

Explaining Geographic Differences in Young Disability Insurance Rates¹

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Abstract

Although much research has explored the rise in young 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 (age 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. Second, we show that DI take-up of children from low income families exhibits heterogeneity both over time (cyclically) and over place which is not apparent for children from richer families. Third, we show that places where poor children grow up to have the highest rate 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 structures each tend to have higher DI take-up. These are also the characteristics of places that tend to produce higher income mobility. We show that the relationship between child outcomes in terms of DI take-up and income mobility across places is mixed, but the places that tend to generate good outcomes on both measures are more rural. By comparison, this appears to be less true for the places generating particularly bad outcomes on both measures.

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

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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 & Duggan, 2006; Burkhauser & Daly, 2012).² Prominent researchers have argued that such rises in disability insurance rolls are fiscally unsustainable (Autor & 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, & Sanders, 2002; Autor & Duggan, 2003), a pattern that held strongly as DI applications rose during the Great Recession (Mueller, Rothstein, & von Wachter, 2015). Less educated workers and older workers are also more likely to claim disability benefits (Social Security Administration, 2014). There is also considerable variation in disability insurance receipt across areas related to compositional differences in the population with respect to age, education, and industrial structure (Ruffing, 2015).

Our aim in this paper is to explore the environmental predictors of DI receipt for a subgroup of particular interest: young adults. Increases in DI receipt among younger people has been one of the driving forces behind rising DI rolls, with receipt by those age 25-39 increasing by nearly 45% from 1984 to 2004 (Autor & Duggan, 2006). For that reason, understanding the precursors of DI take-up for younger people may provide further insight into the forces underlying broader changes in DI receipt. We also focus on less-explored geographic differences in DI receipt.

We make three key contributions. First, we show that children from low income families display much greater probabilities of receiving DI, and DI receipt among children from lower income families is more cyclical. Second, we show that children from lower income families demonstrate sharply varying probabilities of receiving DI depending on the place where they grew up, while children from rich families show no similar differences. Third, we show that places where poor children grow up to have the highest DI rates 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

²This 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.

rates; states with more generous EITCs, lower tax rates, and less progressive tax structures, each tend to have higher DI rates. We provide evidence that some of these correlations may be due to place-based sorting; measures of segregation and social capital being most affected. These are also the types of places which generate high income mobility for poorer children, though we find that the direct relationship between DI take-up and income mobility is mixed. In an attempt to characterize the types of places that generate good outcomes on both measures (lower DI take-up and higher income mobility), we find that these places tend to be less populous.

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 documents local predictors of DI. Section 6 compares DI take-up and income mobility measures across places, and compares local predictors of DI to local predictors of adult income.

2 Data

Our dataset is the universe of IRS administrative data from 2002-2015.³ Our sample of potential DI claimants includes those born in the 1980-1993 birth cohorts. We measure DI receipt for young adults (ages 21-34) through the receipt of Form 1099-SSA, which the SSA files with the IRS for all DI payment (our data do not include SSI payments). We cannot distinguish disabled workers from others claiming benefits (spouses, adult children, or dependents), but for individuals receiving SSDI payments at ages 21-34, less than 2% of program recipients are spouses and dependents would be ineligible (Social Security Administration, 2016). This leaves a mix of disabled workers and disabled adult children. 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 an individual receives 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, Hendren, Kline, & Saez, 2014).

³John N. Friedman accessed these data under contract TIRNO-16-E-00013 with Statistics of Income (SOI) Division of IRS.

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 44.9 million young adults and 258.1 million individual-year observations.

To isolate behavior at each age, we calculate the total fraction of individuals who have *ever* received DI by age a . To the extent that DI receipt is an absorbing state (arguably a reasonable approximation in the full population of DI beneficiaries, where beneficiaries rarely exit for reasons other than death or reaching retirement age), the age at which an individual first receives DI completely characterizes their benefit receipt over the life cycle. Figure 1 reports survival functions of DI receipt by age of first entry into DI for our sample, for the bottom and top quintiles of the parent income distribution. Most young DI beneficiaries continuously receive DI for a long time; 85% of beneficiaries continuously receive benefits for at least 5 years regardless age of first entry or position in the parent income distribution. Supposing most young DI beneficiaries who exit are recovering (rather than dying), this does reflect a somewhat larger recovery rate relative to the total beneficiary population. The five year survival rate on SSDI from 1980-2000 for the general population of beneficiaries was about 95% when we exclude those who died or transition to retirement (Raut, 2017). We can observe in our data that individuals who first enter DI at older ages stay on DI slightly longer. It is also possible that changing relationship to a beneficiary (e.g., divorcing a 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.

Even if it is *not* approximately true that young DI beneficiaries remain on DI indefinitely, the age at which they first receive benefits may be an outcome of special interest. If individuals continue *interacting* with the DI system over their lifetime, then age of first receipt is arguably our best proxy for when that lifetime of interactions with the system begins. Table 1 present summary statistics for the key variables in our analysis. In Panel A, we present data at age 24, an age at which we observe data for cohorts 1980-1990. At that age, 0.66% of individuals in the sample have ever received DI. Panel B presents the same statistics at age 34 (for cohort 1980 only). At that age, 2.24% of individuals have ever received SSDI

payments.

When we examine spatial differences in DI take-up in Section 4 and onward, we measure DI take-up as the share of individuals in our sample who have ever been on DI *by 2011*. Our objective in these sections is to provide a characterization of DI take-up through young adulthood; because we cannot observe all cohorts in our data at the end of young adulthood (e.g., age 30), we measure DI take-up in a fixed year (2011 in particular). We view this as an intuitive means of trading off between discarding data on younger cohorts versus providing a less complete picture of DI in young adulthood. We pick 2011 in particular because our oldest cohorts enter their early 30's at this point, and it coincides with the midpoint of the range of years from which Chetty and Hendren (2018a, 2018b) take their income mobility data, and against which we will compare our findings in Section 6. We further restrict to the sample of individuals age 24 and older in 2011, to maintain consistency in our sample when we implement the strategy of Chetty and Hendren (2018b) to produce estimates for DI take-up based off children moving across commuting zones (CZs).

Our state-level data is subject to a small amount of masking in less populous states due to low cell counts by cohort and parent income rank; the only state meaningfully impacted is Wyoming (even so, less than 7% of Wyoming's data is being masked). At the commuting zone level, we restrict throughout to CZs with a population of at least 25,000 in the 2000 Census (mirroring restrictions in Chetty and Hendren (2018a)). We restrict DI take-up measures to the 593 CZs with sufficient data that no masking occurs in the bottom parent income quintile; this overlaps closely with the 595 CZs for which Chetty and Hendren (2018b) report mover estimates for income mobility (leaving a set of 577 CZs for which both measures are reported). We present mover effect estimates for DI take-up for all 593 CZs for which we may estimate them. We will introduce those measures of income mobility when we compare the types of places which produce high DI to the types which produce higher income for children from poorer families in Section 6.

We can also calculate for each individual in each year whether they are covered by the SSDI program as a disabled worker. 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 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 $2 \times (\text{Age} - 21)$ 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. Individuals age 24 and younger may qualify with 6 QCs in the previous 3 years. With our income data beginning at age 20, we can therefore begin reliably measuring eligibility at age 23. Once an individual is 31 or older in our sample, they must have earned a minimum of 20 QCs since age 21. Table 1 shows averages for this variable as well; at age 24, 85.2% of individuals are eligible, and this fraction increases to 89.3% by age 34.

3 National Results

We begin our analysis by studying the relationship between DI and parental income nationally. Figure 2a plots the fraction of the sample that has ever been on DI by age and parent income rank, after pooling together all cohorts in our data. It shows that the probability of ever receiving DI is roughly linearly decreasing in parent income rank at all ages, with a slope which is steeper at older ages. This is confirmed explicitly at ages 24 and 34 in Figure 2b, which plots DI against parent income rank specifically at these ages. The percentage ever on DI at age 34 decreases from about 3.06% at the 10th percentile of parent income, to about 1.16% at the 90th percentile of parent income (a 0.024 percentage point decrease in DI per increase in parent income percentile). At age 24, this percentage decreases from 1.04% at the 10th percentile to 0.34% at the 90th percentile (a 0.008 percentage point decrease in DI per increase in parent income percentile). The DI-age relationship is also approximately linear with a slope increasing in parent income rank. Figure 2c makes this easy to see between the 10th and 90th percentiles of parent income rank. The stock of individuals ever receiving DI benefits from the 10th percentile of the parent income distribution increases by 0.205 percentage points per year of age. The slope at the 90th percentile of the parent income distribution implies a much smaller 0.089 percentage point increase per year of age.

We next address several concerns with the robustness of this relationship between DI, parent income, and age. A consequence of pooling data across all available cohorts is that our age-specific probability measures are imbalanced with respect to cohort. With data running up to 2015, we have data on fewer and fewer cohorts as we move to older ages. The first concern is that heterogeneity across cohorts may drive the qualitative relationship between differences in DI over age (e.g., older cohorts which make up larger shares of the individuals at older ages might enter DI at younger ages). That heterogeneity may also drive differences in the DI-income relationship over age when we pool cohorts (e.g., if older cohorts have a steeper DI-income slope). Figure 3 depicts the same plots when we restrict exclusively to

the 1980 birth cohort, the only cohort for which we have the data at all ages depicted. It shows that patterns observed in the pooled data are virtually identical when we restrict to a single birth cohort.

A second concern is that the relationship between DI and parent income is driven by the intergenerational links in DI take-up within the family. This seems plausible ex-ante, as parents receiving DI take-up likely fall lower in the parent income distribution. While we cannot check the role of a child’s family and household environment in a broad sense, we can check if the relationship between DI, parent income, and age persists among children with a parent who claimed DI benefits. We check this in Figure 4a, by restricting to the small sub-sample of children who have at least one parent on DI at age 20 (5.2% of the total sample). Unsurprisingly, this sub-sample is heavily concentrated in the lower tail of the parent income distribution; child DI take-up in upper parent income percentiles is measured off of national cells containing as few as 123 children at age 34 (which includes only the 1980 birth cohort). While DI take-up is in levels very high for the sub-sample of children with parents on DI (about 1.5% for even the youngest children with the richest parents), the qualitative patterns persist remarkably and show important differences in relative DI take-up over age and parent income rank in this sub-sample. DI take-up remains roughly decreasing in parent income rank and linearly increasing in age. Lines of best fit in the cross-sections of DI take-up for fixed age in Figure 4b show that DI take-up more than doubles from the 90th percentile of parent income to the 10th percentile of parent income at age 24, and the same holds true for age 34. DI take-up is also increasing more rapidly over age at the bottom of the parent income distribution than at the top. Comparing the 10th and 90th percentiles of parent income specifically, DI take-up is increasing over age at a rate 1.66 times higher at the 10th percentile (Figure 4c). There is a noticeable dip in DI take-up at later ages in many parts of the parent income distribution (easiest to see in Figure 4c). This dip is attributable to the restrictions on cohorts observed at later ages (mechanically, our measure of ever taking up DI cannot decrease over age with a balanced panel). Rather than reflecting systematic differences across cohorts, it most likely arises due to the small cohort-specific cell sizes. Smaller cell sizes appear to contribute to greater noise in DI take-up general at older ages; this is particularly noticeable in Figure 4b, when comparing relative dispersion in the cross-section of DI take-up over parent income at age 24 (containing cohorts up to 1990) against the same cross-section at age 34 (containing only the 1980 cohort).

A third concern is that differences in eligibility for DI benefits as a disabled worker might explain some of the relationship between DI, parent income, and age. Supposing the propensity for *medical* eligibility is randomly distributed over age and parent income rank, DI take-up may increase with age and decrease with parent income merely because individuals

who are older and who have poorer parents more often have the work histories that make them eligible to apply as disabled workers. We do not observe patterns in eligibility which are consistent with this explanation for the relationship between DI, parent income, and age. Eligibility to apply as a disabled worker varies substantially over the parent income distribution, but it is increasing with parent income rank—not decreasing with parent income rank. Furthermore, it is remarkably stable across age beyond age 24. Figure 5a presents eligibility rates for all ages and the full parent income distribution, but both of these facts are easiest to see in Figure 5b where we present age profiles of child DI eligibility for select cross-sections of the parent income distribution. A more formal adjustment for eligibility to the relationship between DI, income, and age is impeded by the fact that we cannot separate out disabled adult children nor identify how they are distributed among our beneficiaries with respect to age of entry and parent income rank (a reasonable share of disabled adult children entered DI at ages as late as the mid-30’s in 2016, though these may not be first entries (Social Security Administration, 2016)). To the extent that disabled workers mirror the overall population of beneficiaries in terms of the relationship between DI take-up, parent income, and age, differential constraints in the ability to apply over age and parent income (supposing other eligibility conditions are orthogonal to these characteristics) will not explain this relationship.

3.1 Cyclicalities of DI

We next examine the extent to which parent income interacts with the strong and well-documented cyclicalities of national DI receipt. We do this nonparametrically by plotting first entry hazard rates by parent income quintile against changes in the national unemployment rate, estimated for all individuals age 16 and older using CPS basic monthly files. We define the first entry hazard rate as

$$Hazard_t = \frac{EverDI_t - EverDI_{t-1}}{1 - EverDI_{t-1}}$$

where $EverDI_t$ is the fraction of individuals who ever received DI benefits on or before year t .

Figure 6 produces this plot with the full dataset. Years in which changes in the unemployment rate were high also tend to be years in which the entry rate of first-time DI beneficiaries is high, though there is a difference in the timing of the peak in unemployment rate changes and the peaks in the quintile-specific first entry hazard rates. The extent to which DI entry varies over time is much greater at the bottom of the income distribution than the top. The standard deviations (weighted by year-specific sample sizes) in the first DI entry hazard rate

over 2001-2014 are 0.034 percentage points and 0.010 percentage points for the bottom and top parent income quintiles respectively. From 2006 to 2010 (respectively the trough and peak for DI entry hazards over our sample), the hazard rate of first entry into DI from the bottom income quintile increases by 0.06 percentage points, from 0.17% to 0.23%. At the top income quintile, the hazard rate increases by about 0.02 percentage points, from 0.07% to 0.09%. Contemporaneous yearly unemployment changes also seem to explain more of the variation in DI entry among poorer children than among richer children in a relative sense. A simple regression of the yearly DI entry hazard rate on the yearly changes in the national unemployment rate suggests that variation in changes in unemployment explain 46% of the variation in contemporaneous first entry hazard rates over time at the bottom parent income quintile, and 36% of the variation in contemporaneous first entry hazard rates over time at the top parent income quintile.

One concern with the previous plot is that individuals in our sample are aging over time, and variation in DI entry over time may reflect the unfolding of life cycle patterns rather than a relationship with macroeconomic conditions. We reproduce the same plot using only data on individuals at age 24 in each year, to check that the patterns in first DI entry persist when the age at which entry is being measured remains fixed over time (at the expense of exclusively comparing entry across cohorts). This plot is presented in the right frame of Figure 6. Unemployment and DI entry appear to comove more closely when we hold fixed age and compare DI entry for cohorts over time. This is true at both the bottom and top of the income quintile, where changes in unemployment explain comparable shares of the variation in DI first entry hazards—52.7% and 51.9% respectively. We still see greater variation across time in first DI entry among poorer children relative to wealthier children. From 2006 to 2010, the hazard rate at the bottom income quintile increases from 0.16% to 0.22%, whereas it increases from 0.07% to 0.09% at the top income quintile. The standard deviations in the first DI entry hazard rate over 2001-2014 are 0.036 percentage points and 0.012 percentage points for the bottom and top parent income quintiles respectively.

4 Geographic Variation in DI Rates

This section explores variation across place in the relationship between parent income and DI take-up through young adulthood. To do so, we examine the relationship between parental income and whether or not a child received DI *by 2011* within each state and CZ. In each case, it is important to note that these are the places we believe children grew up, defined as the earliest location in which we observed the child (typically when claimed as a dependent in 1996) .

We also present estimates of DI take-up for each CZ which have been constructed using variation in outcomes of children moving across CZs, following the approach employed by Chetty and Hendren (2018b). These estimated outcomes are likely less contaminated by place-based sorting. We will compare our mover estimates for DI take-up in 2011 to the estimates for income mobility constructed by Chetty and Hendren (2018b) for the same age. We discuss these mover estimates in Section 4.2.

4.1 Unconditional Estimates of DI

We characterize the relationship between DI take-up in 2011 and parent income rank in Figure 7. We plot the full DI-income relationship by state in Figure 7a. This shows that the roughly linear relationship between DI and parent income rank persists at the state level, with states differing in the slope of DI with respect to income rank. The percent of young people ever receiving DI at the very bottom of the income distribution reaches in excess of 5% in the states with the highest DI: Maine, New Hampshire, and Vermont. To make a comparison of the DI-income relationship across states more visible, we superimpose plots of the DI-income relationship for only Nevada and Alabama (states at the 10th and 90th percentiles of the distribution of states with respect to overall young DI receipt) along with their associated lines of best fit in Figure 7b. States are similarly ordered in terms of ever being eligible for DI at the bottom of the parent income distribution (Figure 8), but the variation relative to the mean in eligibility is far smaller than the variation relative to the mean in benefit receipt across states. While DI take-up rates are indistinguishable at the 80th percentile of parent income (about 0.06% of young adults ever receiving DI), the line of best fit suggests a 0.0289 percentage point increase in DI take-up for each percentile increase in income rank in Alabama, but a 0.0085 percentage point increase in DI take-up for each percentile increase in Nevada. Consequently, by the 20th percentile of parent income, we predict DI take-up rates in Alabama (2.53%) which are nearly two times higher than those in Nevada (1.30%). Figure 7a shows very little meaningful differences across states in DI receipt at the top of the income distribution, relative to differences at the bottom of the income distribution. This is easier to see when we compare DI among poor children and wealthy children within each state. To do this, we compare construct a heat map of the U.S. with respect to state-level DI take-up within a given parent income quintile. We present this map Figure 7c for the bottom parent income quintile and in Figure 7d for the top parent income quintile. In virtually all states, fewer than 1.3% of children at the top parent income quintile have ever been on DI by 2011. Only 5 states have DI take-up for children in the bottom parent income quintile this low. Overall, DI take-up in 2011 at the bottom parent income quintile is as high as 5%, with the middle 40 states ranging between 1.3% and 3.0%.

The states with the highest DI among poorer children are scattered within the Northeast, Midwest, and Southeast. Excluding Alaska and Hawaii, the states with the lowest DI among poorer children are in the West: Arizona, California, Nevada, and Utah.

Figure 9 shows that the same characterizations at the state level persists at the commuting zone level: differences across place in DI uptake is substantial at the bottom of the parent income distribution, but not at the top of the distribution. Nearly all commuting zones have DI take-up at the top parent income quintile which is below 1.4%, whereas over 80% of CZs (conditioning on those with enough young people to avoid disclosure restrictions) have DI take-up in the bottom parent income quintile exceeding 1.4%.

4.2 Conditional Estimates of Young DI Among Movers

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—if for instance, perhaps the parents in poor households in Alabama are less educated than those in Nevada, even conditional on income—the differences in eventual DI rates might reflect the direct impact of these other differences on DI rates rather than outcomes associated with place, *per se*.

In this subsection, we address this concern by constructing place-specific predicted outcomes using variation in the timing of childhood moves from one CZ to another (mimicking the strategy of Chetty and Hendren (2018b)). Intuitively, this design exploits differences in outcomes over children in moving families, as a function of the age at which they move, to linearly predict outcomes for children who spend their entire childhood in a particular place but belong to a moving family. The result is a predicted location-specific outcome for children of moving families, in the 25th percentile of the parent income distribution. The key assumption is that, conditional on belonging to a moving family, the determinants of child outcomes (other than place characteristics) are not correlated with the age at which the move takes place. If this assumption is true, the estimates produced should be robust to the endogenous sorting of children into places. We include details regarding our implementation of this design in Appendix A.

Figure 10 characterizes the distribution of mover estimates and observational measures of DI take-up in CZs across the United States, with heat maps of observational and mover estimates of DI take-up in Figures 10a and 10c respectively. Our mover estimates represent the difference in the share of DI take-up (relative to the average CZ) expected for a child from a moving family that spends 20 years of childhood (before age 23) in that CZ. The sheer magnitude of the estimates at the right tail and left tail reflect the substantial noise in some of these estimates—particularly for smaller CZs. The mover estimate for International Falls, Minnesota suggests a 33 percentage point increase in DI take-up for children who

reside there for 20 years of childhood. On the other side of the distribution, the estimate for Nantucket, MA suggests massive *negative* DI take-up among long-time residents—a 117 percentage point decrease in DI take-up in 2011 for children residing in that CZ for 20 years. However, the range of values for the middle 66% of CZs, for which estimates are generally more precisely estimated, are quite reasonable—ranging from a 3 percentage point increase in DI take-up to a 4 percentage point decrease in DI take-up.

These figures reveal some interesting differences across observational and mover estimates. Many of the CZs which produce the highest observational measures of DI (e.g., in Maine, Vermont, and New Hampshire) fair better in the distribution of CZ mover estimates. Some of these CZs actually have estimated mover effects below the national average. On the other hand, a cluster of CZs in the northwest (occupying parts of Wyoming, Montana, and Idaho) yields some of the highest mover estimates in the US, despite these CZs producing little observational DI. More generally, the West coast (which yields low observational DI take-up) contains several mover estimates which are above the national average. Mover estimates of DI vary substantially across CZs; moving from the 25th to the 75th percentile CZ in terms of the distribution of mover estimates implies a 4.76 percentage point swing in DI take-up by 2011. Figure 11 presents the observational and mover DI estimates in a scatter plot. While the population-weighted line of best fit has a very shallow slope (suggesting a 0.04 percentage point increase in observational DI take-up for a 1 percentage point increase in the mover estimate), this weak relationship seems to be attributable to noise in the mover estimates. We estimate a correlation between these two measures of 0.65 when accounting for noise in the mover estimates. We construct that estimated correlation in the same manner we describe for correlations between mover estimates and local characteristics in Section 5.

5 Place-Specific DI Take-up and Area Characteristics

The analyses in Sections 4.1 provide evidence that growing up in some areas of the country is associated with significantly greater incidence of Disability Insurance claiming in young adulthood, but only for children from poorer families. Section 4.2 provides evidence that this fact is robust to place-based sorting. In this section, we explore what CZ-level characteristics predict high DI rates for children from poor families. In order to do so, we estimate the correlation of local characteristics with observational DI take-up and mover DI take-up. Mover DI take-up estimates are subject to substantial noise, though, which will bias correlations with local characteristics toward zero (thinking of the correlation between unobserved *true* mover outcomes and local characteristics, the signal correlation, being the parameter of interest). We follow Chetty and Hendren (2018b) in addressing this issue by

directly estimating the signal correlation. To construct signal correlations from mover estimates, we regress mover estimates on normalized local characteristics, and then divide the coefficient from this univariate regression by an estimate for the standard deviation of the true mover outcomes, across CZs. This estimate is constructed by subtracting the average (across CZs) of the square of standard errors of our mover estimates from the variance (across CZs) of our mover estimates. The identification strategy underlying this approach requires an assumption of homoskedasticity in true mover outcomes across CZs. We follow Chetty and Hendren (2018b) in weighing CZs by the precision of their associated mover estimate in constructing this estimate for the signal standard deviation. We use analytic standard errors rather than bootstrapped standard errors for mover estimates, which are larger in the income mobility application of Chetty and Hendren (2018b) (and therefore generate signal correlation estimates which are slightly lower in magnitude).

We next consolidate the large set of local characteristics into a smaller set of common factors by grouping characteristics into disjoint categories and associating a single factor with each category. This projects the task of characterizing the types of places that produce high DI take-up and high income mobility into a much smaller dimension space. It also reduces the extent to which noise contaminates our correlations, to the extent that we think of the above characteristics as classically noisy measures of a smaller, more fundamental set of local factors.

5.1 Local Sociodemographic Characteristics and DI

For a wide range of covariates, we calculate the univariate Pearson correlation with DI take-up in the bottom parent income quintile, weighing each CZ proportionally by its population according to the 2000 census. We also calculate correlations with mover estimates from Section 4.2 of DI take-up at the 25th percentile of parental income. Figure 12a contains the results. For both measures, we restrict to CZs which had a population greater than 25,000 in the 2000 census. Observationally, we present correlations for all 578 CZs subject to no masking due to few observed children at the bottom of the parent income distribution. For mover effects, we present correlations based on the 593 CZs for which we may estimate them; we find that restricting to the smaller set of CZs for which we report observational DI take-up does not meaningfully impact results.

The difference between the observational and mover correlations, aside from slight differences in the parent income ranks underlying the two measures, represents the nature of selection into place on DI take-up. For instance, average local household income is significantly and negatively correlated with observational DI take-up, with a correlation just below -0.25 . When we compare household income and mover estimates of DI take-up, which are

less sensitive to concerns regarding place-based sorting, we see a *positive* correlation of about 0.25—places with higher average income tend to have higher mover estimates of DI take-up. We calculate all characteristics from the 2000 US Census, unless otherwise indicated.⁴

Our first group of covariates contains measures of segregation, calculated using the Theil index of segregation across Census tracts within each CZ (Theil, 1972). 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 individuals in tract j from race r . We then define the degree of racial segregation in a CZ 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} 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 CZ as a whole. Figure 12a 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 the extent to which individuals below national income percentile p are separated from individuals above income percentile p . We use the formula above, where for income segregation $E(p) = p \log_2 \frac{1}{p} + (1 - p) \log_2 \frac{1}{1-p}$. 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. Figure 12a shows that DI rates are negatively and significantly correlated with income segregation, so that less segregated cities have higher DI rates. Figure 12a also shows that the share of workers with a commute time of less than 15 minutes is strongly and significantly correlated with higher observational DI, while the fraction of the total

⁴We thank the authors of Chetty et al. (2014) for help with constructing CZ-level covariates, and in most cases we follow their methods for the precise construction of these variables.

population identifying only as black is not significantly correlated with DI.

Our mover estimates would suggest, though, that these negative correlations with segregation measures arise primarily due to sorting; segregation measures are at best weakly correlated with DI take-up among movers. Mover estimates suggest a slightly stronger, negative correlation between DI take-up and the fraction of the CZ identifying as black. Mover correlations with the commute measure are also somewhat large, though going in the opposite direction; they suggest that the share of workers with a commute time less than 15 minutes is *negatively* correlated with DI take-up, among movers in the CZ.

Second, we study different moments of the CZ-specific income distribution. We first correlate DI rates with mean household income; this statistic of level income is negatively and significantly correlated with DI rates. We find the same for two measures of income inequality estimated on tax record data for parents of children born in 1980-1983: the fraction of income earned by the top 1%, the Gini coefficient, and the fraction of the parents in the CZ falling between the 25th and 75th percentile of the national parent income distribution. Overall, measures of higher income inequality within a CZ are consistently and significantly negatively correlated with DI. Our mover estimates, though, suggest that this relationship is not robust to sorting; correlations between these income measures and mover estimates of DI take-up are negligible in the case of measures of income inequality, or positive in the case of average household income.

Third, we study measures of quality of local education. Using both measures of inputs (public student-to-teacher ratios, public school spending per student, college tuition and colleges per capita) and outputs (test scores, high school dropout rate, and college graduate rate), CZs with higher quality education have higher DI rates. Correlations are strongest for measures of elementary school quality. Specifically, we find a strong, significant, and 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. We find no meaningful correlation with public school spending per student. On the output side, we find a strong and positive correlation between average grade 3-8 test scores (taken from the Global Report Card, based on National Assessment of Educational Progress (NAEP) scores). DI take-up is correlated in the same way, though to a weaker extent, with *lower* high school dropout rate (from the Global Report Card), higher college graduation rate (from the Integrated Post-secondary Education Data System 2009), and more colleges per capita (from IPEDS 2000). DI take-up is not significantly correlated with higher college tuition per capita (from IPEDS 2000), though tuition could be a proxy for both college cost and college quality. For the most part, these correlations appear robust to place-based sorting. The only notable exception is the correlation between DI take-up and colleges per capita, which is modest and negative

for movers. School per capita spending, though, is largely and positively correlated with our estimate of DI take-up among movers. This suggests that the observational correlation, close to zero, might be dampened significantly by place-based sorting.

We also correlate DI rates with measures of social capital. Our measures of social capital include 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 local measures (other than the fraction foreign born, which has somewhat of a mechanical relationship due to eligibility for DI), social capital is the single strongest correlate for observational DI. Correlations with arrests for violent crime per capita (from Uniform Crime Reports) and the share of religious adherents (from the Association of Religion Data Archives) are consistent with higher social capital being correlated with higher DI, though only strong and significant for violent crime. These correlations all persist, albeit substantially dampened for crime and social capital, when we check for robustness to sorting by correlating these measures with mover estimates of DI take-up.

We also correlate DI take-up 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 the nominal household income in these CZs. We measure local government spending per capita using the same data source. 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.⁵ A lower tax burden and less government spending is generally associated with higher DI; states with larger EITCs, higher taxes, and higher spending tend to have lower DI rates. Our measure of tax progressivity is an exception to this generalization; we find it is modestly but statistically insignificantly positively correlated with DI rates. The same characterization is true when we look at mover DI take-up, though it is driven by different local measures; a modest and negative correlation between state EITC and mover DI take-up persists, but it is largely state tax progressivity which is positively and substantially associated with DI take-up among movers.

⁵We 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.

We correlate DI rates with several measures of the local labor market. We find no relationship between labor force participation rate in 2000 and DI, or average unemployment from 2004-2011 (aggregated from county-level reports of the BLS Local Area Unemployment Statistics, with counties matched to CZs using a crosswalk constructed by the USDA Economic Research Service) and DI, but a positive correlation between DI and measures associated with unskilled or manufacturing-oriented employment (growth in imports from China from 1990 to 2000, teenage labor force participation of birth cohorts 1985-1987, and share of employed persons working in manufacturing in 2000). The lack of a relationship between DI take-up and local labor market conditions cross-sectionally is somewhat striking, given the prominent cyclicity in DI take-up among poorer children nationally. Our mover estimates would attribute virtually all of the correlation between DI take-up and the manufacturing share to place-based sorting, while it suggests that the local unemployment rate may be *negatively* correlated with DI take-up among movers.

We also correlate DI rates with measures of migration and family structure. CZs with lower out-migration (and in-migration) rates have higher DI rates. A large fraction of foreign-born residents is very negatively correlated with DI rates, though this relationship is likely in part mechanical due to lower eligibility rates for foreign born residents, since workers must have a minimum number of covered quarters in order to apply for disability insurance. All three of these observations largely persist when we correlate DI take-up among movers with these measures of migration. Measures of family structure yield mixed correlations with DI; both greater share of people married and divorced are positively correlated with observational DI, though only the former correlation is statistically significant. The share of households with children which are led by a single mother has no correlation with DI. Among movers, the picture painted by family structure measures is more consistent; the correlation between DI take-up and the fraction of people divorced is actually negative, as is the share of children living with a single mother. That is, among movers, places where family environments are more stable tend to generate more DI take-up.

Finally, we correlate DI rates with two measures of access to local SSA field offices: whether or not an SSA office was present in the CZ in 2000, and the number of field offices per capita in the CZ in 2000 (conditional on one existing). Local field offices provide assistance with filing disability applications, reducing the cost of applying for benefits for those with access to one. Data on SSA field office locations is collected for Deshpande and Li (2018) and provided by the SSA. While the date of field office openings is unknown, the first recorded office closings occurred in 2001. At least one office is present in 502 of the 741 US commuting zones. Figure 13 describes the distribution of SSA offices per capita in each commuting zone, across the United States. Correlations in Figure 12a show a modest and

significant positive correlation between DI take-up and the presence of SSA offices, but not offices per capita among the CZs containing at least one office in 2000. This is consistent with the availability of local SSA field offices being associated with lower costs of applying for DI benefits. Interestingly, the correlation between DI take-up among movers and the presence of an SSA office is *negative*, suggesting that the observational relationship may be subject to substantial place-based sorting.

5.2 Consolidating Local Characteristics into Factors

The set of local characteristics included in the previous section is large, and can be naturally consolidated into a small set of groups, each of which containing a set of closely related characteristics. Consolidating the characteristics in this way allows us to more tractably describe in broad terms the types of places which generate high DI among poorer children, and may allow us to formalize the generalizations made in the previous section. Furthermore, to the extent we believe that the observed characteristics are classical noisy measures of the smaller set of fundamental local factors which we identify ex-ante, estimating the factors directly will help average over that noise.

To map local characteristics into a smaller set of factors, we group observed CZ characteristics into categories, largely following the groupings used by Chetty et al. (2014) in organizing figures. Those categories are measures of: segregation, inequality, tax rates, education outcomes, local labor outcomes, migration, social capital, and family structure. We associate with each category a single common latent factor, which we estimate by confirmatory factor analysis following Heckman, Pinto, and Savelyev (2013). This method requires each category contains at least three observed measures, and is described in Appendix B. For each category, we estimate the associated factor using the set of all CZs which contain non-missing values for all measures in that category. Each estimated factor is denominated in the units of its first associated measure according to Figure 12a. Factor loadings are reported in Table 2.

We present the correlations between these factors and both observational DI take-up at the bottom parent income quintile as well as mover estimates of DI at the 25th percentile of parent income in Figure 12b. We find that the correlations between DI take-up and the estimated factors corroborate the generalizations we drew from correlations between DI take-up and the underlying measures. Segregation, migration and taxes are all significantly negatively correlated with observational DI (inequality being negatively correlated but marginally insignificant). Education and social capital are significantly and positively correlated with observational DI. Local labor and family structure are not significantly correlated with observational DI take-up. These characterizations qualitatively persist when we examine factor

correlations with mover DI take-up, with a few notable exceptions. The negative correlation with migration is dampened substantially, while the positive correlation with social capital is more than halved. The negative correlation with segregation not only completely vanishes, but turns moderately positive when we examine movers. On the other hand, taxes seem quite robust to place-based sorting in terms of associations with DI take-up. The correlation between the education factor and DI take-up is actually higher for the mover estimates, suggesting that individuals with lower DI take-up self-sort into places with higher education.

6 Relationship between DI and Income Mobility

The analyses of Sections 5.1 and 5.2 suggest a counterintuitive relationship between some characteristics of cities and DI take-up. In particular, it seems that CZs that generally appear “better”—for instance, with better schools and higher social capital—have *higher* DI take-up. This is surprising in light of recent evidence from Chetty et al. (2014) and Chetty and Hendren (2018b) showing that these characteristics correlate causally and observationally with higher rates of upward mobility and employment for children from poor families in such areas. We now compare directly the places that generate high DI take-up to the places that generate high absolute income mobility for children at the 25th percentile of the parent income distribution. We borrow this measure from Chetty and Hendren (2018b), defined as the expected income rank at age 26 for a child born at the 25th percentile of the parent income distribution and constructed using 1980-1986 US birth cohorts.

We represent the overall relationship between DI take-up and income mobility at the bottom of the parent income distribution in two ways. First we, compare in Figures 10 a heat map of DI take-up to a heat map of income mobility, for both the observational measures and mover estimates. Figures 10a and 10b show a mixed relationship between observational DI take-up and income mobility. Income mobility is mixed in Maine, Vermont, and New Hampshire (where DI take-up is very high) and in the west (where DI take-up is very low). On the other hand, DI take-up is mixed in the southeast (where income mobility is very low). However, there is a notable concentration of places in the heartland states which produce very low DI take-up and very high income mobility. These are relatively less populous parts of the country. To test formally and more generally if the types of places that jointly generate low DI take-up and high income mobility are particularly rural, we group states into three bins: one bin for those that lie in the top quartile of the distribution of CZs in income mobility and bottom quartile in the distribution of CZs for DI take-up (“Good CZs”), a second bin those that lie in the bottom quartile for income mobility and the top quartile for DI take-up (“Bad CZs”) and a third bin for the remaining CZs. We

test if the “Good” CZs differ significantly from comparison CZs which are neither “good” nor “bad” with respect to population size in Table 3, reporting bin sizes associated with each group alongside these tests. We find very large and statistically significant in average population across these bins, but there is good reason to be skeptical of this test. One major concern is that less populous CZs may occupy the tails of both measures simply because child outcomes are more noisily measured in these places. Restrictions we have imposed on the CZs included in our sample should help with this concern, to the extent that they limit the noise in observational measures. Back-of-the-envelope calculations suggest that differences between the “good” CZs and comparison CZs are very unlikely to be attributable to noise, at least for observational DI take-up. Supposing DI take-up is independent across individuals, we observe enough children in even the least populous CZs in our restricted sample that standard errors are small relative to local averages. It appears, furthermore, that “good” CZs are *uniquely* less populous. While “bad” CZs are also less populous than CZs which are neither “good” nor “bad,” this difference is *not* significantly different from zero. “Bad” CZs are still on average twice as large as “good” CZs. “Bad” CZs have a population of about 344 thousand on average, whereas “good” CZs have an average population of 128 thousand and the remaining CZs have an average population of 521 thousand. It seems possible that low DI take-up in less populous areas with high income mobility may reflect limited *access* to DI in these areas, confounding an otherwise positive relationship between income mobility and DI take-up. We leave a deeper investigation of these areas for future research.

We present a scatter plot of CZs by observational DI take-up and income mobility in Figure 14a, which shows virtually no relationship between observational DI take-up and observational income mobility in aggregate. We present the same scatter plot for mover estimates in Figure 14b, where we see little relationship between the two measure again. When we construct a measure of correlation between the two mover estimates which accounts for noise, we find a weak negative overall relationship between DI take-up and income mobility (a correlation of -0.22). Following our strategy for adjusting correlation measures between mover estimates and local characteristics for noise in the mover estimates, we construct this correlation by simply dividing the covariance between the two measures by (already constructed) estimates for the standard deviations across CZs of the underlying two true mover measures.

The overall relationship between DI take-up and income mobility is remarkably weak, despite the fact that these two measures both correlate with other local characteristics. A natural question to follow with is: what are the local characteristics that jointly predict uniformly “good” outcomes (low DI and higher income mobility) or “bad” outcomes (simultaneously higher DI and higher income mobility)? We answer this question by comparing

the univariate Pearson correlations for observational and mover estimates of DI take-up in Sections 5.1 and 5.2 (presented in Figure 12) against analogous correlations constructed for observational and mover estimates of absolute income mobility. Figure 15a plots these correlations for observational estimates of DI take-up and absolute income mobility. A dot presents the correlation with observational DI take-up (on the x-axis) and absolute income mobility (on the y-axis) for a single local observable characteristic (right frame) or estimated factor (left frame). Most measures tend to correlate in the same direction with observational DI take-up and income mobility (occupying the upper right and lower left quadrants): predicting higher DI take-up and higher income mobility, or lower DI take-up and lower income mobility. The exceptions to this characterization tend to be measures which correlate strongly with only DI take-up or income mobility and weakly with the other. Measures of local migration (in-migration, out-migration, and share foreign born) and measures of family structure (fraction married, children with single mothers, or divorced) are good examples. Measure of migration correlate strongly and negatively with DI take-up, while correlating weakly and positively with income mobility. Measures of family structure correlate strongly with income mobility, while producing weaker and more mixed correlations with DI take-up.

Figure 15b plots the same correlations for the mover estimates of DI take-up and income mobility. Comparing to the correlations between observational estimates, we see similar patterns. Measures that moderately predict both DI take-up and income mobility tend to predict them in the same direction, higher income mobility and higher DI take-up or lower income mobility and lower DI take-up. There are some measures which appear to be an exception to this characterization: places where more people have a shorter commute to work tend to have higher mover estimates of income mobility and lower estimates for DI take-up, while places where household mean income is higher tend to have higher DI take-up and lower income mobility. When we project measures onto a smaller group of factors though, all the factors continue adhering to this characterization except segregation. Greater segregation is weakly and positively correlated with higher DI take-up, and strongly and negatively correlated with higher income mobility. The most notable factor, in terms of jointly predicting mover estimates of DI take-up and income mobility, is social capital. This factor has a correlation of over 0.6 with income mobility, and approximately 0.25 for DI take-up.

The analysis of this section shows that the relationship between DI take-up and income mobility at the local area level is surprisingly mixed. While both outcomes tend to correlate positively or negatively with the same local characteristics, the direct relationship between the two outcomes is mixed and weak at best. However, there appears to exist a subset of places which tend to be less populous and which jointly produce low DI take-up and

high income mobility. DI take-up may be lower in these places because opportunities are especially good, or because access to DI is low in these more rural areas (casting some doubt on the extent to which low DI take-up in these places is a “good” outcome). It remains for future work to explore the nature of the relationship between these outcomes more deeply.

7 Conclusion

This paper studies the drivers of DI take-up among the young. We find that DI take-up is especially high among young children with poorer parents. These children appear to be the drivers of variation in DI take-up both spatially (take-up varies greatly over states and commuting zones for children with poorer parents, but not children with richer parents) and intertemporally (take-up is more cyclical for children with poorer parents). We find that the places that generate high DI take-up among these children tend to be places which have otherwise “good” observable characteristics: low segregation, better schools, more income, and less income inequality. While some of these characterizations seem sensitive to place-based sorting, many are not. Strikingly, local labor market conditions do not well-predict DI take-up cross-sectionally, despite the strong sensitivity of DI take-up to *changes* in labor market conditions nationally. The characteristics that predict high DI take-up in a place also tend to predict high income mobility. However, the overall relationship between DI take-up and income mobility across CZs is in aggregate null, with some evidence that places performing well on both measures are unusually less populous. When we turn to estimates based on children who move across CZs, we find a direct relationship between DI take-up and income mobility across commuting zones which is weakly negative.

Our results motivate further research regarding the mechanisms by which differences across the parent income distribution in DI take-up, and differences geographically in DI take-up arise, and the nature of the relationship between DI and work opportunity. Is child DI take-up differentially sensitive across parent income and place to *changes* in local labor market conditions? More generally, is it differentially sensitive across parent income and place to observable changes in the costs of receiving benefits? In future research, we aim to answer these questions.

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Table 1: Summary Statistics

Income Group	All	Bottom Quintile	Top Quintile
(A)			
Children at Age 24			
Percent Ever Receiving SSDI	0.66	0.95	0.32
SSDI Eligibility Rate (%)	85.2	71.3	90.9
Sample Size	44,866,576	8,973,546	8,973,093
(B)			
Children at Age 34			
Percent Ever Receiving SSDI	2.24	3.16	1.22
SSDI Eligibility Rate (%)	89.3	79.5	94.0
Sample Size	3,601,815	720,378	720,346

Notes: This table presents summary statistics for SSDI 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 2: Factor Loading Estimates

	Local Labor
Labor part	1
Share Manuf	8.734308
Growth in China Imp	154.4728
Teenage Part	-.0787539
Mean Unemp, 2001-2011	1.262956
	Family
Frac married	1
Child w/ single mom	-1.917353
Frac divorced	-.1974361
	Social Capital
Soc cap index	1
Frac Relig	.0680953
Violent Crime	-.0005134
	Inequality

Gini	1
HH Inc	.1446438
1% Inc Share	.0194334
Frac in Nat IQR	1.617623
Tax	
Tax Rate	1
Govt \$ PC	.0723523
State Tax Prog	-11.64428
State EITC	459.5637
Segregation	
Theil	1
Frac Black	.7932566
Theil (Inc)	.4848033
Seg (p25)	.4500771
Seg (p75)	.5078433
Short Commute	-2.237642
Education	
School \$ PC	1
Stud/teach	-3.044853
Test Score res	-.8159088
HS Drop rate	-.01615
College grad rate	.13852
College Tuition	2.348841
Colleges PC	-.1151804
Migration	
Inflow Rate	1
Outflow Rate	.9721864
Frac Foreign	2.389436

Table 3: Test for Population Differences in 2000 across CZs generating Good and Bad Child Outcomes (Population in thousands of people)

	Observational			Movers		
	Means	Difference	N	Means	Difference	N
Comparison CZs	521.1 (73.24)		507	504.6 (70.40)		538
Bad CZs	344.3 (69.69)	176.9 (238.3)	27	233.1 (55.74)	271.5 (246.2)	24
Good CZs	128.5 (40.05)	392.6* (188.7)	43	79.96 (6.451)	424.7 (216.4)	31
<i>N</i>	577			593		

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: “Good” CZs are defined as those which fall in the top quartile of CZs in terms of absolute income mobility, and the bottom quartile of CZs in terms of DI take-up. Bad CZs are defined in the opposite manner. Comparison CZs are the remaining CZs with information on both outcomes. Standard errors are clustered at the state level.

Figure 1: DI First Entry Survival Functions

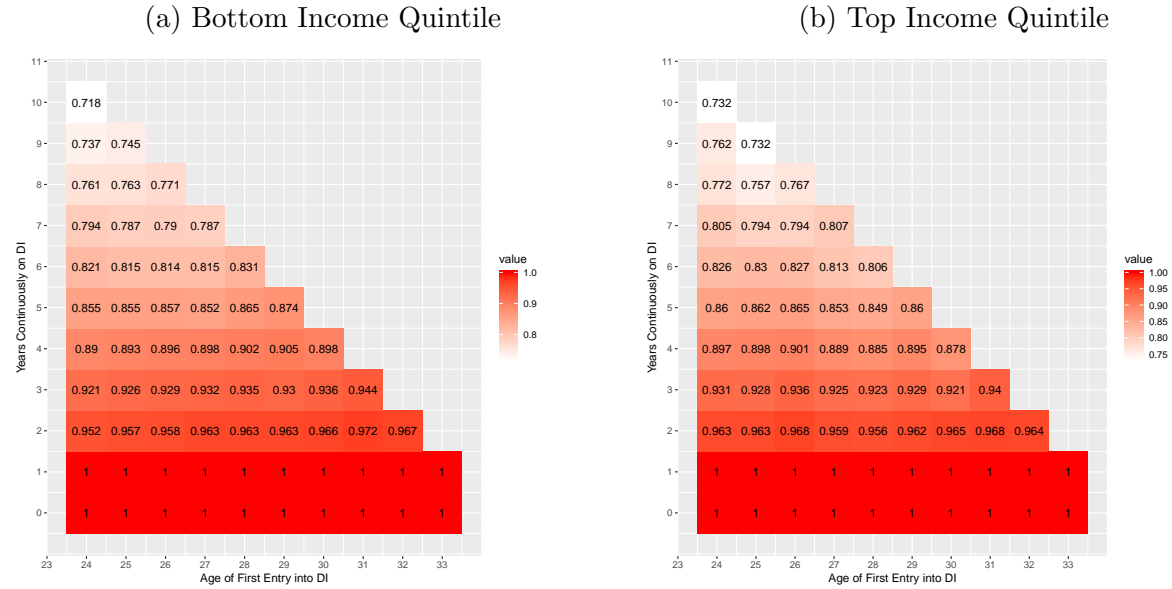
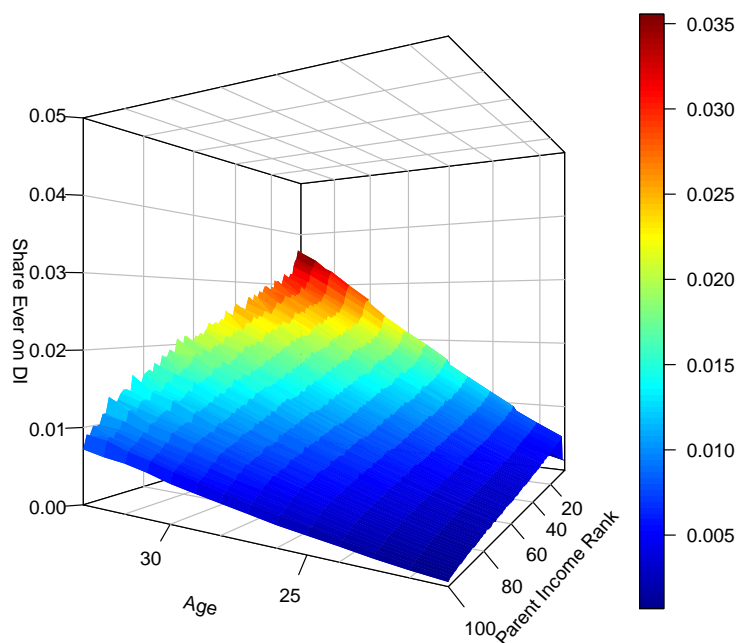
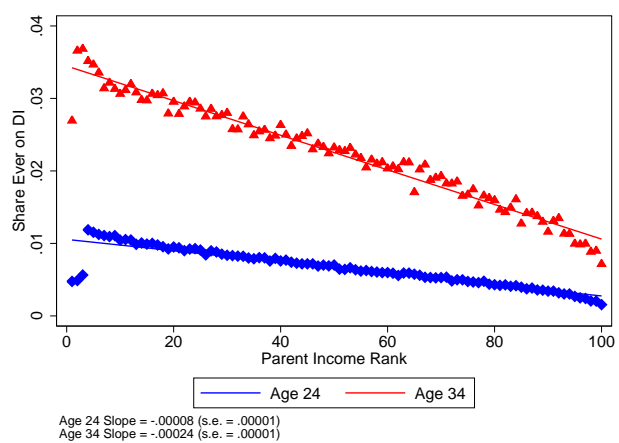


Figure 2: Characterizing DI Receipt by Age and Parent Income Rank, Pooling Birth Cohorts

(a) Ever on DI by Age and Income Rank



(b) Select Age cross-sections



(c) Select income rank cross-sections

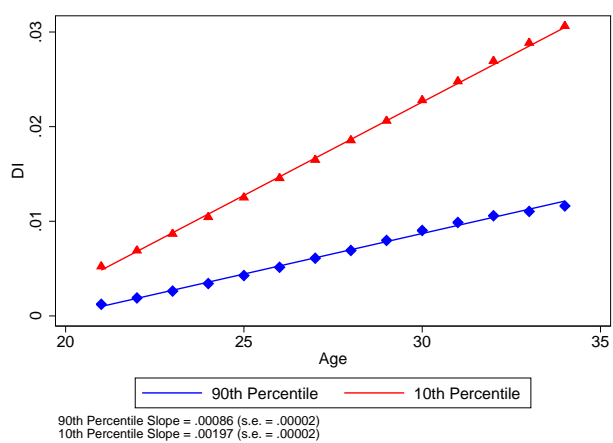
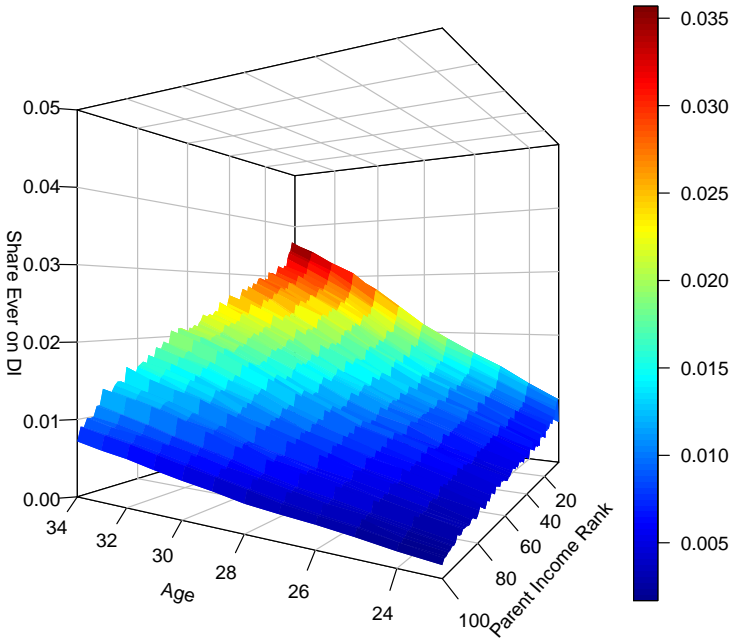
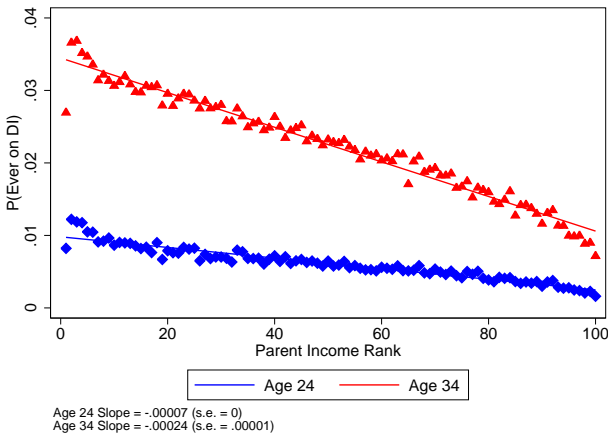


Figure 3: Characterizing DI Receipt by Age and Parent Income Rank, 1980 Birth Cohort

(a) Ever on DI by Age and Income Rank



(b) Select Age cross-sections



(c) Select income rank cross-sections

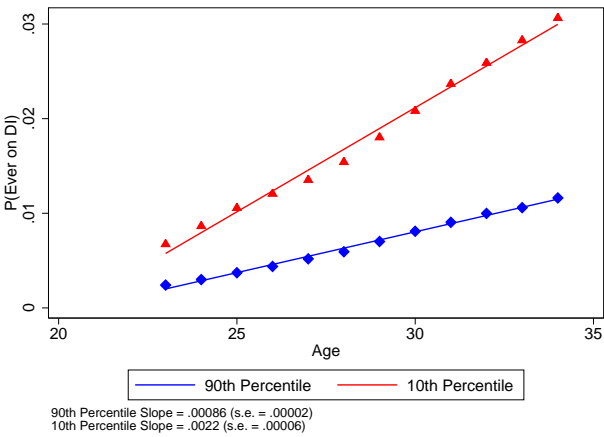
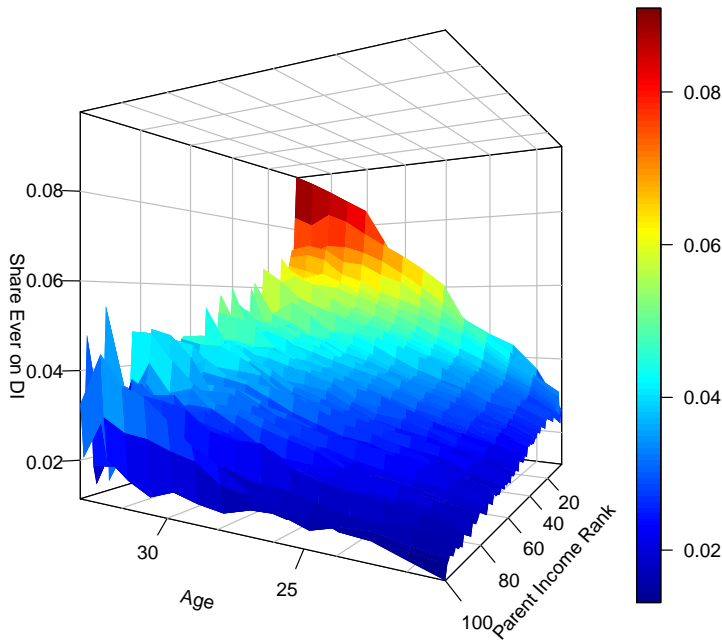
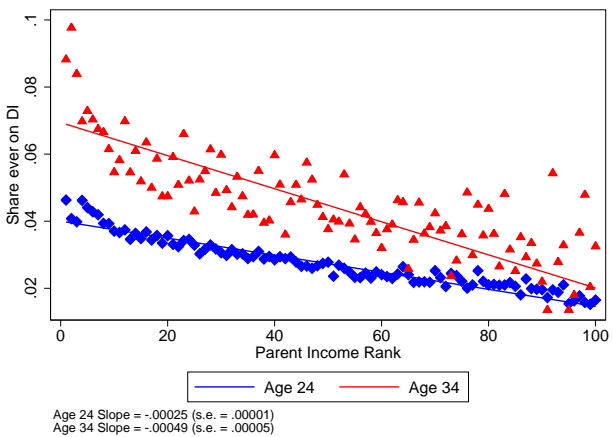


Figure 4: Characterizing DI Receipt by Age and Parent Income Rank, with Parent on DI

(a) Ever on DI by Age and Income Rank



(b) Select Age cross-sections



(c) Select income rank cross-sections

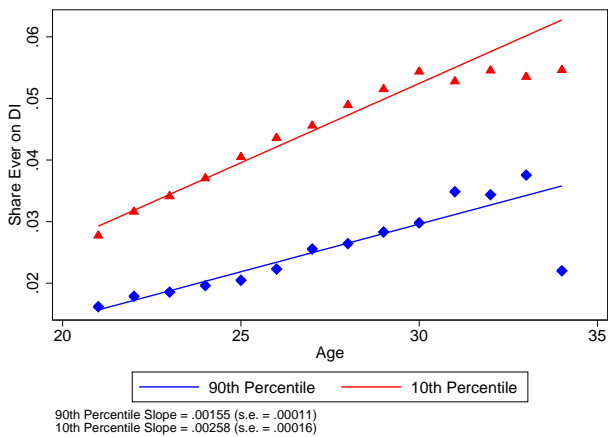
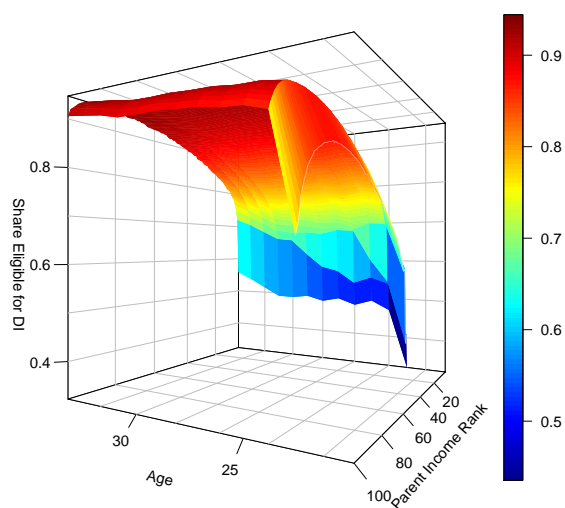


Figure 5: Characterizing Eligibility for DI as a Disabled Worker, by Age and Parent Income Rank

(a) Eligibility by Age and Income Rank



(b) Eligibility by Age and Income Rank

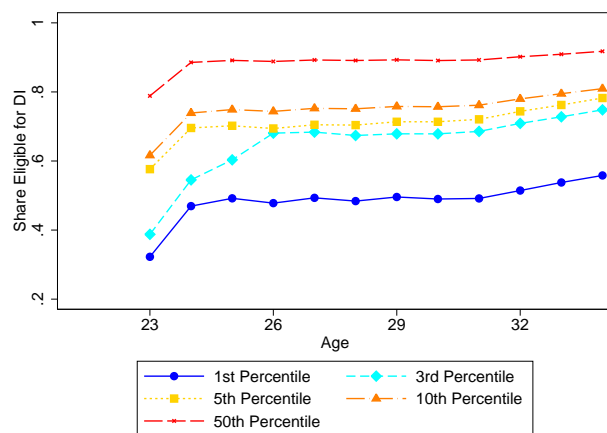
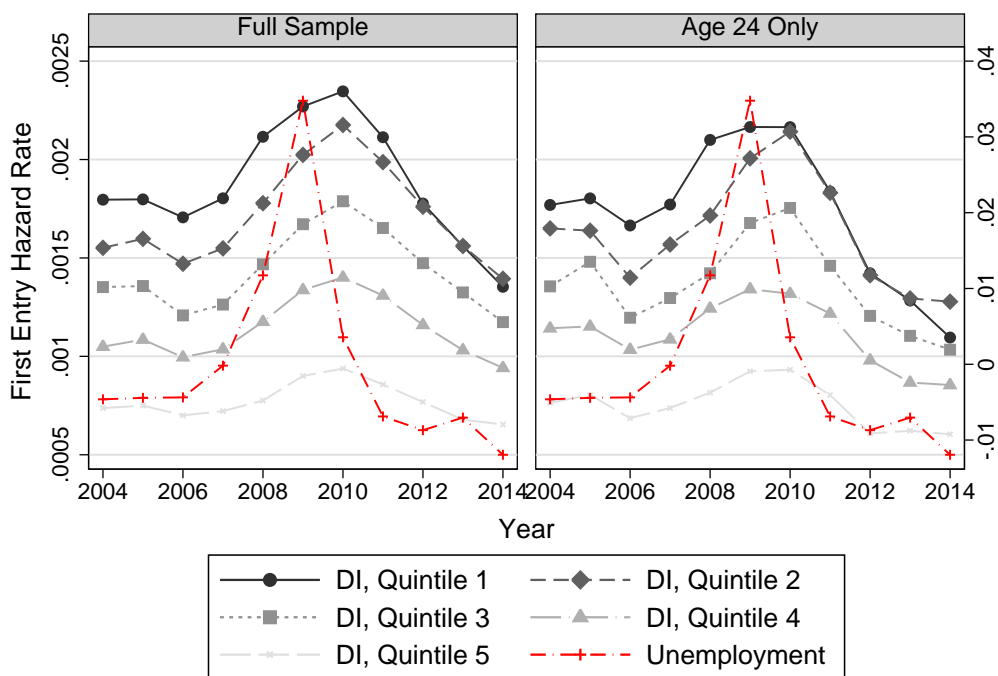


Figure 6: National First DI Entry Hazards by Parent Income Quintile, and Changes in the National Unemployment Rate

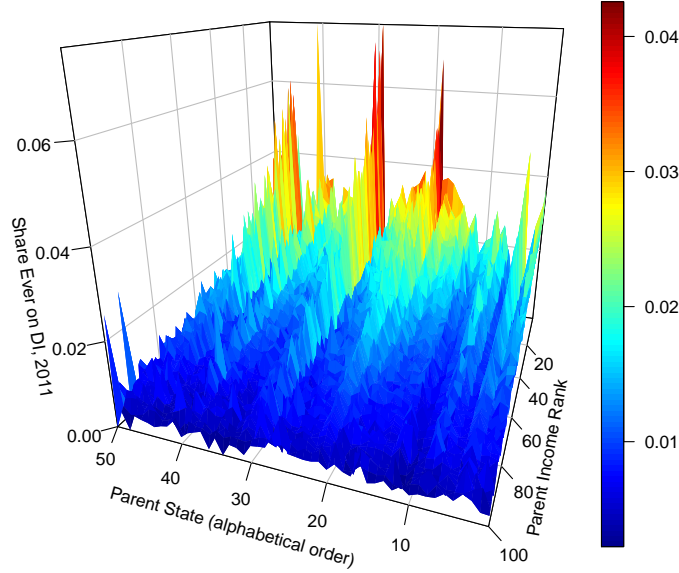


Graphs by group

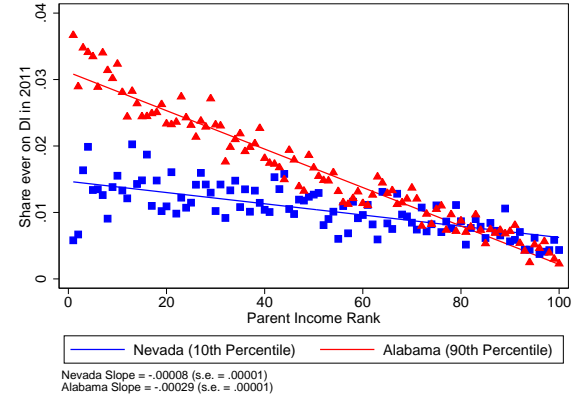
Notes: Changes in the unemployment rate are plotted in red. Hazard rates of first entry into SSDI are plotted, by parent income quintile, in shades of gray. Darker shades of gray correspond to lower income quintiles.

Figure 7: State Heterogeneity in DI in 2011

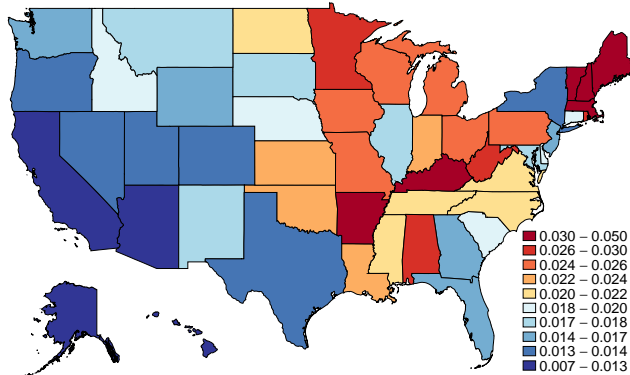
(a) Ever on DI by Age and Income Rank



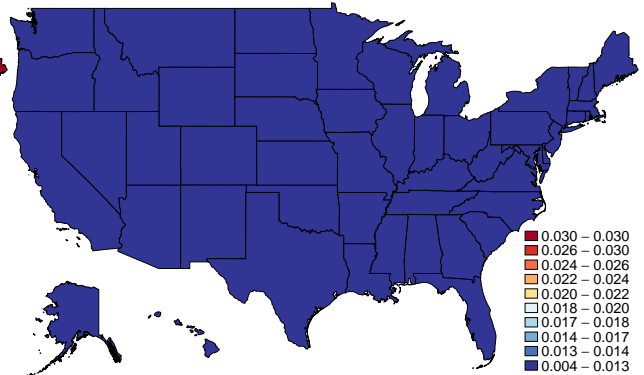
(b) Select state cross-sections



(c) DI at the Bottom Parent Income Quintile



(d) DI at the Top Parent Income Quintile



Notes: Color bins are defined by deciles of the distribution of state DI, for individuals in the bottom income quintile. Predicted DI is constructed using the coefficients from a linear regression of an indicator for ever being on DI in 2011 on parent income rank, for each state.

Figure 8: State Heterogeneity in Share Ever Being Eligible for DI in 2011, Bottom Quintile

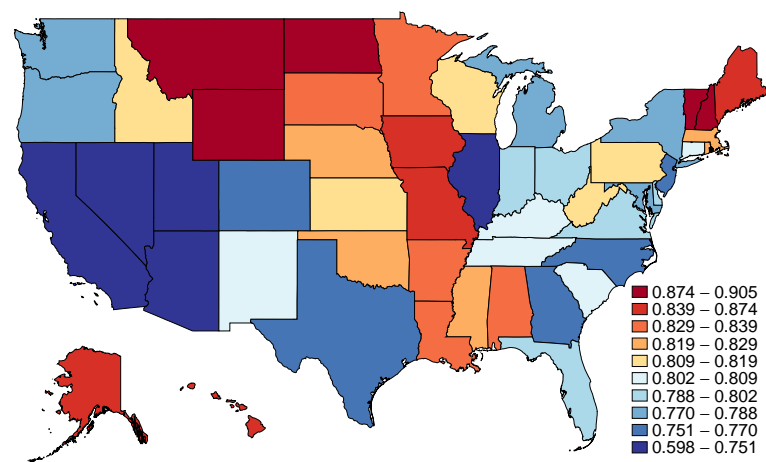


Figure 9: Commuting Zone Heterogeneity in DI in 2011

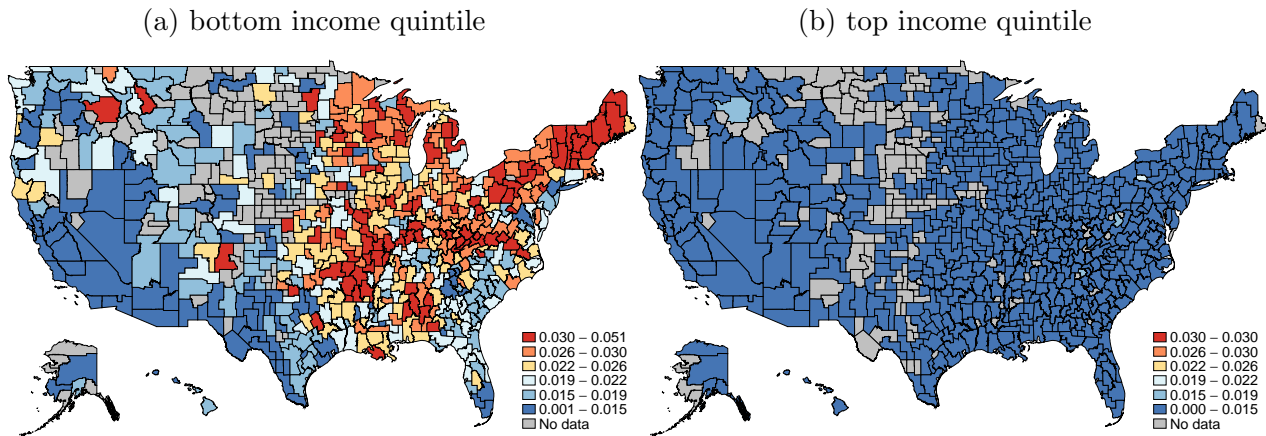


Figure 10: Maps of CZ Heterogeneity in DI Take-up in 2011 and Income Mobility at Age 26

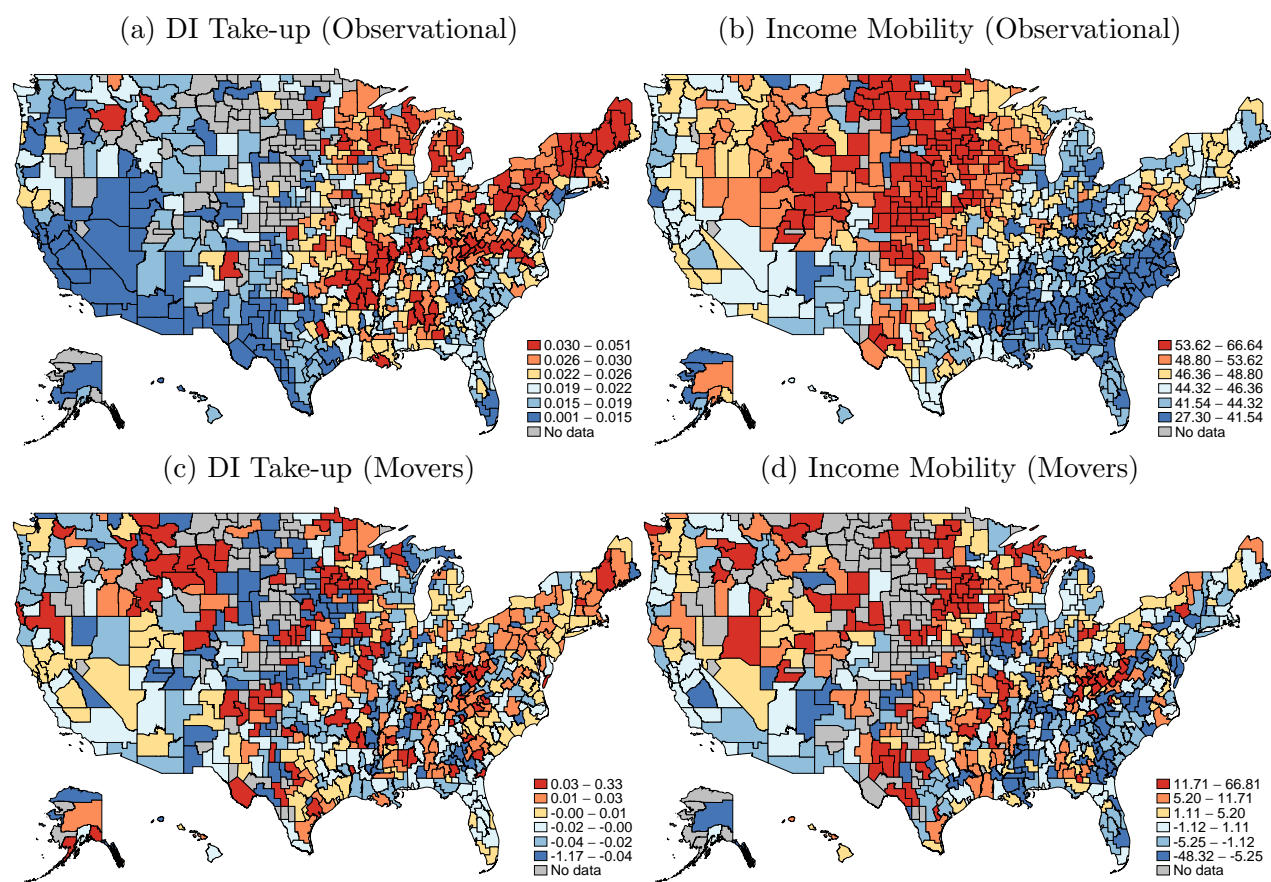
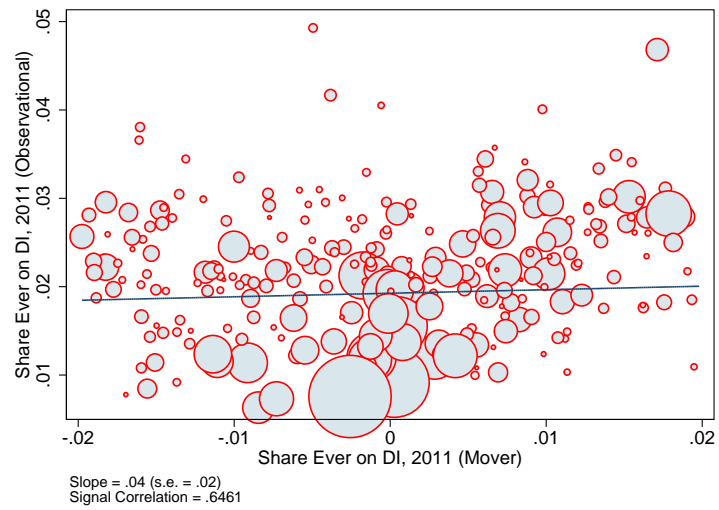


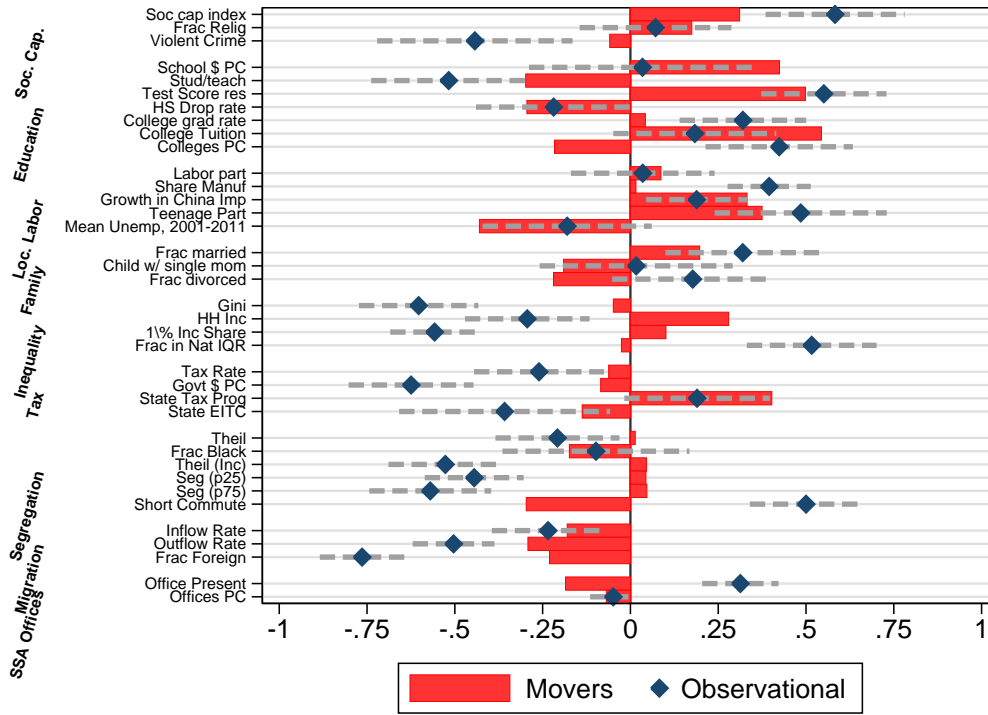
Figure 11: Comparing CZ-level Observational DI take-up in 2011 to Mover Estimates of DI take-up in 2011



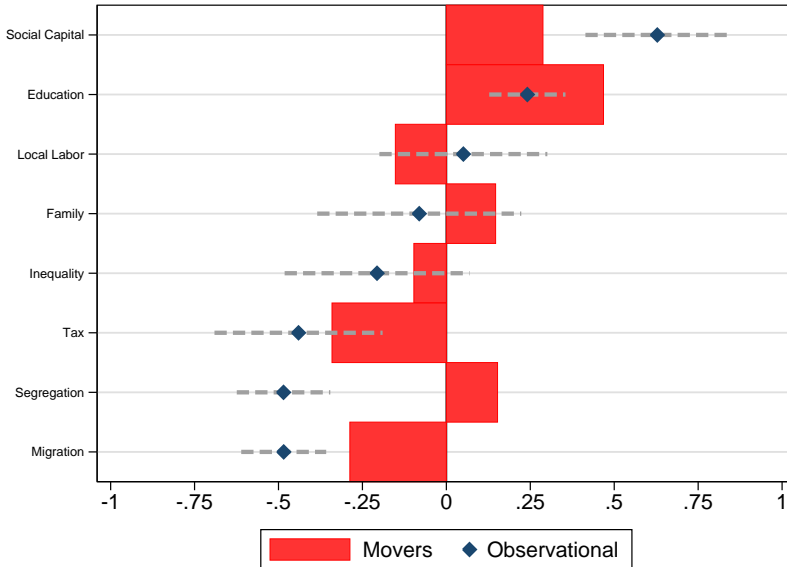
Notes: The estimated correlation in this plot is calculated in the manner described in Section 5.

Figure 12: Local Characteristic Correlations with Share Ever on DI in 2011

(a) Measures



(b) Factors



Notes: Commuting zones are weighted by their 2000 Census population for all correlation estimates. Each factor in sub-figure b) is denominated in the units of its first associated measure in sub-figure a). Gray dashed lines denote confidence intervals for the observational correlations. Mover correlations are constructed by the method described in Section 5.

Figure 13: SSA Field Offices per Capita in 2000, by CZ

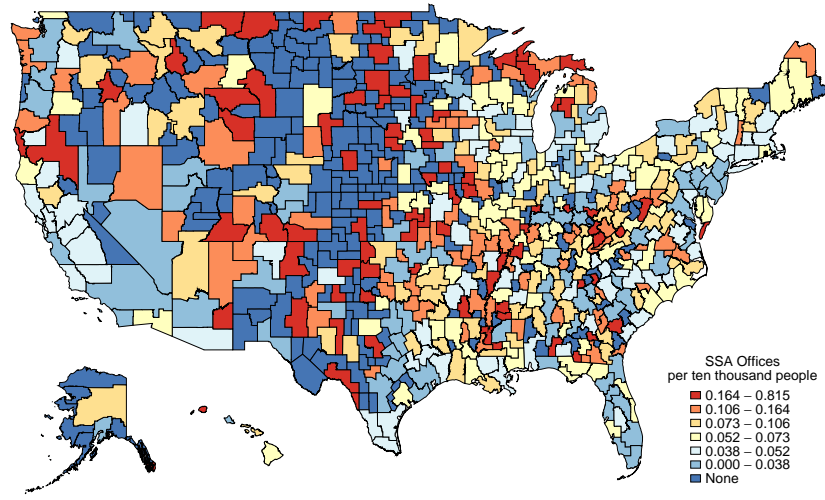
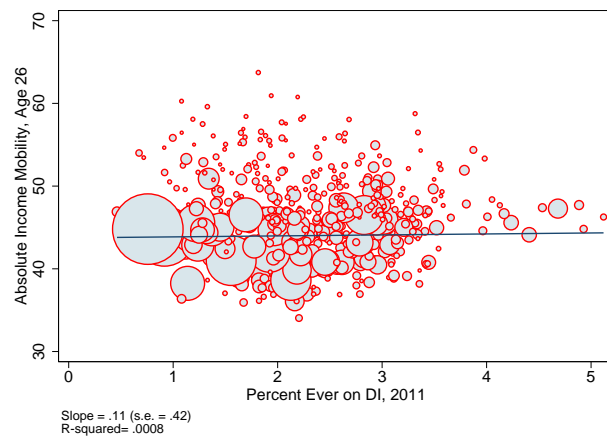
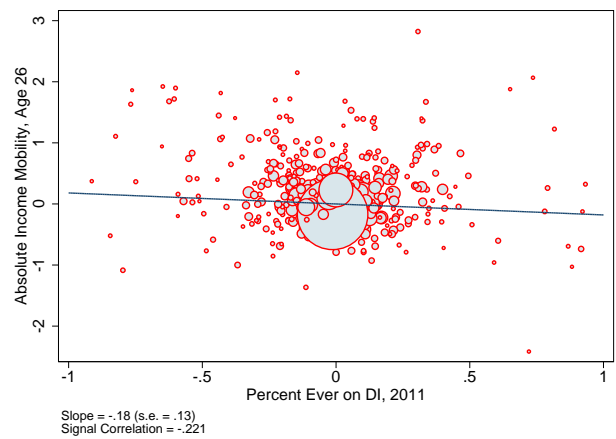


Figure 14: Comparing CZ-Level DI Take-up in 2011 and Income Mobility at Age 26

(a) Observational Estimates



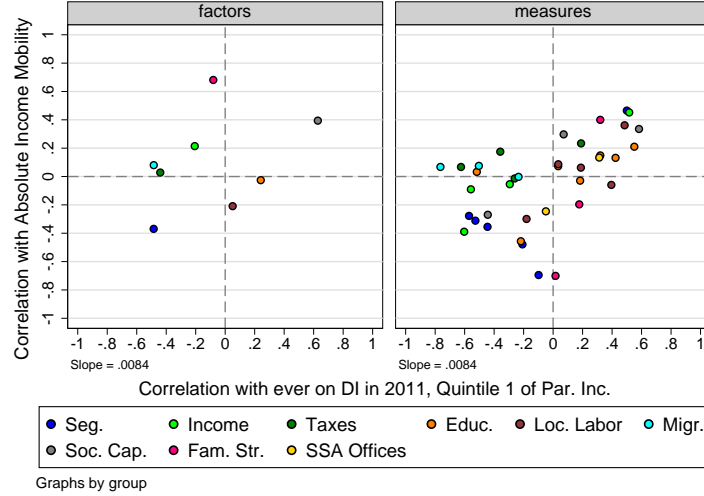
(b) Mover Estimates



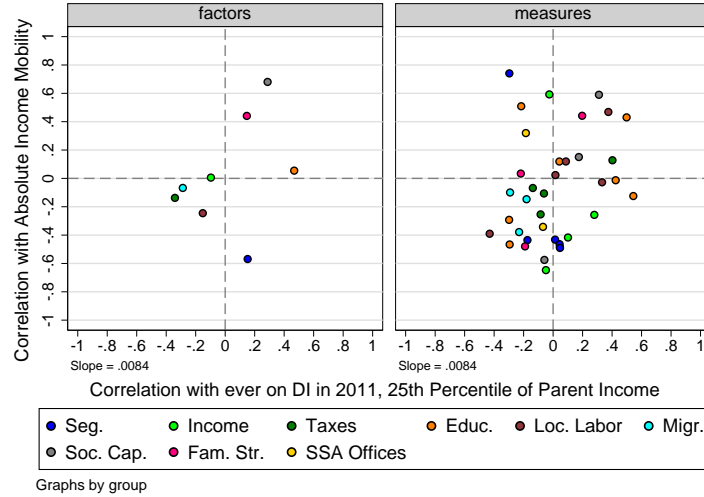
Notes: Mover estimates in this plot reflect the change in the given outcome (relative to the value associated average CZ) associated with spending 1 year of childhood in a given CZ.

Figure 15: CZ predictors of DI in 2011 and Income Mobility at Age 26

(a) Observational



(b) Mover Estimates



Notes: Income Mobility is measured for cohorts 1980-1986 at age 26. It is measured as the expected income rank in 2010 of a child with parents at the 25th percentile in 1996-2000. Lines of best fit are estimated after weighing each correlation pair by the standard error of the estimate for the correlation with ever on DI by 2011.

Appendix A Estimation of Mover Outcomes

We estimate the following equation:

$$DI_i = \alpha_{od} + E_{od} * A_i + E'_{od} * A_i * p_i + f_{od}(s_i, p_i) \quad (1)$$

where A_i is age of move (restricting to moves occurring on or before age 23 and before 2011) 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 birth year s_i and parent income percentile p_i .

We interact the exposure coefficient with parental income percentile, because the evidence of Section 4.1 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 parent 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.

Appendix B Factor Methods

We express each measure j as a linear function of its associated factor F :

$$M_{ij} = \mu_j + \lambda_j F_i + \epsilon_{ij}$$

For each factor, we normalize the first measure so that $\lambda_1 = 1$ and $\mu_1 = 0$ which denominates the factor in terms of units of that measure (e.g., the segregation factor is denominated in units of the Theil index of segregation, the inequality factor in units of the Gini coefficient). Loadings λ_j for $j > 1$ are identified from ratios of covariances

$$\lambda_j = \frac{Cov(M_{ij}, M_{ik})}{Cov(M_{ik}, M_{i1})}, \quad \forall k \notin \{i, 1\}$$

whereas levels μ_j for $j > 1$ are then identified off of measure means:

$$\mu_j = E[M_{ij}] - \lambda_j E[F_i]$$

We assume that the common factor in each category is uncorrelated with the measure-specific errors of measures in that category. We impose that measure errors are mutually uncorrelated within each category. Estimation is performed via two step GMM with the

system of moments described above.

With the factor loadings estimated, we apply the regression method to estimate factor scores, which is equivalent to the Bartlett method used by Heckman, Pinto, and Savelyev (2014) for the single factor model. For each category, our estimate for the associated individual factor score F_i takes the form:

$$\hat{F}_i = \Lambda'(\tilde{M}'\tilde{M})^{-1}\tilde{M}_i$$

where Λ is the column vector (length m) of factor loadings, \tilde{M}_i the column vector (length m) of demeaned individual measures, and \tilde{M} the stacked ($N \times m$) matrix of those vectors, and m is the number of measures associated with factor F . The estimate for the factor score of individual i F_i is a weighted sum of the measures associated with factor F for individual i , with the weight on a measure increasing in the estimated loading for that measure and depending on the variance-covariance matrix for the system of associated measures, $(\tilde{M}'\tilde{M})$.