the responsiveness to local labor market conditions, we decompose the first term of Equation 7:

$$Var(E[\beta_{1az}UE_{zt}|z]) = \underbrace{Var(E[\beta_{1a}UE_{zt}|z])}_{variation\ in\ local\ labor\ market\ conditions} + \underbrace{Var(E[\beta_{1az}UE_{zt}|z] - E[\beta_{1a}UE_{zt}|z])}_{variation\ in\ responsiveness\ to\ labor\ market\ conditions} + \underbrace{2Cov(E[\beta_{1a}UE_{zt}|z], E[\beta_{1az}UE_{zt}|z] - E[\beta_{1a}UE_{zt}|z])}_{covariance\ term} \quad (8)$$

where β_{1a} is the average national responsiveness of the DI entry hazard rate to local unemployment, computed by restricting β_{1az} to not vary with z in Equation (5). This implies that β_{1a} is estimated as a weighted average of coefficients β_{1az}:

$$\beta_{1a} = \sum_{z} \frac{Var(\widetilde{UE}_{zt}|a)P_a(z)}{\sum_{z'} Var(\widetilde{UE}_{z't}|a)P_a(z')}\beta_{1az}$$

where $P_a(z)$ denotes the probability that an individual of age a is drawn from commuting zone z, and $\widetilde{UE}_{zt}$ denotes measured unemployment after removing aggregate time trends and age-specific commuting zone trends. We find that $Var(\beta_{1a}UE_{zt}|z)$ is a negligible fraction of $Var(\beta_{1az}UE_{zt}|z)$, less than 1 percent in the overall sample and no more than 3 percent for any quintile of the parental income groups. By comparison, the variation in responsiveness to labor market conditions account for the vast majority of the contribution of labor market factors to the geographical variation in DI hazard rates.

7. Conclusion

This paper studies the drivers of geographic differences in disability insurance take up rates. We find that two factors – childhood exposure and local economic conditions – explain a large fraction of the observed variation. These results suggest two important take aways.

First, 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?

Second, local labor market conditions are not just important, but some cities are much more sensitive to employment conditions than others. In future work we hope to examine in more detail the reasons why some cities are so responsive, and why.

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.

Friedman, John N., Ithai Lurie, Magne Mogstad, and Raj Chetty (2016). "Long-Run Drivers of Disability Insurance Rates." SSA DRC Paper.

Glaeser, Edward L. and Bruce Sacerdote (2007). "Aggregation Reversals and the Social Formation of Beliefs," NBER Working Paper No. 13031.

Hotz, Joseph V., and John K. Scholz (2003). "The Earned Income Tax Credit." In Robert A. Moffitt, ed., *Means-Tested Programs in the United States*, University of Chicago Press, pp. 141-197.

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

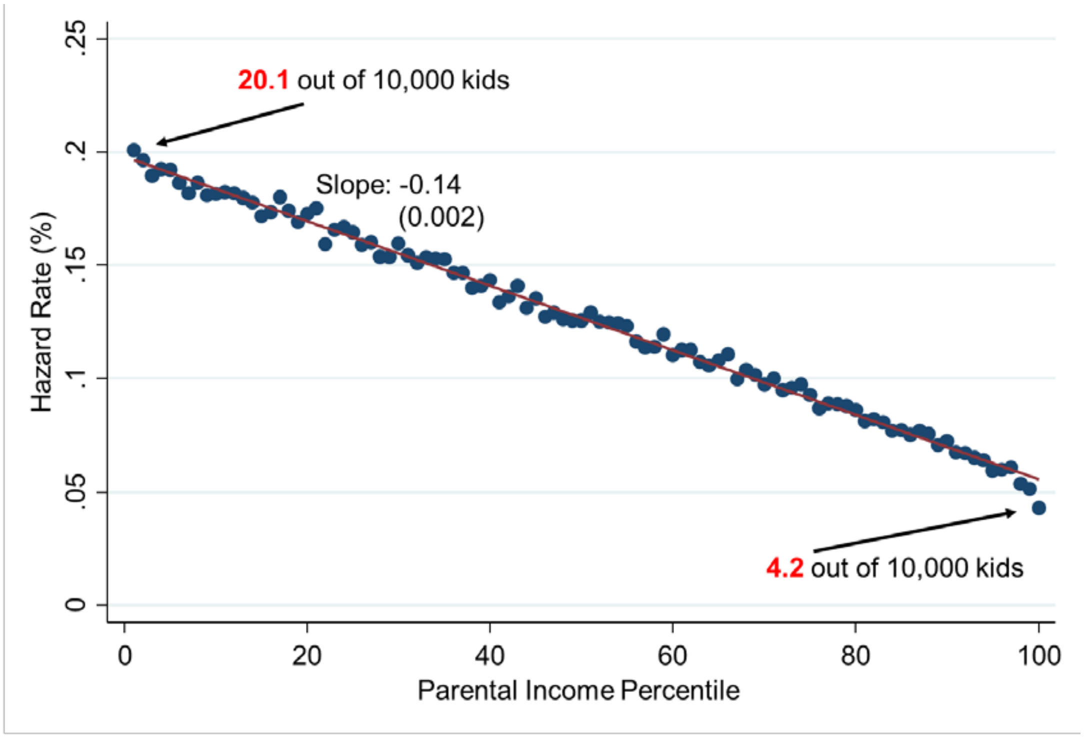


Figure 2: Net Hazard Rates of DI Receipt by Parental Income Percentile: California vs. Pennsylvania, Ages 24-34

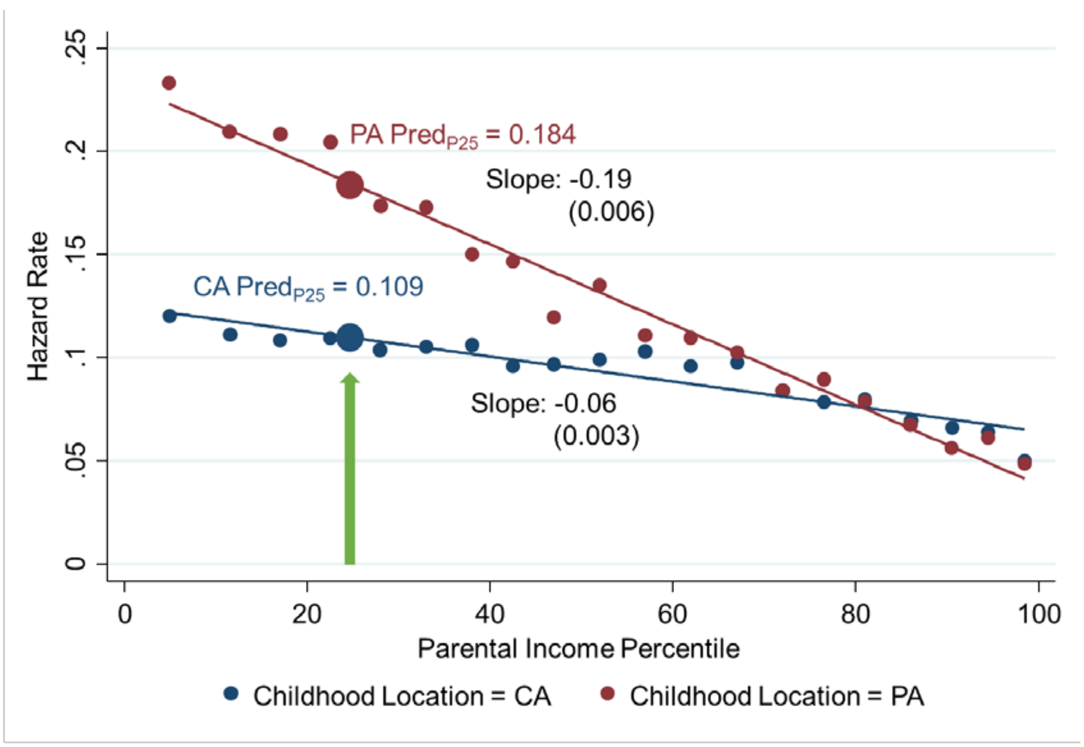


Figure 3: Hazard Rates of DI Receipt by Parental Income Percentile: Top vs. Bottom Quartile States

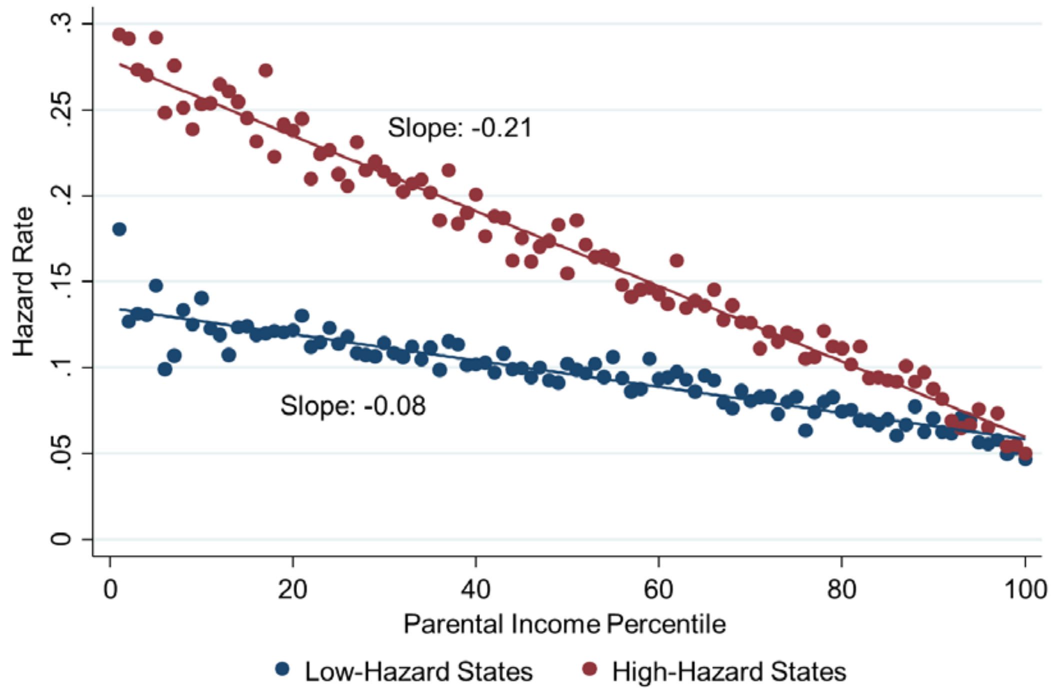


Figure 4: Observed Rates of DI Receipt for 25th Percentile Households, by CZ

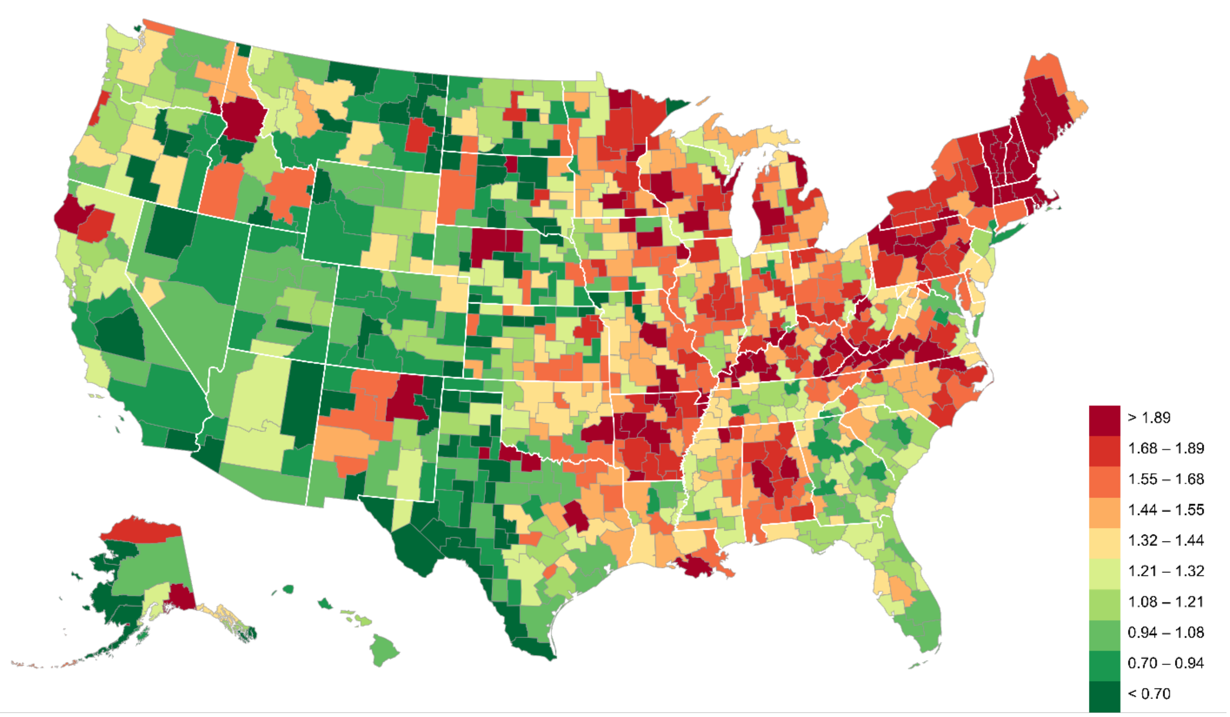


Figure 5: Childhood Exposure Effects on DI Ranks

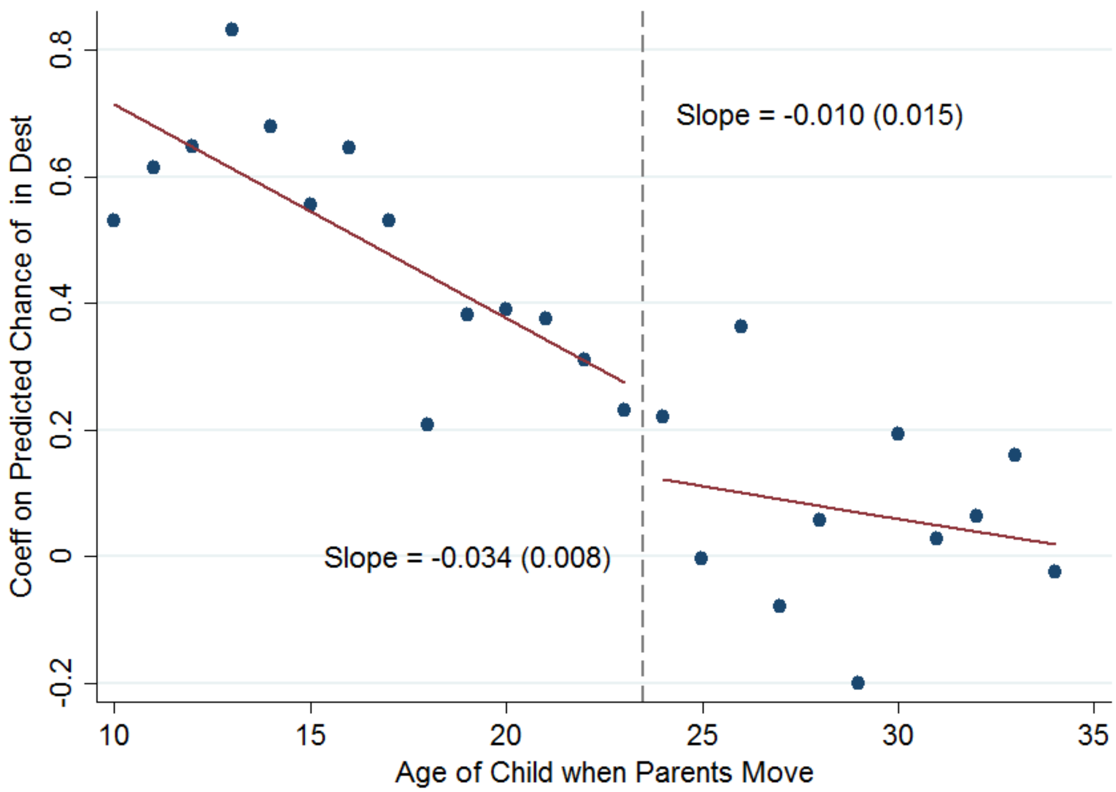


Figure 6: Causal Effect Estimates vs. Permanent Residents' DI Outcomes for Low-Income Families

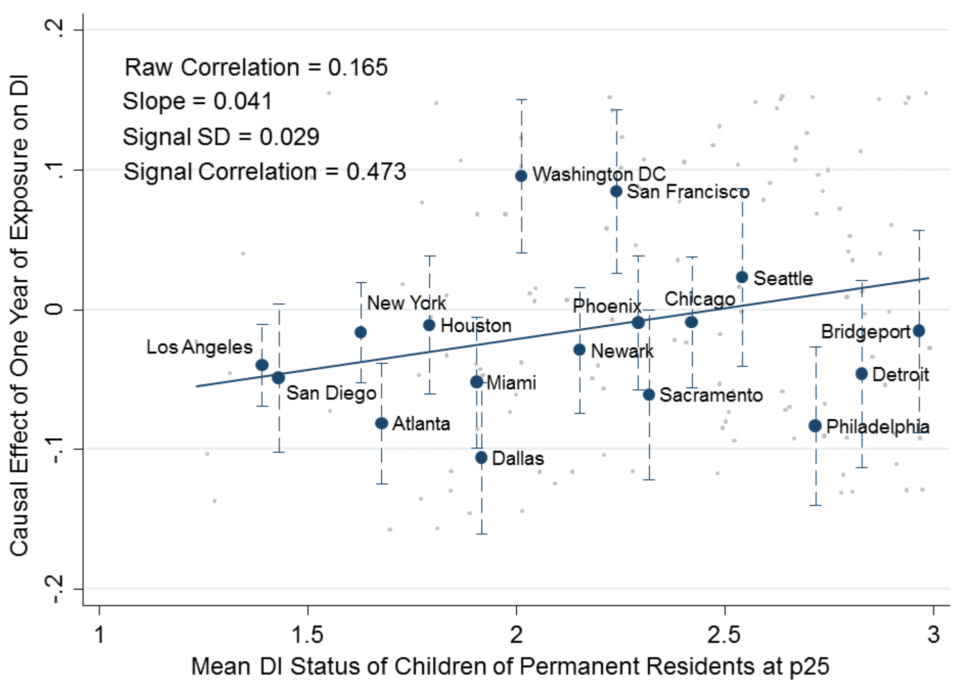


Figure 7: Predicted Causal Effects on DI Receipt for 25th Percentile Households, by CZ

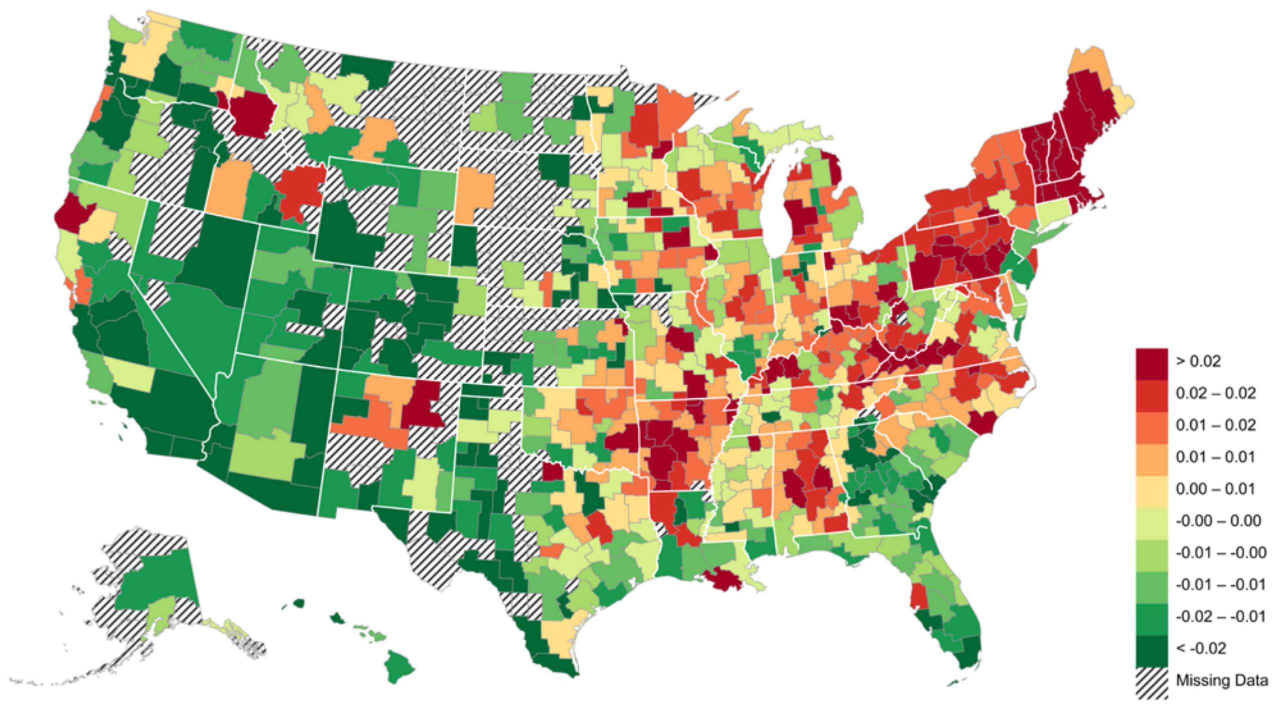


Figure 8: Correlation of DI Observational & Causal Estimates with CZ-Level Characteristics

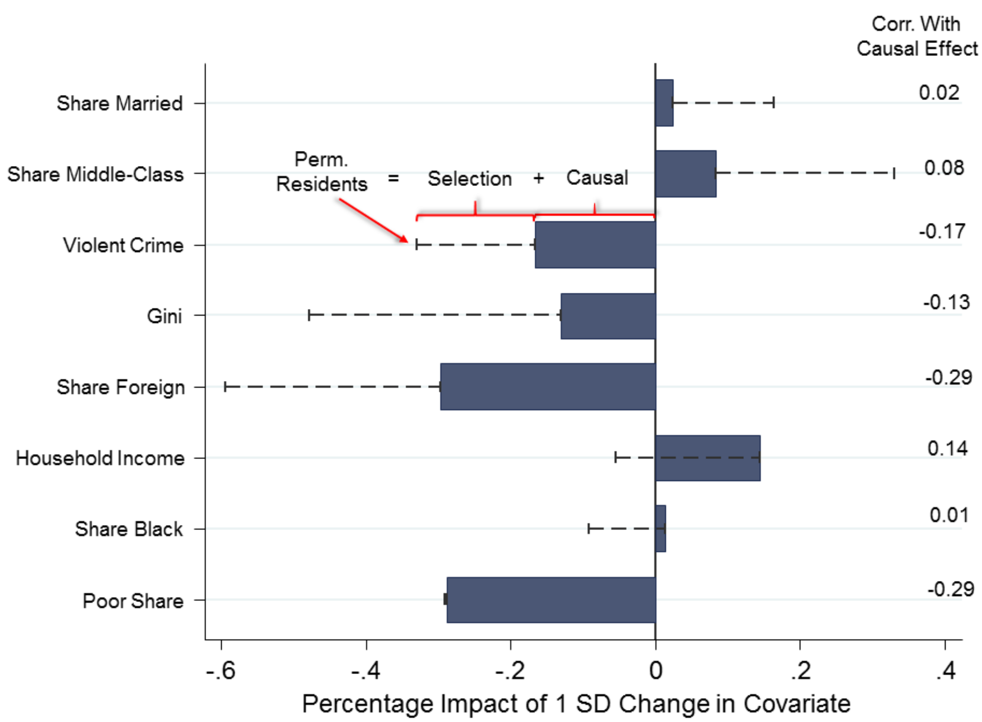
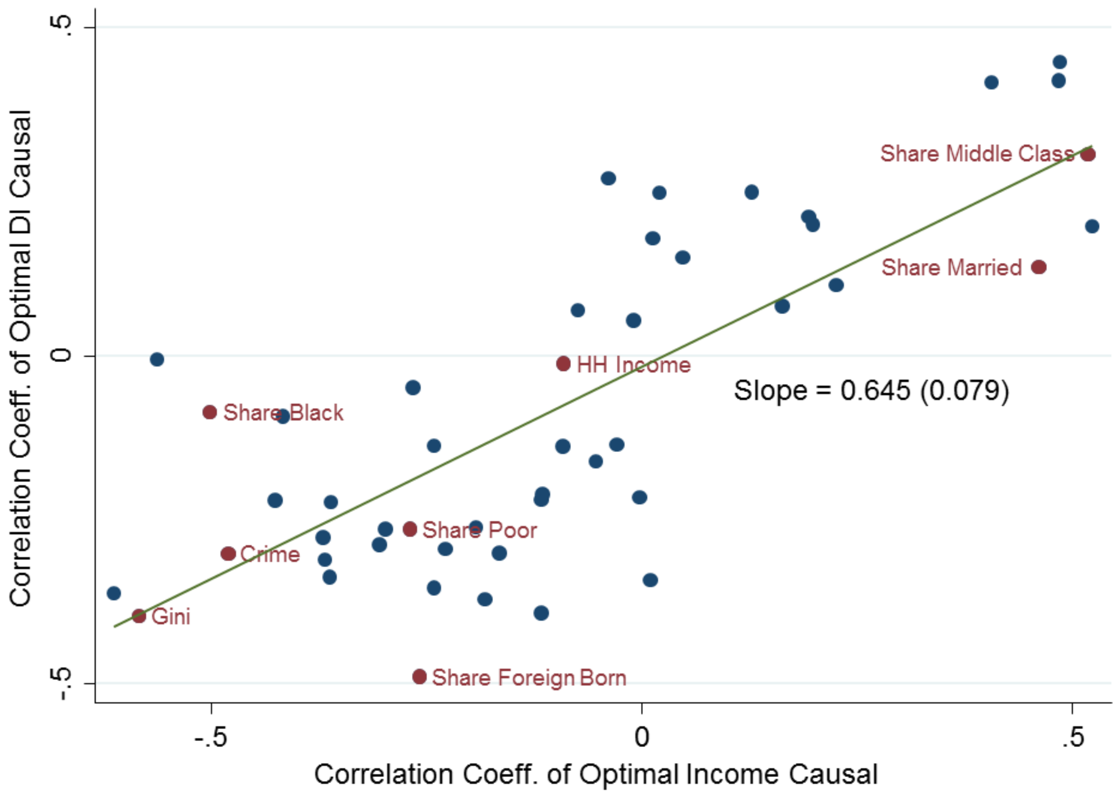
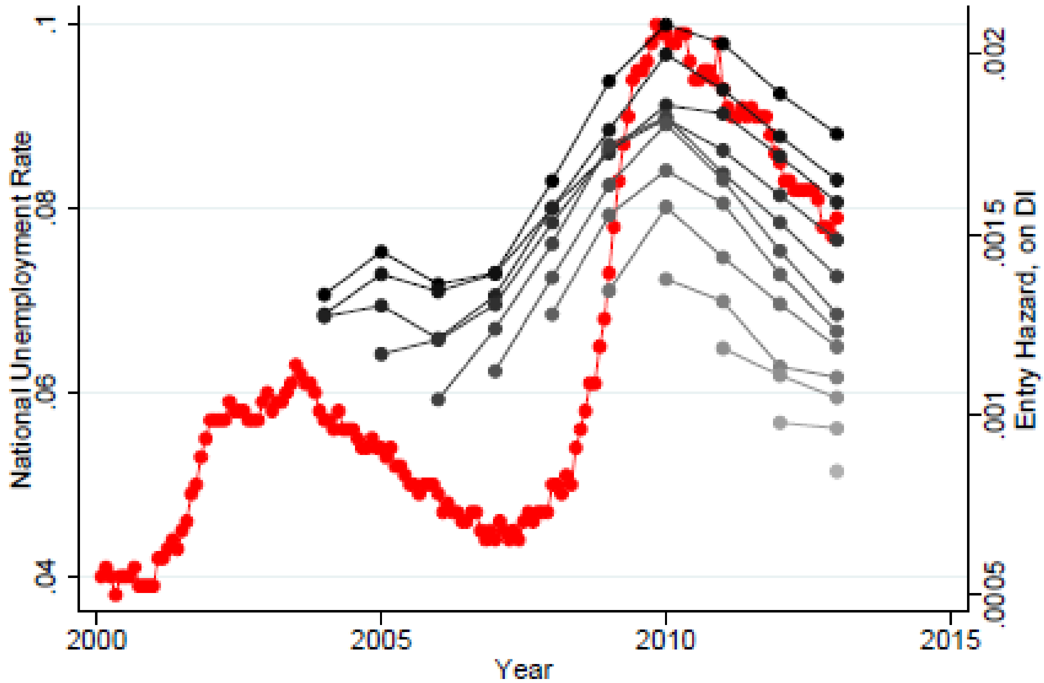


Figure 9: Correlation of Predicted DI & Income Causal Estimates with CZ-Level Characteristics



<u>Figure 10: Time Trends in National Unemployment and National SSDI Entry Hazards, by Cohort, All Parental Income Quintiles</u>



Year of birth cohorts run from 1980 to 1994. Darker curves correspond to older cohorts.
National Monthly Unemployment Rates plotted in red, from CPS data and reported by the BLS

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						
Variable / 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
	(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		Predicted Hazard Rate at p25		Rank-Rank Slope		Predicted Hazard Rate at p25
	Coefficient	Standard Error			Coefficient	Standard Error	
	(1)	(2)	(3)		(4)	(5)	(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 DI Observational and Raw and Optimal Causal Estimates

	Coefficient				Coefficient		
	DI Obs (1)	DI Causal (2)	DI Causal Optimal (3)		DI Obs (1)	DI Causal (2)	DI Causal Optimal (3)
Los Angeles	0.734	-0.017	-0.019	Memphis	1.396	-0.031	-0.003
New York	0.859	-0.007	-0.011	Oklahoma City	1.384	0.061	0.011
Chicago	1.277	-0.004	-0.003	Toms River	1.305	0.082	0.018
Newark	1.135	-0.012	-0.011	Virginia Beach	1.407	0.045	0.011
Philadelphia	1.433	-0.035	-0.016	Reading	1.799	0.059	0.026
Detroit	1.491	-0.020	-0.005	Louisville	1.891	-0.063	0.016
Boston	2.284	0.020	0.032	Syracuse	1.688	0.056	0.018
San Francisco	1.181	0.036	0.014	Albany	1.893	0.039	0.025
Washington DC	1.061	0.041	0.015	Greensboro	1.476	0.022	0.008
Houston	0.945	-0.005	-0.010	Harrisburg	1.836	0.161	0.042
Miami	1.005	-0.022	-0.019	Richmond	1.719	-0.073	0.001
Atlanta	0.885	-0.035	-0.029	Birmingham	1.724	0.028	0.017
Seattle	1.340	0.010	0.004	Tucson	0.973	-0.049	-0.023
Dallas	1.011	-0.045	-0.030	Brownsville	0.664	-0.044	-0.032
Bridgeport	1.563	-0.007	0.003	Eugene	1.138	-0.120	-0.032
Phoenix	1.209	-0.004	-0.005	Tulsa	1.359	0.090	0.013
Minneapolis	1.865	-0.067	0.004	Greenville	1.449	0.042	0.010
San Diego	0.754	-0.021	-0.023	Honolulu	0.709	0.017	-0.020
Cleveland	1.384	0.088	0.024	Poughkeepsie	1.604	0.022	0.013
Sacramento	1.222	-0.026	-0.015	El Paso	0.674	-0.058	-0.035
Pittsburgh	1.798	0.082	0.031	Scranton	1.631	0.054	0.020
Baltimore	1.613	0.036	0.019	Toledo	1.740	-0.037	0.012
Denver	0.935	-0.058	-0.033	Youngstown	1.532	-0.094	-0.003
Tampa	1.376	0.039	0.019	Baton Rouge	1.378	-0.091	-0.011
San Jose	0.819	-0.031	-0.025	Omaha	1.568	-0.055	0.006
Buffalo	1.719	0.019	0.016	Sarasota	1.243	-0.089	-0.021
St. Louis	1.611	-0.024	0.003	Albuquerque	1.586	0.039	0.014
Cincinnati	1.739	0.197	0.045	Modesto	0.895	-0.067	-0.030
Portland	1.104	-0.053	-0.022	Knoxville	1.628	0.107	0.019
Fort Worth	1.042	0.029	0.004	Columbia	1.061	0.052	-0.003
Kansas City	1.355	-0.027	-0.005	Canton	1.166	-0.044	-0.011
San Antonio	1.255	-0.009	-0.006	Cape Coral	1.013	-0.020	-0.015
Orlando	1.177	-0.003	-0.005	Portland	2.526	0.281	0.061
Columbus	1.602	0.022	0.013	Springfield	3.101	0.028	0.070
Milwaukee	1.533	-0.038	-0.002	Gary	1.165	-0.024	-0.010
Providence	2.217	0.057	0.040	Bakersfield	0.986	0.045	-0.000
Las Vegas	1.062	-0.016	-0.014	Erie	1.984	-0.024	0.023
Port St. Lucie	1.054	-0.026	-0.018	South Bend	1.390	0.064	0.009
Indianapolis	1.429	0.064	0.013	Santa Barbara	1.315	-0.036	-0.008
Salt Lake City	1.072	0.005	-0.006	Fayetteville	1.475	0.018	0.007
Charlotte	1.187	0.043	0.009	Allentown	1.893	0.094	0.034
Fresno	0.693	-0.019	-0.024	Little Rock	2.212	0.039	0.036
Raleigh	1.490	0.048	0.017	Pensacola	1.335	-0.120	-0.010
New Orleans	1.635	-0.043	0.002	Rockford	1.692	-0.151	-0.002
Austin	1.206	0.019	0.002	Spokane	1.443	-0.115	-0.009
Grand Rapids	2.011	0.085	0.034	Santa Rosa	1.216	0.046	0.003
Nashville	1.166	0.127	0.014	Mobile	1.562	-0.110	-0.000
Manchester	2.879	0.077	0.065	Lakeland	1.465	-0.056	-0.008
Dayton	1.632	-0.005	0.009	Des Moines	1.451	0.273	0.010
Jacksonville	1.151	-0.021	-0.012	Madison	1.904	-0.010	0.021

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	
Segregation	Racial Segregation Theil Index	-0.092	(0.041)
	Segregation of Poverty (<p25)	-0.224	(0.040)
Income Distribution	Mean Household Income	-0.013	(0.041)
	Gini coefficient for Parent Income	-0.397	(0.038)
	Top 1% Income Share for Parents	-0.265	(0.040)
Education	Student Teacher Ratio	-0.371	(0.039)
	Test Scores (Adj)	0.415	(0.038)
	High School Dropout Rate (Adj)	-0.221	(0.044)
	College Graduation Rate (Adj)	0.249	(0.042)
Social Capital	Social Capital Index	0.446	(0.037)
Other Variables	Local Tax Rate	-0.136	(0.041)
	State EITC Exposure	0.211	(0.040)
	Tax Progressivity	-0.161	(0.041)
	Migration Outflow	-0.342	(0.039)
	Net Migration	0.023	(0.041)
	Fraction Foreign Born	-0.489	(0.036)