Online Resource 1

Table S1. White Low Weight Births Only: OLS Models of Income Mobility Outcomes by Income Percentile on Incidence of Low Birthweight Births, Fixed Effects

	(1) 10th Percentile	(2) +Controls	(3) 25th Percentile	(4) +Controls	(5) 50th Percentile	(6) +Controls	(7) 75th Percentile	(8) +Controls
Low Weight Births (%)	-0.046*	-0.053**	-0.034*	-0.042**	-0.014	-0.023*	0.006	-0.003
	(0.023)	(0.020)	(0.017)	(0.014)	(0.011)	(0.009)	(0.015)	(0.016)
Total Population (Log)		-2.191		-2.740		-3.656		-4.572
		(2.299)		(2.003)		(1.969)		(2.495)
Population Density (Log)		-1.141		-1.040		-0.871		-0.703
		(1.859)		(1.596)		(1.653)		(2.245)
Black (%)		0.107		0.035		-0.087		-0.209**
		(0.078)		(0.065)		(0.060)		(0.074)
Latino (%)		0.313**		0.232**		0.098		-0.037
		(0.097)		(0.087)		(0.085)		(0.102)
Single Parent HHs (%)		0.444		0.355		0.208		0.060
		(0.255)		(0.219)		(0.193)		(0.217)
College Grads (%)		0.233***		0.185***		0.106***		0.027
		(0.041)		(0.035)		(0.029)		(0.031)
Less than HS (%)		0.184***		0.110***		-0.013		-0.136***
		(0.036)		(0.031)		(0.027)		(0.031)
Some College (%)		-0.029		-0.040		-0.057*		-0.074**
		(0.034)		(0.030)		(0.026)		(0.028)
Unemployed (%)		0.536***		0.512***		0.472***		0.432***
		(0.099)		(0.082)		(0.064)		(0.069)
Labor Force Pop		0.171*		0.145*		0.101		0.056
		(0.085)		(0.073)		(0.070)		(0.091)
Total HH Income (log)		0.000		0.000		0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)
Poverty Rate		-0.550***		-0.401***		-0.152		0.098
		(0.120)		(0.103)		(0.090)		(0.102)

Foreign Born (%)		-0.598***		-0.521***		-0.394***		-0.266**
		(0.101)		(0.091)		(0.085)		(0.094)
Median HH Inc (Log)		-18.702***		-16.449***		-12.694***		-8.940***
		(2.714)		(2.339)		(2.057)		(2.323)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,416	9,416	9,416	9,416	9,416	9,416	9,416	9,416
R-squared	0.020	0.132	0.013	0.168	0.001	0.232	0.010	0.186

Robust standard errors in parentheses; *** p<0.001, ** p<0.01, * p<0.05

Figure S1. Extreme Bounds Analysis of the Coefficients Predicting Relative Mobility

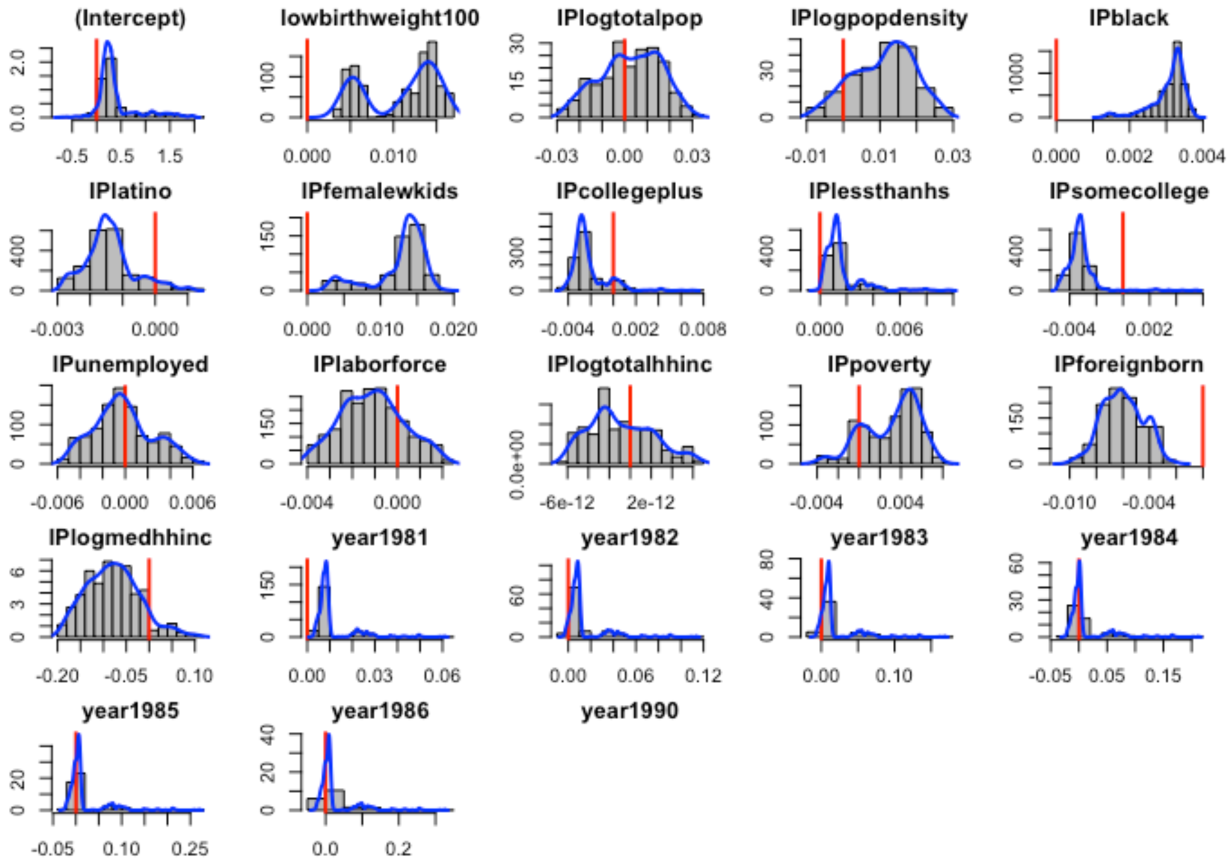


Figure S2. Extreme Bounds Analysis of the Coefficients Predicting Absolute Mobility

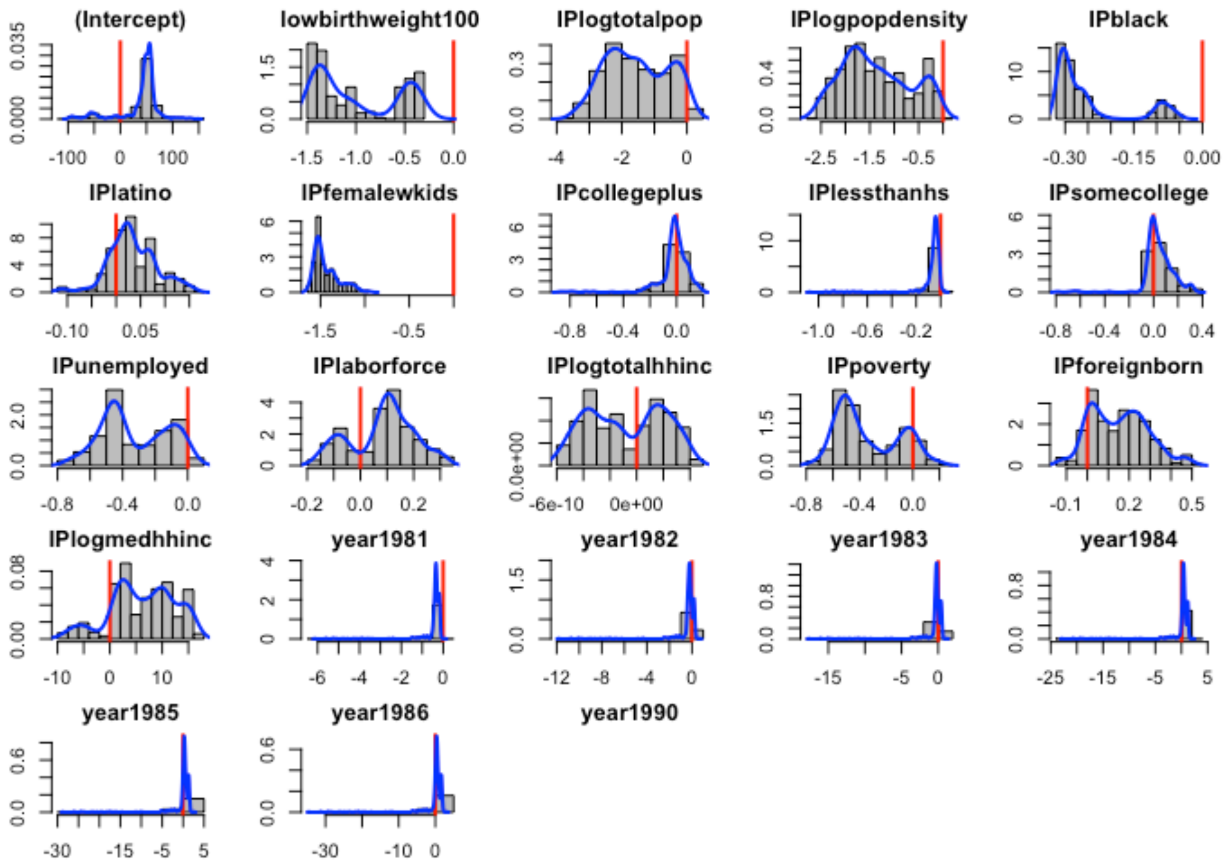


Figure S3. County Level Predicted Mean Income Rank by Percentage of Single Mother Households and Low Birthweight

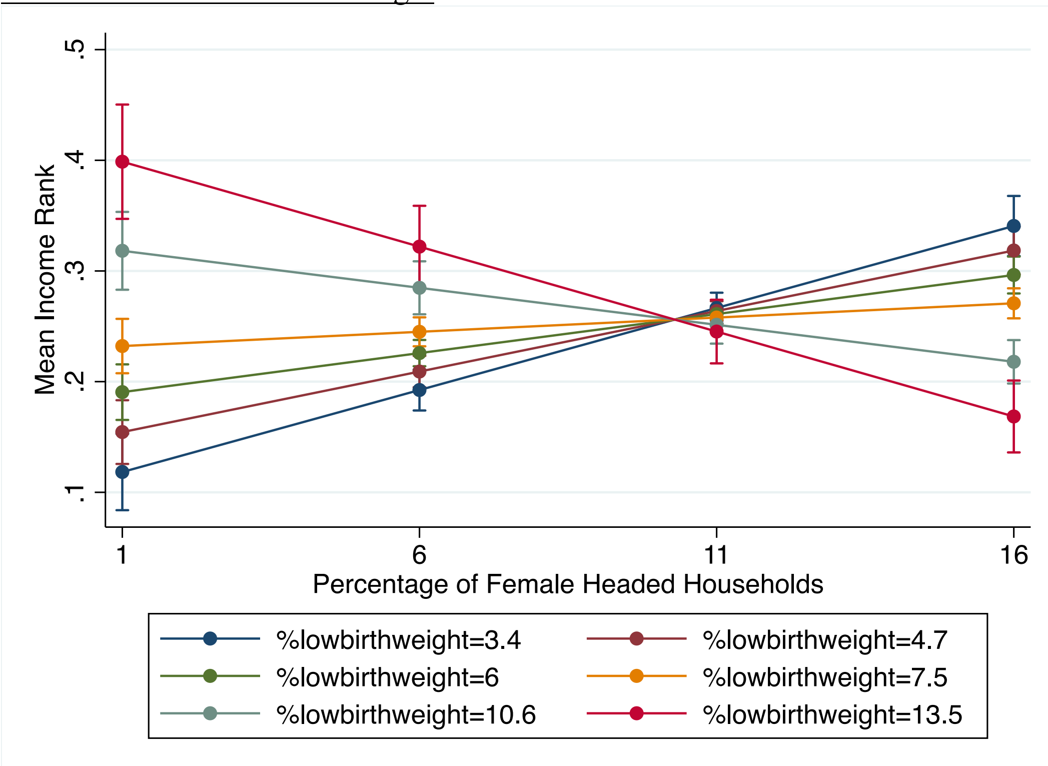
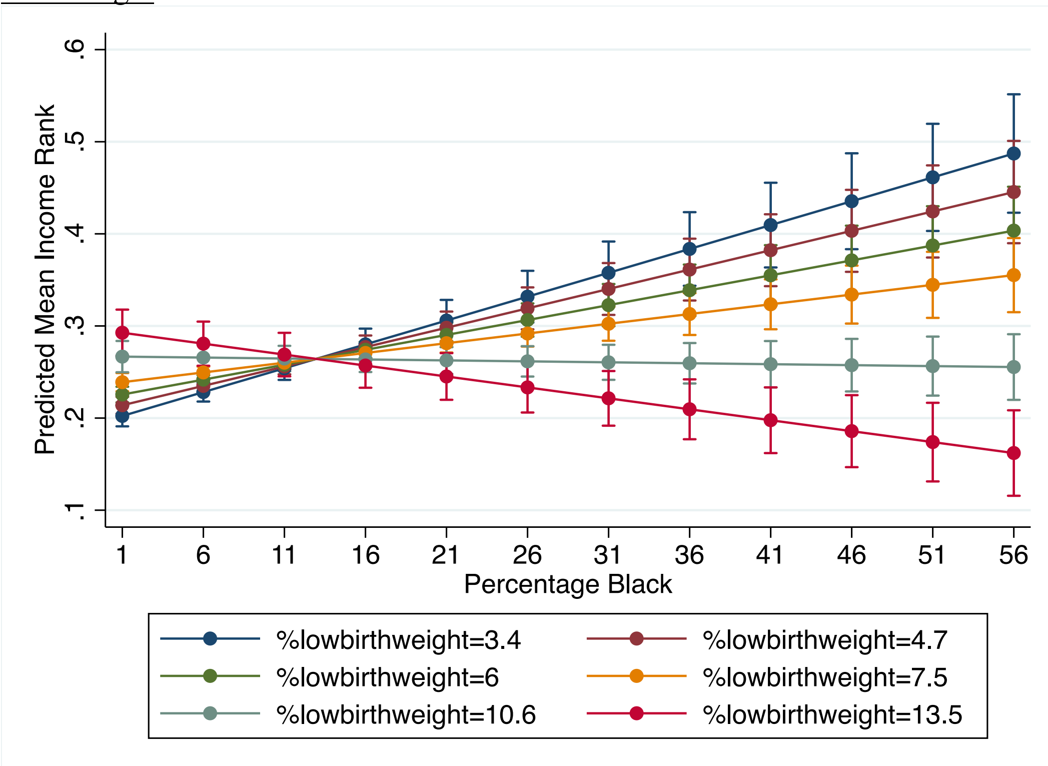


Figure S4. County Level Predicted Mean Income Rank by Percentage Black and Low Birthweight



Data Appendix

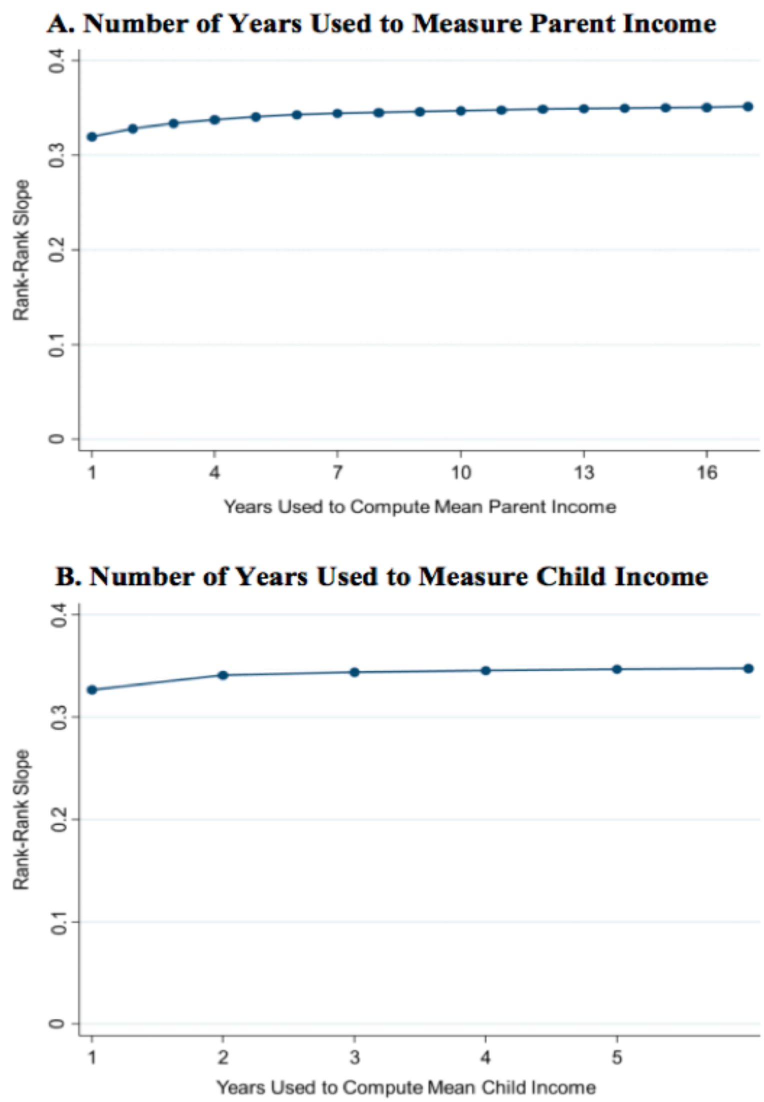
On Measuring Income

Our paper utilizes Chetty et al (2014) public-use data, and thus follows their operationalization of key constructs and data construction processes. Chetty et al (2014a) construct a linked parent-child sample for children born after 1980 using population tax records spanning 1996-2012. This population-based sample includes all individuals born between 1980-1993 who are U.S. citizens as of 2013 and are claimed as a dependent on a tax return filed in or after 1996, obtaining a sample with 3.7 million children per cohort. Population tax records are only available starting in 1996, which is why income is measured at age 12-16 (for the earliest cohort). Parent family income is defined by as adjusted gross income plus tax exempt interest and the non-taxable portion of social security benefits for those who file tax returns. For non-filers, they use the sum of wage earnings (form W-2), unemployment benefits (form 1099-G), and social security and disability benefits (form SSA-1099) to calculate income.

On Only Using One Year of Income Data for Parents

Chetty et al (2014) recognize that using only one year of parental income data may affect the soundness of their mobility estimates. To test for potential bias, Chetty et al compare mobility estimates generated using one year of data for parent and child to estimates generated from using up to five years of data for child income and up to sixteen years of data for parental income (chart reproduced below). They find that their mobility estimates are substantively unaffected by the number of years of income data used. This is due in part to their use of IRS administrative tax data, which likely provides a more accurate estimate of income than what would be reported in longitudinal surveys such as the PSID or NLSY. Using more years of income data certainly increases our confidence in the estimated income correlation between a particular parent and child dyad; however, our mobility estimates are at the county level, averaging across all parent-child dyads in a county for a given birth cohort, so measurement error is less of a direct concern. Therefore, while the reviewer is correct that Behrman and Taubman (1990), Solon (1992, 2002) and Zimmerman (1992 show that annual income overstates economic mobility in comparison with permanent income measures, each of these authors used longitudinal samples, either PSID or NLSY, as opposed to more accurate tax data. As Figure S5 demonstrates, this source of bias is not present in these data.

Figure S5. Attenuation Bias: Rank-Rank Slopes by Number of Years Used to Compute Parent and Child Income (source: Chetty et al, 2014a)



Notes: These figures (reproduced from CHKS) evaluate the robustness of the rank-rank slope estimate to changes in the number of years used compute parent income (Panel A) and child income (Panel B). The figures are based on the population sample of children in the 1980-82 cohorts. In Panel A, each point shows the slope coefficient from an OLS regression of child income rank (based on mean income in 2011-12) on parent income rank as we vary the number of years used to compute mean parent income from 1 to 17. The first point uses parent income data for 1996 only to define parent ranks. The second point uses mean parent income from 1996-1997. The last point uses mean parent income from 1996-2012, a 17 year average. In Panel B, each point shows the coefficient from the same rank-rank regression, but here we always use a five-year (1996-2000) mean to measure parent income and vary the number of years used to compute mean child income. The point for one year measures child income in 2012 only. The point for two years uses mean child income in 2011-12. We continue adding data for prior years; the 6th point uses mean income in years 2007-2012.

Linearity Assumption

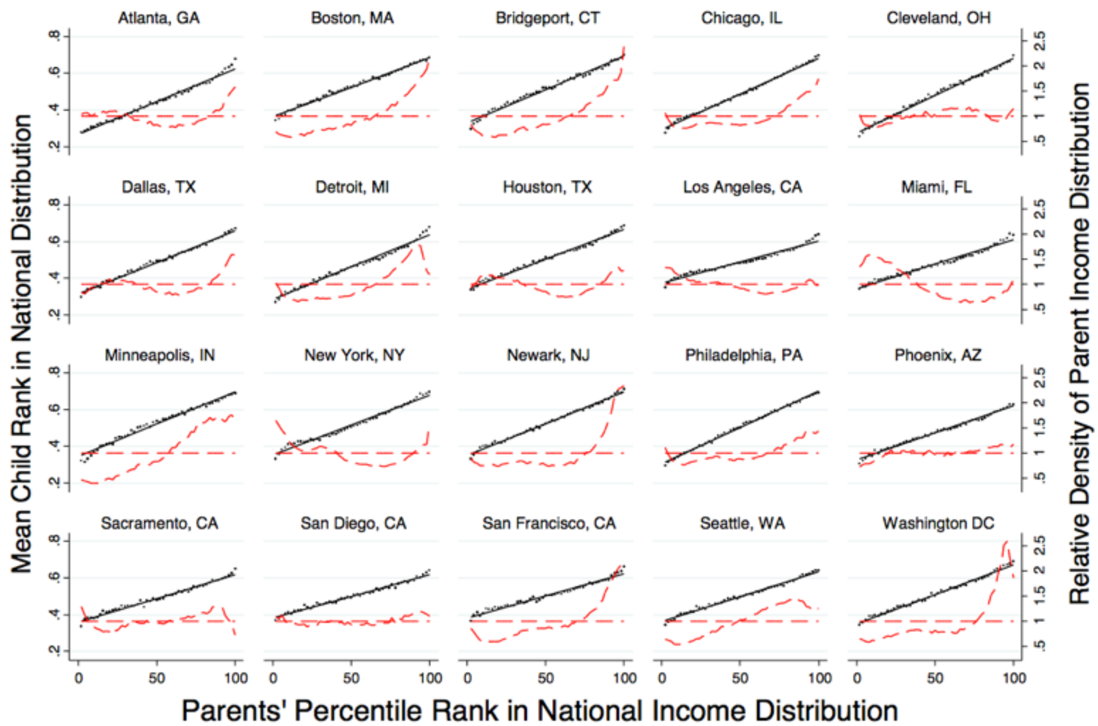
In their 2014 paper, Chetty et al find that the relationship between mean child ranks and parent ranks is almost perfectly linear and highly robust to alternative specifications. Therefore, the slope and intercept generated by the 25th and 75th provide a succinct summary of the conditional expectation of a child's rank given his parent's rank. Importantly, these values are generated from children observed across the income distribution, that is, they observe children at every percentile. Therefore, the 25th percentile and the 75th percentile that we use to calculate other points in the distribution are predicted values from a linear regression, not raw data. Our interpolation is drawn from the same equation used to generate the 25th and 75th percentile. As Figure S6 shows, the relationship is strongly linear, so the assumption of a linear functional form seems appropriate. Chetty et al (2014a) chose rank-rank slope as opposed to the IGE because it is a more robust relationship that is not as contingent on income distributions (one problem is changes in distribution, hard to know), and strongly linear, but therefore not entirely comparable to previous work that used other measures of mobility.

Chetty et al (2014) consider two biases that have been documented in other studies: lifecycle bias due to measuring income at early or late ages (discussed above) and attenuation bias due to noise in annual measures of income (Black and Devereux 2011). They show that estimates of the rank-rank slope are fully stabilized once children reach age 30. By age 26, the estimates are within 20% of the measures of mobility at 30 and are highly correlated across the United States. Thus, although the rank-rank slope is calculated at slightly younger ages than in the majority of the literature, it still gives a reliable prediction of trends in mobility at later ages.

Figure S6 demonstrates the relationship between parent and child income. The conditional expectation of a child's rank given his parents' rank is almost perfectly linear across urban areas. While there appears to be a slight curvature in some of the cities pictured in Table 5 (drawn from Chetty et al 2014a), we unfortunately do not have access to individual level data and must rely on the results in Chetty et al (2014a). They found that overall, across all counties and years, the linearity assumption was appropriate. Though it is possible that some deviate from the linearity assumption, overall, across more than 9,000 observations, the linearity assumption is accurate. Given the numerous specifications that they attempted, as well as a series of robustness checks, detailed in their paper, we believe we may trust their findings and use their data.

Furthermore, the rank-rank slope estimates are generally quite similar across subsamples. The relationship between child and parent ranks is nearly linear in Denmark and Canada as well, suggesting that the rank-rank specification provides a good summary of mobility across diverse environments. The rank-rank slope is 0.180 in Denmark and 0.174 in Canada, nearly half that in the U.S.

Figure S6. Rank-Rank Relationships and Income Distributions in the 20 Largest CZs (source: Chetty et al, 2014a)



Notes: These figures present non-parametric binned scatter plots (shown by the points and solid line, left y-axis) of the relationship between child and parent income ranks in the twenty largest CZs based on population in the 2000 Census. All figures are based on the core sample (1980-82 birth cohorts) and baseline family income definitions for parents and children. Children are assigned to commuting zones based on the location of their parents. Parent and child percentile ranks are always defined at the national level, not the CZ level. To construct each rank-rank series, we group parents into 50 equally sized (two percentile point) bins and plot the mean child percentile rank vs. the mean parent percentile rank within each bin. The dashed curve (right y-axis) in each panel depicts the income distribution in the CZ relative to the national distribution. This curve plots the share of parents with income in each bin in the CZ divided by the share in the same bin in the national income distribution. By construction, this curve averages to one in each CZ, shown by the horizontal dashed line in each panel.

Movers vs Stayers

There are approximately 37.7 million individuals in the "stayers" sample, and 3.7 million individuals in the "movers" sample, therefore, this it a fairly small portion of the sample that we are excluding. To determine whether a child moved during their childhood, Chetty and Hendren had to rely on several different measures, given data limitations. For the 1980 cohort, they measured the location of a child's parents between the ages of 16 and 32. For the 1993 cohort, the looked at parents' location between the ages of 3 and 19. They found that the results do not vary significantly across cohorts. They find that most families who stay in a given area for several years tend not to have moved in the past either – for example, among families who were in the same commuting zone when their child was between the ages of 16 and 24, 91.5% of them were in the same area when their children were 8. Therefore, this is reliable measure. We have added this discussion to the data appendix.

Less than ten percent of the sample is a "mover", a fairly small portion, and thus selection is less of an issue. However, Chetty and Hendren conducted a series of analyses to ensure that there was no selection bias in residential moves. They used three methods to test for selection: controlling for observable factors, isolating moves triggered by exogenous events, and implementing a set of sharp placebo (or overidentification) tests. The most compelling is the placebo test, in which they analyze the heterogeneity in place effects across cohorts. They find that the outcomes of children who move to a new area converged to the outcomes of children who grew up in that area, but interestingly, not the outcomes of the surrounding birth cohorts. Given that parents are probably unable to make such fine grained adjustments to their mobility patterns, and that the effects are observed only after the children grow up, this convergence demonstrates the effect is not confounded by selection and omitted variables. Another compelling test was their examination of sibling pairs. They found a cumulative effect of living in a neighborhood, so younger siblings' outcomes converged on those of permanent residents, while the older siblings showed less of a convergence. This indicates that there is an effect of geography, apart from selection.

The movers sample is somewhat less advantaged than the stayers sample, which we observe. Therefore, the effect of selecting only stayers is more probably underestimating our effect, as we lose from the aggregate data individuals who are below the mean. However, as such a small portion of the sample, it is unlikely to have a large effect. Below, please find the table from Chetty and Hendren outlining key statistics, such as teen birth rate, mean income, and education level for each group[1].

Table S2: Summary Statistics for Permanent Resident and Movers (source: Chetty and Hendren, 2017)

Variable	Mean (1)	Std. Dev. (2)	Median (3)	Sample Size (4)
Panel A: County Permanent Residents and Movers				
Non-Movers				
Parent Income	81,932	320,026	54,800	37,689,238
Child family income at 24	25,066	136,016	19,900	19,956,828
Child family income at 26	34,091	157,537	26,600	15,364,222
Child family income at 30	48,941	133,264	36,200	6,355,414
Child individual earnings at 24	20,686	202,833	17,300	20,069,124
College attendence (18-23)	0.703	0.457	1.000	20,418,691
College quality (18-23)	31,608	13,207	31,400	20,418,691
Teen Birth (13-19)	0.107	0.309	0.000	14,503,588
Teen employment at age 16	0.276	0.447	0.000	37,464,779
County Movers Sample				
Parent Income	76,285	276,185	51,500	3,772,532
Child family income at 24	24,569	54,583	19,500	1,756,981
Child family income at 26	32,985	70,944	25,700	1,323,455
Child family income at 30	47,500	104,900	34,700	532,388
Child individual earnings at 24	19,832	45,082	16,800	1,756,981
College attendence (18-23)	0.637	0.481	1.000	2,316,963
College quality (18-23)	29,691	12,521	29,200	2,316,963
Teen Birth (13-19)	0.115	0.319	0.000	1,356,990
Teen employment at age 16	0.274	0.446	0.000	3,772,532

[1] While the standard deviations on income appear very large, they have no impact on the analysis because we use income ranks, not raw income.