SORTING AND GEOGRAPHIC VARIATION IN INTERGENERATIONAL MOBILITY

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Where children grow up matters for their long-term outcomes. However, sorting, or differences in parent characteristics across locations, biases the best causal estimates of mobility in the literature. I improve on these by estimating sorting-adjusted causal effects of place in the United States. I show that much of the variation across regions is due to sorting. Controlling for sorting reduces the variance across Census regions, divisions, and states by 74, 50, and 39 percent respectively.

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1. Introduction

Recent research has shown that where children grow up is strongly associated with their outcomes as adults. Studies have also shown considerable geographic variation within the United States. Hertz (2008) found that mobility was lowest in the South and highest in the West Census regions. Using administrative data for nearly every child in the United States born after 1980, Chetty, Hendren, Klein, and Saez (2014, hereafter CHKS) are able to characterize the variation at a much finer geographic level. Some U.S. cities have more mobility than even the most mobile countries while others have less mobility than any country for which there is data.[1] They find that parent income is more strongly associated with child income in the South and parts of the Midwest than in the Great Plains or Western states. However, even within regions, there is considerable heterogeneity. In the South and Midwest respectively, Texas and Pennsylvania are characterized by high upward mobility, while Georgia and Ohio are not.

However, these differences could be caused by geographic variation in two sets of factors: 1) local area policies and characteristics or 2) characteristics of the parents and families that live in these areas. Researchers, policy-makers, and parents are may be more interested in which local areas and what local characteristics *cause* better outcomes for children than the geographic variation in parent and family characteristics, or sorting, which is associated with them. Due to data limitations, these can be very difficult to separate.

Chetty and Hendren (2015; 2016a) do so by comparing outcomes of children who move between locations at different ages. With this identification strategy, they are able to control for

[1] Comparing mobility across countries, Jäntti et al. (2006) find that the United States has less intergenerational mobility than the United Kingdom and much less than the Nordic countries. Corak (2013) shows that the United States, United Kingdom, and Italy have less intergenerational mobility than Canada, Germany, and the Scandinavian countries, among others.

both differences between locations in family characteristics as well as selection into moving.[2] They estimate that 50 to 70 percent of the observed geographic variation found by CHKS is causal (Chetty and Hendren, 2015). For a child of low-income parents, a one standard deviation improvement in their location increases their expected income rank at 26 by 2.6 percentage points and their expected income by $2,160 (8.3 percent).

The aforementioned analysis, however, does not identify *which* places matter. It is one thing to know that place is extremely important for the outcomes of children, but another to know which are the better and worse places. To adjust their location choices and policy decisions, parents and policy makers likely require knowledge of the impact of specific places, not just the general rule. To address this, in a companion paper Chetty and Hendren (2016b) estimate the causal effect of each place, at the commuting zone (CZ) and county levels.[3] However, even with as many as 7 million individuals in their sample of movers, they cannot precisely estimate these causal effects.[4]

Given this sampling error, Chetty and Hendren create a forecast to identify the "best" and "worst" places for children to grow up. The forecast involves taking the weighted average of two terms: 1) the unbiased but imprecise causal estimate and 2) the precisely estimated mobility experienced by permanent residents, which is biased due to sorting. The weight on movers in each

[2] They control for sorting across places by studying movers under a fixed effects model. Further, they control for selection into moving by comparing movers of different ages. Their identification relies on the assumption that the timing of parents' moves is orthogonal to children's potential outcomes. This assumption is validated in a variety of ways.

[3] Commuting zones were constructed by Tolbert and Sizer (1996) from the 1990 census. They analyzed data on county-to-county commuting patterns, identified those with strong commuting ties, and grouped them into 741 CZs. Unlike Metropolitan Statistical Areas (MSA), CZs cover the entire country.

[4] The exact mover sample size depends on the particular sample restrictions for a given estimate, but generally exceeds 1 million. Their CZ and county estimates have a sample of 1,869,560 and 1,323,455 children respectively. Chetty and Hendren find that 71 percent of the spatial variation in their CZ-level causal mobility estimates reflects sampling variation, not the causal effects of place. As they acknowledge, these estimates are too noisy to reliably identify which places cause better or worse outcomes for children.

location is a function of the uncertainty of that place's causal estimate. The forecast admits some bias from 2) to reduce the imprecision in 1). Unfortunately, the admitted bias may not be trivial.

This presents a challenge. On the one hand, the causal estimates are too imprecise to reliably identify whether a place causes better outcomes or not. On the other hand, the forecast estimates are likely biased due to sorting. Together, this leaves us uncertain about the true causal impact of each location. As the uncertainty is present despite the near universe file of 44 million children born from 1980-1991 used, it seems unlikely that it can be easily resolved directly.

In this paper, I address this sorting bias by controlling for a set of observable family and demographic characteristics, including parent education, race, and family type. I create sorting-adjusted forecasts of mobility in each location.

Controlling for geographic variation in family characteristics changes our understanding of which regions cause better outcomes for children of low-income families. Forecasts in the South are systematically biased downward by the characteristics of the families that live there. On the other hand, the higher upward mobility forecasts in other the regions are overstated without controlling for sorting. For children of below-median income parents, I estimate that controlling for family and demographic characteristics reduces the population-weighted variance of upward mobility by 74 percent across Census regions, 50 percent across Census divisions, and 39 percent across states.

2. Sorting and Location Effects

2.A. Model

Given n children across C locations, consider a model of intergenerational mobility where the outcome for child i who grows up in location c is a function of J parent family and demographic characteristics $X_i = (x_{1i}, \dots, x_{Ji})$ and K location characteristics $Z_c = (z_{1c}, \dots, z_{Kc})$.[5] Let $X = (X_1, \dots X_n)$ and Z be a K by n matrix of the location vectors Z_c for all children. Allowing for interactions between family and location characteristics, the model for outcome y is:

$$y_i = \alpha + \beta X_i + \gamma Z_c + \sum_{j=1}^{J} \sum_{k=1}^{K} \delta_{jk} x_{ji} z_{kc} + e_i \tag{1}$$

We can estimate the outcomes of permanent residents in a given location (superscript s for stayers), given the average stayer family characteristics in c, $\bar{X}_c^s$, as:

$$S_c = \alpha + \beta \bar{X}_c^s + \gamma Z_c + \sum_{j=1}^{J} \sum_{k=1}^{K} \delta_{jk} \bar{x}_{cj}^s z_{kc} \tag{2}$$

This estimate is subject to sorting if stayer characteristics in c differ from the average, or $\beta(\bar{X}_c^s - \bar{X})$.

CHKS document the tremendous spatial variation in outcomes for children from parent families at each percentile p across locations. They estimate outcomes for permanent residents, where superscript p is added to the family characteristics model in (2) as:

$$S_c^p = \alpha + \beta \bar{X}_c^{sp} + \gamma Z_c + \sum_{j=1}^{J} \sum_{k=1}^{K} \delta_{jk} \bar{x}_{c,ji}^{sp} z_{kc} \tag{3}$$

These estimates include a "pure" sorting component through βX_c^{sp} and a heterogeneous location-sorting component through interactions between location and family characteristics.

2.B. *Fixed Effect Estimation of Location Effects*

It is this sorting that Chetty and Hendren (2016a, 2016b) address. They summarize the family characteristics as a family fixed effect and location characteristics as a location fixed effect. By

[5] The parent family and demographic characteristics can include any information at the family or household level that determines child outcomes, such as parent education, income, wealth, genetics, parent investment in children, etc.

studying movers, they can hold the family fixed effect constant over a child with exposure to two locations.[6] Due to non-random selection into moving, Chetty and Hendren estimate the average treatment effect of living in location c conditional on the distribution of family characteristics of children who move to and from that location.

Let superscript m denote movers so that $\bar{x}_{cj}^{mp}$ is the average of characteristic j for movers to and from location c in parent income percentile p. The causal effect of location c for movers is:

$$M_c^p = \gamma Z_c + \sum_{j=1}^{J} \sum_{k=1}^{K} \delta_{jk} \bar{x}_{cj}^{mp} z_{kc}. \tag{4}$$

The effect of place includes both the pure location effect through γZ_c and the heterogeneous location-sorting component, conditional on mover characteristics. Chetty and Hendren estimate this effect relative to the average across all movers and locations, where $d = (1, \ldots, C)$. Let n_c^m be the number of movers to and from location c and $n^m = \sum_{c=1}^{C} n_c^m$. Using their fixed effect model, Chetty and Hendren estimate μ_c^{mp} separately for children below and above the national median, where:

$$\hat{\mu}_c^{mp} = M_c^p - \sum_d \frac{n_{M_d}}{n_M} M_d^p. \tag{5}$$

If $\hat{\mu}_c^{mp} > 0$, location c has a positive causal impact on child outcomes relative to the average place. Their estimates for $\hat{\mu}_c^{mp}$ are the per-year causal effect of location c.[7]

[6] By comparing movers of different ages with different years of exposure to the origin and destination locations, they can control for selection into moving, conditional on the move being invariant to child age.

[7] For simplicity, I assume M_c^P can be estimated in each location directly without conditioning on the differences in the characteristics of movers between a given location and the origins/ destinations of moves to/from that location, as estimated by Chetty and Hendren. It would be an interesting area for future research to understand how the characteristics of movers differ by location and how that might affect causal estimates in each place.

Unfortunately, even with their extremely large samples, Chetty and Hendren do not have enough observations to precisely estimate the causal effect of growing up in the 741 CZs or 3,142 counties in the U.S.[8] At the CZ level, they find that about 71 percent of the estimated variation in causal impacts is sampling variation, not true causal differences. At the county level, sampling variation accounts for 85 to 90 percent of the observed variation (Chetty and Hendren, 2015). For children of below-median income parents, only 9 percent of CZs representing 24 percent of the population have a statistically significant positive or negative effect on child outcomes relative to the national average, shown in Figure 2 Panel A.[9]

To address this imprecision, they construct a root-mean-square error (RMSE) minimizing forecast for each place c that is a linear combination of S_c^p and $\hat{\mu}_c^{mp}$.[10] First, they regress $\hat{\mu}_c^{mp}$ on S_c^p to get $\hat{\beta}_s$, a constant which reflects the share of permanent resident outcomes not due to sorting from $\beta\bar{X}_c^{sp}$, and, if necessary, rescales S_c^p to match the scale of the estimated $\hat{\mu}_c^{mp}$.

For each location, they calculate the RMSE minimizing weight, w_c, to be placed on the unbiased $\hat{\mu}_c^{mp}$. The weight is a function of two terms: 1) the estimated true variance of $\hat{\mu}_c^{mp}$ across all places and 2) the estimated sampling variance of the causal effect in the given place c.[11] As

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[8] To understand the challenge they face, consider that with a baseline sample of 1,869,560 movers across 741 CZs, they have an average of 2,523 movers per CZ with which to simultaneously estimate the causal effect of each location. Across the 3,142 counties with a baseline sample of 1,323,455, they have about 421 movers per county. Part of the challenge is that moves to or from less populated locations may contribute little to the estimates. A location with few movers has an uncertain causal impact. Therefore, identifying whether a move from that location to a more populated one would improve a child's adult outcome is also uncertain, which affects the precision of the estimate in the more populated location as well.

[9] At the county level, 4.1 percent of all counties representing 5.4 percent of the 2000 population have a statistically significant causal impact (either positive or negative) on the outcomes of below-median income children.

[10] I have excluded the hat from S_c^p because given the size of their sample of permanent residents, the outcomes of permanent residents are measured nearly without uncertainty.

[11] Given the true variance across places c of σ_c^2 and the sampling variance of an individual location c of s_c^2, $w_c = \sigma_c^2/(\sigma_c^2 + s_c^2)$.

the sampling variance in c approaches zero, the weight approaches 1 and the forecast converges to $\hat{\mu}_c^{mp}$. The forecast can be written as:

$$\hat{\mu}_c^{fp} = \hat{\beta}_s S_c^p + w_c(\hat{\mu}_c^{mp} - \hat{\beta}_s S_c^p). \tag{6}$$

From these forecasts at the CZ and county level, Chetty and Hendren characterize which locations cause better and worse outcomes for children. According to their estimates, a child of below-median income parents in the best of the biggest 50 CZs to grow up poor, Salt Lake City, has an expected income rank that is 3.3 percentage points higher than if she grew up in the average location. In the worst of the biggest 50 CZs, New Orleans, the same child has an expected income rank 4.2 percentage points lower than if she grew up in the average location.[12] Chetty and Hendren estimate that a child of below-median income parents growing up in Salt Lake City instead of New Orleans would have roughly \$6,220 higher family income at 26, 24 percent of the national average for below-median children. For a child of low-income parents, a one standard deviation improvement in the CZ causal effect yields an expected income rank increase at 26 of 2.6 percentage points and expected income that is \$2,160 (8.3 percent) higher.[13]

By construction, the forecasts are biased, with the bias equal to:

$$\mu_c^{fp} - \hat{\mu}_c^{mp} = (1 - w_c)(\hat{\beta}_s S_c^p - \hat{\mu}_c^{mp}), \tag{7}$$

where $\hat{\beta}_s S_c^p - \hat{\mu}_c^{mp}$ is a function of sorting through $\beta \bar{X}_c^{sp}$ in S_c^p. Given the uncertainty in the causal estimates, the weight on the biased term, $1 - w_c$, can be large. Figure 2 Panel B shows w_c across CZs. Only 2 percent of CZs have $w_c \geq 0.5$ for forecasts of below-median income children. For the other 98 percent of places, more than half of the weight in the weighted average is on the biased

[12] All estimates for the causal effect of place are calculated as in Chetty and Hendren (2016a, 2016b) by multiplying the annual impact over 20 years of exposure.

[13] This estimate comes from the calculated standard deviation of the true causal estimates σ_c^2, not from the standard deviation of the forecast estimates.

permanent resident term. Across all forecast CZs, the average weight on the unbiased causal estimate is 7.8 percent (34.0 percent weighted by the 2000 CZ population).[14]

This presents a challenge. The imprecise causal estimates and the biased forecasts limit our ability to know if a given location is truly causing better child outcomes. Without more data, a tall order given the near universe file of 44 million children used by Chetty and Hendren, this uncertainty will be difficult to resolve directly.

3. Adjusting for Sorting

Therefore, I take an alternative approach. In an ideal world, I could estimate the causal effect of place directly from permanent residents. Suppose X and Z were observed. From (3), I could decompose S_c^p into the pure sorting component $\beta\bar{X}_c^{sp}$, the pure location causal component γZ_c, and the location-sorting causal component $\sum_{j=1}^{J}\sum_{k=1}^{K}\delta_{jk}\bar{x}_{cj}^{sp}z_{kc}$. As the causal estimates from Chetty and Hendren (2016b) include both the pure location and location-sorting components (although conditional on the characteristics of movers), I could control for the pure sorting component by subtracting $\alpha + \beta\bar{X}_c^{sp}$ from S_c^p to derive the sorting-adjusted causal effect of place, $\tilde{S}_c^p$, directly from the permanent resident mobility as:

$$\tilde{S}_c^p = S_c^p - \left(\alpha + \beta\bar{X}_c^{sp}\right) = \gamma Z_c + \sum_{j=1}^{J}\sum_{k=1}^{K}\delta_{jk}\bar{x}_{cj}^{sp}z_{kc} \qquad (8)$$

Alternatively, I could replace the biased S_c^p term with an unbiased one by subtracting $\beta\bar{X}_c^{sp}$ when creating the forecast $\hat{\mu}_c^{fp}$. This would give an unbiased "forecast":

$$\widetilde{\mu}_c^{fp} = (1-w_c)\widetilde{\beta}_s\left(S_c^p - \beta\overline{X}_c^{sp}\right) + w_c\hat{\mu}_c^{mp} = (1-w_c)\widetilde{\beta}_s\tilde{S}_c^p + w_c\hat{\mu}_c^{m}, \qquad (9)$$

[14] For estimates of above-median income children, the average w_c across all CZs is 2.8 percent, or 17.6 percent weighted by the 2000 population.

which is a weighted average of two unbiased terms, the sorting-adjusted permanent resident term and the mover causal effect term, given the $\tilde{\beta}_P$ coefficient from regressing $\hat{\mu}_c^{mp}$ on $\left(S_c^p - \beta \bar{X}_c^{sp}\right)$.

In this ideal world, (8) would be preferable to (9) as it involves estimating the relevant causal effect directly. Unfortunately, it is nearly certain that many of the variables in X and Z are unobserved, and $\beta \bar{X}_c^{sp}$ cannot be estimated.

However, suppose there exists a subset of observed family characteristics X_O with the remaining X_U unobserved, where X_O has J_O characteristics, X_U has $J_U = J - J_O$ characteristics. We can decompose βX_i into $\beta_O X_O + \beta_U X_U$. If β_O were known, we could eliminate a portion of the contribution of sorting to permanent resident outcomes in location c by subtracting $\beta_O X_{Oc}^p$ from S_c^p. We could consider this a lower bound on the sorting adjustment if we assume that the sign of $\beta_O X_O$ and $\beta_U X_U$are the same.[15] We could use the sorting-adjusted permanent resident outcomes to estimate sorting-adjusted forecast $\tilde{\mu}_c^{fp}$ from (9) as:

$$\tilde{\mu}_c^{fp} - \hat{\mu}_c^{mp} = (1 - w_c)\left(\tilde{\beta}_s\left(S_c^p - \beta_O \bar{X}_{Oc}^{sp}\right) - \hat{\mu}_c^m\right). \tag{10}$$

However, if we estimate β_O given the available data as:

$$y_i = \alpha_O + \beta_O X_{Oi} + v_i, \tag{11}$$

omitted variable bias is almost certainly present due to the absence of X_U, Z and all interactions. The expected value of $\hat{\beta}_O$ from (11) is:

$$E\left(\hat{\beta}_O | X_O\right) = \beta_O + E\left[(X_{Oi}' X_{Oi})^{-1} X_{Oi}' \left(\beta_U X_{Ui} + \gamma Z_c + \sum_{j=1}^{J} \sum_{k=1}^{K} \delta_{jk} x_{ji} z_{kc}\right)\right] \tag{12}$$

Because X_O is very likely correlated with X_U and Z, estimates from (11) of the relationship between family characteristics and child outcomes are not causal. The correlations with X_U are

[15] It seems reasonable to assume that observed and unobserved characteristics are sufficiently correlated so that if observed characteristics are associated with better (worse) outcomes, generally so are unobserved characteristics.

not necessarily a concern. We would like the sorting adjustment to control for as much of the true underlying variation in parent characteristics as possible. To the extent that X_O and X_U are correlated, $\hat{\beta}_O X_O$ captures a greater share of the true sorting than would be captured under the true causal parameter β_O. As an extreme example, if X_O and X_U were perfectly correlated and neither were correlated with Z, $E\left(\hat{\beta}_O X_O\right)$ would equal βX.

Unfortunately, correlation between X and Z does present a problem. In their preferred forecast estimates, Chetty and Hendren find worse outcomes for children in the South, including many areas with high concentrations of Black children. A regression coefficient for Black estimated from (11) could therefore be biased by the omitted location characteristics.

Even if I assume Z is not observable and that the location effect coefficients γ and δ_{jk} cannot be estimated, I do have information on the location effects. From CHKS and Chetty and Hendren, I have estimates of permanent resident outcomes (S_c^p), unbiased causal effects ($\hat{\mu}_c^{mp}$) and forecast causal effects ($\hat{\mu}_c^{fp}$). I can test how large the likely biases are by including these or functions of these location fixed effects in the regression with X_O. In the simplest form, I include location fixed-effect estimates $\theta_c = S_c^p$, $\hat{\mu}_c^m$, or μ_c^f in the regression as:

$$y_i = \alpha_O + \beta_{O|\theta} X_{Oi} + \gamma_\theta \theta_c + \sum_{j=1}^{J_O} \delta_\theta x_{Oji} \theta_c + v_i. \qquad (13)$$

This strategy allows me to control for the relationship between the effect of place (as a fixed effect) and the individual characteristics in the CSD data. To the extent that the average effect of $\gamma Z_c + \sum_{j=1}^{J} \sum_{k=1}^{K} \delta_{jk} x_{ji} z_{kc}$ in each location c is correlated with individual characteristics and biases the regression of y_i on X_{Oi}, the results from (13) and (11) should differ. If, on the other hand, $\hat{\beta}_O \approx \hat{\beta}_{O|\theta}$, then we can assume that, conditional on the average characteristics of those individuals used to estimate θ_c, the location omitted variable bias is not severe. This would imply that we can use $\hat{\beta}_O X_O$ to adjust for sorting in the Chetty and Hendren forecasts as in (10).[16]

4. Data

This paper uses three data sources to control for sorting bias and improve estimates of the causal effects of place. The first source are the results made available by Chetty and Hendren on their website[17] for other researchers to use. The second source is survey data linked to longitudinal administrative earnings data, which I use to construct a sample of parents and children with information on their family characteristics and earnings. This data is used to estimate the relationship between observable characteristics and child outcomes, controlling for location effects. This allows me to adjust for sorting at the local level using the third data set, microdata from the 1990 Long Form Decennial Census.

To estimate the relationship between observable characteristics and child outcomes, $\hat{\beta}_O$, I construct a sample of parent-child pairs with information on parent family characteristics and parent family and child individual earnings. The parent-child links and information on parent family characteristics come from two surveys conducted by the U.S. Census Bureau, the Current Population Survey Annual Social and Economic Supplement (CPS ASEC) and the Survey of Income and Program Participation (SIPP). The earnings data comes from W-2 records and 1040-

[16] An important caveat is that location characteristics interacted with family characteristics may still introduce bias in this analysis. Suppose most or all location have policies (characteristics) that cause better or worse outcomes by race or parent education. In that case, $\hat{\beta}_O X_O$ will be biased by the location-invariant policy/family characteristic interacted causal impact. However, even in this case, the sorting-adjusted estimates may be preferable. Some of the variation in observed S_c^p would still be due to sorting, or variation in characteristics X, but in this case due to $\bar{x}_{c,ji}^{sp}$ in $\sum_{j=1}^{J}\sum_{k=1}^{K}\delta_{jk}\bar{x}_{c,ji}^{sp}z_{kc}$ and not $\bar{X}_c^{sp}$ in $\beta\bar{X}_c^{sp}$.

[17] http://www.equality-of-opportunity.org/

SE forms filed with the Social Security Administration (SSA) and the Internal Revenue Service and shared with the Census Bureau in the Detailed Earnings Record (DER) extract from the SSA Master Earnings File. Individuals are linked between the Census surveys and the DER by matching survey respondents to their Protected Identification Keys (PIK).[18]

The CPS ASEC data available for linking to the DER and used in this paper come from the following survey years: 1991, 1994, 1996-2009. The SIPP data used in this study come from an internal data product at the U.S. Census Bureau, the SIPP Gold Standard File (GSF), which contains SIPP data linked to administrative records. I use data from the SIPP panels in 1990-1993, 1996, 2001, 2004, and 2008. In the CPS ASEC, only children aged 15 and older were matched to their SSNs to allow matching to the DER. I only include children observed in their parent household up to age 18. The DER file contains annual wage and self-employment earnings from 1978 to 2012.

To be included in the CPS-SIPP/DER (CSD) sample, each parent-child pair must be matched to their individual PIKs. A pair is successfully matched if the child and all parents (both parents in two-parent families and the individual parent in one-parent families) are successfully matched. The match rates for the CPS ASEC and SIPP samples by child age cohort is reported in Table 1. Over all cohort groups in both surveys, the average match rate is 76 percent.

This data has a number of advantages over the data that has been used in the literature. First, in comparison to the administrative tax data used by CHKS and Chetty and Hendren, the CSD data contains a wealth of information on parent family characteristics, including race, education,

[18] The process by which CPS ASEC and SIPP individuals are linked to the DER file is described in Wagner and Layne (2014). Each individual in each survey is matched to their Social Security Number in the Social Security Administration Numident file. The SSNs and personally identifying information are then removed from the data and individuals are given a Personal Identification Key to enable the linkage for researchers working with these datasets.

occupation, industry, health insurance coverage, etc. There are, however, several disadvantages as well. The most obvious is that the CSD sample is orders of magnitude smaller than the administrative tax records. In my baseline sample, there are 49,559 parent-child pairs compared to about 10 million in the CHKS baseline and approximately 1-2 million in the Chetty and Hendren baselines. In addition, the DER file only contains information about wage and self-employment earnings taxable by Social Security, but not about other taxable income sources. The 1040 data used by CHKS and Chetty and Hendren also contains information on the marital status and income of the children's spouses. This information is not present in the DER. This limits me to analyses of intergenerational earnings mobility between parent families and their individual children.

On the other hand, the CSD data set is also much larger than comparable survey data, such as the PSID and NLSYs. Another advantage of the CSD over longitudinal surveys is that the CSD earnings are from administrative data, which may make them less subject to measurement error. However, relative to the PSID and NLSYs, the CSD data contains much less information about the parent and child households, especially for the children as adults. The size of the data set, relative to the alternative longitudinal surveys, is crucial for the analysis. In order to test for omitted variable bias and location effects as in (13), I need a sample large enough to give me sufficiently precise estimates. With too few observations, failure to reject that $\hat{\beta}_O = \hat{\beta}_{O|\theta}$ could be due to either insufficient power or the absence of omitted variable bias.

As the CSD data comes from surveys using stratified random sampling, for all regressions and summary statistics, I use the CPS ASEC and SIPP sample weights normalized by survey and cohort age.[19] As I combine observations from two surveys over multiple survey years, the weights are adjusted by child age cohort and survey, which is discussed in greater detail in Appendix A.

[19] For a discussion of the use of weights in OLS, see Solon, Haider, and Wooldridge (2013).

An important step in analyzing mobility is to determine at what ages to measure parent and child earnings as a proxy for lifetime earnings. For parents, I average family earnings over the 5 years when the older parent is 40-44 years old. This was chosen for two reasons. First, the literature on life-cycle bias in estimates of intergenerational mobility suggests measuring income around 40 to minimize bias (Haider and Solon 2006). Second, this choice allows me to better compare my results to CHKS and Chetty and Hendren as they use a 5-year average of parent income in their analysis.

For children, I follow CHKS in measuring earnings near the age of 30. They find little lifecycle bias in rank-rank income mobility by age 30 in child income.[20] To test for bias in the CSD sample, I plot the rank-rank slope of intergenerational earnings mobility with child earnings measured over two years varying child age from 24 to 32, shown in Figure 1.[21] Panel A shows the effect of measuring earnings by age for the full sample. The general trend is similar to that in CHKS with increases at younger ages and potentially slight decreases at higher ages, but few of the differences are statistically significant. Panel B shows the trend for sons, which is increasing up to about 29 and relatively flat above. The slight downward trend in Panel A is due to a decrease in the rank-rank slope of individual earnings for daughters, shown in Panel C. I use average child earnings at 29 and 30 for the baseline sample to match the period used in CHKS, where income was measured at 29-32 years old depending on the child's year of birth.

[20] Mazumder (2015) shows that lifecycle bias is present in the CHKS and Chetty and Hendren results. However, that bias is relatively small in rank-rank mobility measures. He also notes that the bias likely has little effect on the geographic variation they find.

[21] I assign ranks to each parent family by comparing them to all parents in any year of the CPS ASEC and SIPP in the same age cohort as the older parent. For children, I assign an earnings rank by comparing each child to the cohort of all individuals in the same age cohort observed in any year of the CPS ASEC and SIPP, whether the individuals were observed as children or adults. In both cases, the comparison groups are much larger for each cohort than my sample of parents or children in the intergenerational mobility analysis. For more detail, see Appendix A.

To estimate $\bar{X}_{Oc}^{sp}$ in the sorting adjustment, I use microdata from the 1990 Long Form Decennial Census. The Long Form census contains information on 5.1 million households with 10.1 million children 18 and under. It is a roughly 1/6th sample of the population and represents 32 million child families with 64 million total children. The census microdata contain all of the same family and demographic characteristics I use from the surveys in the CSD file. The data also contain survey responses for parent income and earnings, which I use to assign parent ranks in the national distribution for the purpose of adjusting for local differences in parent family and demographic characteristics.

In Table 2, I report summary statistics for family and demographic characteristics of the baseline sample for three groups: 1) the sample of children 18 and under in the 1990 Long Form census (column 1), 2) the sample of all parent-child pairs in the Census surveys (columns 2-4), and 3) the sample of parent-child pairs where both generations were successfully matched to their SSNs (columns 5-7).[22] The family characteristics are taken from the first observation in a CPS ASEC or SIPP survey. I measure parent education as the level achieved by the more educated parent.

For the sample of all parent-child pairs, the share of Blacks and Hispanics in the CPS ASEC and SIPP are not statistically significantly different from one another or the 1990 Census. However, for parent education and share of single parent families, there are statistically significant differences. The SIPP has a higher share of parents with no high school degree and a lower share of parents with a college degree than the CPS ASEC.

[22] Kernel densities of the parent and child earnings distribution of matched parent-child pairs in each survey are available in Appendix Figure 1.

Comparing the SSN-matched parent-child pairs to the full set in each sample shows that there is some selection into matching. Blacks, Hispanics, and families with less educated parents are less likely to be matched than Whites and families with more educated parents. Despite this selection, the matched sample is broadly representative of the underlying full set.

More details about the data, weighting, and ranking of parents and children is available in Appendix A.

5. Results

As a first step, I establish that the CSD data and the data used by CHKS and Chetty and Hendren are comparable, which I summarize briefly here and discuss in detail in Appendix B. First, I find a rank-rank regression coefficient for parent family earnings to child individual earnings in the CSD data that is very close to the most comparable coefficient in CHKS, shown in Appendix Table 1.[23] Next, I show that the spatial variation in upward mobility in CHKS is also present in the CSD data. Because the CSD sample is too small to estimate CZ-level mobility directly, I compare it to the CHKS results by grouping CZs based on the observed upward mobility in CHKS. I compare the CZ-group mobility estimates from CSD to the CHKS results, shown in Appendix Table 2. Despite the differences in the samples (survey-linked vs. administrative data) and outcome measures (parent family earnings-child individual earnings in the CSD vs. parent family income to child family income in CHKS), I find very similar patterns of spatial variation in child outcomes.

[23] The CSD estimate is 0.251 compared to 0.282 in CHKS despite differences in the measure of income/earnings used to define parent rank.

5.A. Baseline Model

I regress child earnings on parent earnings and a small set of family characteristics available in both the CPS ASEC and SIPP. I include parent family earnings rank, race and ethnicity (Black and Hispanic), education of the most educated parent, child gender, family type (teen, single, and unmarried parents), as well as various interactions between these characteristics and parent earnings rank. A subset of the results are shown in Table 3, Column 1.[24]

For the coefficients on Black, both the dummy (level) and dummy interacted with rank (slope) are statistically significantly different from Whites. The greater slope for Blacks means that parent earnings are more strongly associated with outcomes for Black children. The lower intercept means that Black sons start at a considerable disadvantage before accounting for parent earnings.

Some examples can help convey the magnitude of the gap between Black and White sons. Given a White son whose parents have earnings at the median, for a Black son to have the same expected rank, his parents would have to be at the 97th percentile. For a White son with parents at the 25th percentile, a Black son's parents would need to be above the 78th percentile for their children to have the same expected rank. Black females on the other hand are not disadvantaged relative to Whites.

Even controlling for parent earnings, parent education level is an important predictor of child earnings. Two children have the same expected rank if one child has a parent with a college degree and another's parent has high school diploma and earnings that are 39 percentage points higher ($8.42/0.215 = 39.2$). Likewise, the expected rank is the same for a child with a high school educated parent and another child with no parent that completed high school and a 29 percentage point higher parent earnings rank ($6.19/0.215 = 28.7$). In both cases, the point estimates on the

[24] More complete results are shown in Appendix Table 6.

interaction terms suggest this gap narrows at higher parent earnings levels. Despite the very large effects of parent education, the coefficient on parent rank is largely unchanged from the earnings-only regression. It declines from 0.251 to 0.215, or only 14 percent.

5.B. Testing for Omitted Variable Bias

However, these results could be due to bias from the omitted location characteristics, which I test for as in (13). I test three measures of location effects from Chetty and Hendren: 1) the observed outcomes for permanent residents, 2) their preferred forecast estimates and 3) the unbiased but noisy causal estimates. I include the location effects 1) as continuous variables and 2) as dummies by CZ quintile.[25]

The results are shown in Table 3, Columns (2)-(7). In Columns (2), (4), and (6), I include only location effect (permanent resident, forecast, and causal respectively) and the effect interacted with each variable in the baseline model.[26] In columns (3), (5), and(7), I replace the continuous location effects with dummies for the location-effect quintile in the CZ distribution.[27] I also add additional location characteristics.[28]

[25] For each child, the location effect and effect quintile is the relevant one for below- or above-median income families.
[26] Because the location effect is different for below- and above-median children, when interacted with parent rank, I subtract 50 from the above-median ranks to put them in the same range as the below-median group.
[27] The third quintile dummy is excluded to better match the coefficients in columns with continuous location effects.
[28] These characteristics are: 1) segregation and spatial mismatch (fraction with a commute under 15 minutes), 2) income inequality (GINI for the bottom 99%), 3) school quality (high school dropout rate), 4) social capital (index constructed and used by Goetz and Rupasingha (2006)), and 5) rate of single parenthood (fraction of single mothers). CHKS show that all of these characteristics are correlated with upward mobility of children from low-income families, and that these relationships are robust to the inclusion of other location characteristics in a regression.

Strikingly, almost none of the coefficients for family characteristics in columns (2)-(7) are statistically significantly different from those in column (1) in the baseline model.[29] The results support that $\hat{\beta}_O \approx \hat{\beta}_{O|\theta}$ and that the sorting adjustment to the Chetty and Hendren forecast proposed in equation (10) is valid.

Despite the absence of omitted variable bias, Chetty and Hendren's preferred forecast location effects do strongly predict child earnings rank, shown in column (4). Children observed in locations with a 1 percentage point per year increase in expected child family income rank have an expected 13.4 percentage point higher individual earnings rank at 29.

5.C. Sorting-Adjusted Causal Effects of Place

Given $\hat{\beta}_O$ from the baseline model, I use the 1990 Long Form Decennial Census microdata to estimate the family characteristics $\bar{X}_{Oc}^{sp}$ in each location c. With $\hat{\beta}_O$ and $\bar{X}_{Oc}^{sp}$, I can apply the sorting-adjustment to the forecast as in (10).

To estimate $\bar{X}_{Oc}^{sp}$, I impute a sorting-adjusted expected child rank for permanent residents at each parent rank in each location as follows. Each set of parents is assigned a rank based on their position in the national earnings distribution of parents in the age cohort of the older parent. The rank is based on the total family earnings in 1989 reported in the census. Using this parent rank, I

[29] Only the less than high school education dummy interacted with parent rank is statistically significantly different in (5) than in the baseline model (1), and the difference reflects a lower intercept (-8.19 vs. -6.17, not statistically significant) and the statistically significant steeper slope from the interaction. This would likely result in a larger sorting adjustment than the baseline model.

assign a predicted rank to each child ($\hat{y}_i$) using the CZ- or county-level slope and intercept estimates from CHKS.[30]

With the baseline model characteristics, I subtract $\hat{\beta}_O X_O$ from the imputed child rank to get the sorting-adjusted expected child rank ($\tilde{y}_i$):

$$\tilde{y}_i^p = \hat{y}_i^p - \hat{\beta}_O X_{Oi}^p. \tag{14}$$

The adjustment converts the expected child rank at each parent rank to that of the model baseline group of White sons of married, high school educated parents – the most common group in each category in the CSD data.

For each location c, I estimate the sorting-adjusted permanent resident slope and intercept by regressing $\tilde{y}_i$ on parent rank. The sorting-adjusted slope and intercept summarize the relationship between parent and child ranks controlling for the observable characteristics in my baseline model. This gives me an estimate of $\left(S_c^p - \beta_O \bar{X}_{Oc}^{sp}\right)$ at each parent percentile for each location c. An example of the sorting adjustment is shown in Figure 3.

Because the CHKS slope and intercept were used in creating $\left(S_c^p - \beta_O \bar{X}_{Oc}^{sp}\right)$, I also use them to calculate my unadjusted permanent resident expected child rank, S_c^p, at the 25th and 75th percentile in my baseline sorting-adjusted estimates.[31] I report all of the results using the Chetty and Hendren permanent residents expected rank (child family income at 26) as S_c^p in the Appendix and note any important differences in the text or footnotes of the paper.[32]

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[30] I use the two-parameter estimates (slope and intercept) from CHKS in each location, which lend themselves to imputing child rank from parent rank. CHKS show that rank-rank relationship is linear both nationally and by location.

[31] Given the linear rank-rank relationship, the 25th and 75th percentile are also equivalent to below- and above-median average outcomes for permanent residents conditional on a uniform distribution of income rank in each location.

[32] The correlation between P_c 1) for below- and above-median children in Chetty and Hendren and 2) at the 25th and 75th percentile using the CHKS slopes and intercepts is 0.97 or above whether weighted or unweighted by 2000 population. The same is true for the correlations

First, I calculate how the sorting adjustment affects the expected child rank (the magnitude of $\beta_O X_O^p$) in each location. Figure 4 Panel A shows the CHKS estimates of expected child rank for children at the 25th percentile by CZ. In Panel B, I map the sorting adjustment. The maps look strikingly similar. The correlation between the CHKS estimate and the sorting adjustment is -0.70 across CZs.[33]

Chetty and Hendren (2015) estimate that 35 to 50 percent of the variation in expected child outcomes across CZs is due to sorting. This can help benchmark how well the characteristics in the baseline model capture sorting. I calculate the sorting-adjusted expected rank for children of 25th and 75th percentile parents. Comparing the unadjusted and sorting-adjusted estimates, I find that 46 percent of the variance for children at the 25th percentile and 0 percent of the variance at the 75th percentile is due to sorting.[34] For low-income children, the observed characteristics (and correlated unobserved ones) appear to capture the majority of the variation in expected rank across CZs that is due to sorting.

Finally, I estimate the sorting-adjusted causal forecast as in (10) at the 25th and 75th percentile, which represent children from below- and above-median income families given the linear rank-rank relationship. Figure 5 Panel A, shows the unadjusted forecast estimate for below-median

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between forecasts calculated using the different permanent resident estimates as S_c^p. Due to the different S_c^p used in the forecasts, the unadjusted forecasts discussed in this paper will differ slightly from those reported by Chetty and Hendren (unless otherwise noted in specific Appendix figures and tables).

[33] Appendix Figure 14 and Appendix Figure 15 show scatter plots of the various measures of mobility by CZ. The figures show the relationship between the causal and unadjusted forecast estimate in Panel A. In the rest of the panels, the relationship between each causal estimate and the unadjusted and adjusted permanent resident mobility is shown. While the permanent resident outcomes are nearly perfectly correlated with the unadjusted forecast, they are much less correlated with the imprecise causal estimates.

[34] Both are weighted by 2000 population. Unweighted, the variance reduction is 39 percent at the 25th percentile and 1 percent at the 75th percentile.

children by CZ. In Panel B, I map the difference between the unadjusted and adjusted forecasts. Again, the maps show similar geographic patterns. The population-weighted correlation between the forecast and the forecast sorting adjustment is -0.44 across CZs.[35]

Figure 6 shows the unadjusted and sorting-adjusted forecast estimates side by side. The two estimates are highly correlated: 0.97 for children of parents at the 25th percentile and 0.92 for children of parents at the 75th percentile. However, that correlation masks important differences.[36]

Figure 7 shows a scatter plot of the unadjusted and sorting-adjusted forecasts. For children of 25th percentile parents, two things stand out. First, there is a mass of CZs which cause worse outcomes according to the unadjusted forecast that are biased downward by sorting (below the 45 degree line). Second, many of the CZs with positive unadjusted effects on children are biased upward by sorting (above the 45 degree line).[37]

Comparing the maps in Figure 6 side-by-side, the region most affected by sorting, the South, is no longer characterized as causing such poor outcomes for children of low-income parents. It is still the case that children in the South experience worse outcomes conditional on their parents' income and earnings. However, the South is not such an outlier in *causing* them. To show the regional differences more clearly, Figure 8 shows the same scatter plot as Figure 7, but separately by Census region. The South is the only region with a mass of points where the sorting-adjusted forecast is greater than the unadjusted estimate. For low-income children, the South contains 90

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[35] When S_c^p in the forecast comes from Chetty and Hendren estimates of permanent residents at 26, the correlation between the adjustment and the forecast is -0.25.

[36] Correlation may not be the best measure of difference between the two forecasts. Suppose the correlation between the adjustment and the forecast were -1. The correlation between the unadjusted and adjusted forecast would be 1 (assuming the variance of the adjustment is less than the variance of the unadjusted forecast). The unweighted correlations are 0.94 and 0.97 at the 25th and 75th percentiles respectively.

[37] This second point is sensitive to the choice of S_c^p. The effect is not present to the same extent in Appendix Figure 16 with the alternative baseline group.

percent of the 94 CZs where the adjusted causal estimate is at least ½ of a weighted standard deviation greater than the unadjusted forecast. These 85 CZs represent 30 percent of all CZs and 24 percent of the population in the South. The nine other sufficiently improved CZs represent 2.0 percent of the CZs and 1.4 percent of the population in the rest of the country.

Half of a weighted standard deviation is 0.054, which is equal to a difference in expected child rank of 1.1 percentage points over 20 years of exposure. Given the Chetty and Hendren estimate of $818 per percentage point for below-median income children, a ½ weighted standard deviation improvement is equal to an increase of $883 (3.4 percent) of annual family income at 26.[38]

On the other hand, the forecasts in the rest of the country are adjusted down by controlling for sorting. Of the 341 CZs with at least a ½ standard deviation decline in their causal effect, 83 percent are outside of the South, covering 62 percent of all non-South CZs and 21 percent of the population in the rest of the country.

I summarize the results by Census region and division in Table 4. Whether unweighted or weighted by CZ population, the South region and three South divisions are the only ones where the sorting adjustment is positive. The causal effect of place is biased downward in the South on average by 1.3 percent of income at 26 for children of low-income parents (from the weighted 25th percentile adjustment). The Northeast, Midwest, and West regions are biased upwards by 0.9, 0.7, and 1.8 percent of income respectively.[39] These regional biases range from 11 to 28 percent of the

[38] The same results hold at the county level. 32 percent of counties representing 20 percent of the population in the South have a ½ standard deviation improvement in the forecast estimate. Outside of the South only 1.9 percent of counties representing 4.3 percent of the non-South population have a ½ standard deviation improvement. The weighted standard deviation at the county level is slightly higher at 0.12 compared to 0.11 by CZ, so that a ½ standard deviation at the county level corresponds to 3.9 percent of expected income at 26. County-level scatter plots of the unadjusted and adjusted forecasts overall and by region are shown in Appendix Figure 12 and Appendix Figure 13.

[39] Appendix Table 9 shows the state-level summary of the sorting adjustment shown in Table 4 at the region and division level.

CZ-level weighted standard deviation. The division-level variance for 25th percentile children is reduced by 50 percent. At the region level, the variance reduction is 74 percent. State level variation in causal effects is reduced by 39 percent.[40]

The most populated CZs and counties should be among the least affected by sorting as the weight on the unbiased mover term in the forecast is generally larger in more populated places. However, the magnitudes of the adjustments can be very large.

Table 5 shows the largest 50 CZs ordered by the forecast sorting adjustment (from most improved to least). For the city with the most negative bias from sorting (and the most positive sorting adjustment), Baltimore, MD, I estimate that sorting biases the causal estimate downward by 2.7 percent of income over 20 years of exposure. For the most adversely affected city, Manchester, NH, sorting biases the causal estimate upward by 3.9 percent of total income over 20 years of exposure. The standard deviation of the sorting-adjustment across all 50 CZs is 1.5 percent of income over 20 years of exposure.

Table 6 shows a subset of the largest 100 counties with the most positive and negative sorting biases. As noted before, the bias is correlated with the unadjusted estimate. For example, the average unadjusted rank of the 25 most negatively biased counties is 69.7 (60.3 after adjusting for sorting). The downward bias over 20 years of exposure in the most affected county, the District of Columbia, is 8.1 percent of income. The standard deviation of the sorting-adjustment across the largest 100 counties is 1.9 percent of income over 20 years of exposure.

[40] Each CZ is assigned to a specific state (and then division and region). From the county-level sorting-adjusted estimates, the variance reduction at the division, region, and state level are 52, 60, and 35 percent respectively.

Adjusted for sorting, the expected difference for a child of low-income parents between growing up in the best and worst of the largest 50 CZs is 7.2 percent of average total income. For the largest 100 counties, the difference is 10.5 percent of average total income.

6. Conclusion

Where children grow up matters. However, even with nearly the full universe of administrative data on parent-child pairs, it is not possible to precisely estimate *which* places are good or bad to grow up. I build upon work by Chetty and Hendren (2015; 2016a; 2016b) to create causal estimates of place that are further control for sorting, or geographic variation in parent characteristics. I estimate the sorting-adjusted causal impact of each CZ and county in the United States. For children of below-median income parents, I show that sorting explains the more than half of the variation in the causal effects across census regions and divisions and more than a third of the variation across states.

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Table 1
Match Rate Between Parent-Child Pairs in Surveys to Administrative Records

Child Cohort (By Birth Year)	Match Rate (%)		
	CPS ASEC	SIPP	Total
1972		78.1	78.1
1973	81.2	78.3	80.0
1974	80.0	77.5	78.8
1975	80.0	77.2	78.5
1976	77.5	77.6	77.5
1977	75.7	76.3	76.1
1978	78.5	74.2	76.1
1979	78.6	76.1	77.5
1980	77.5	74.3	76.0
1981	74.4	75.4	74.8
1982	65.4	73.9	69.0
Total	75.4	75.6	75.5

This table show the match rate between parent-child pairs in the CPS ASEC and SIPP. Each parent-child pair is successfully matched if the child and all parents (both parents in two-parent families and the individual parent in one-parent families) are matched to a valid SSN. The results in this table are unweighted.

Note that because of the sampling mechanism in the CPS ASEC where housing units are in the survey in consecutive years (subject to nonresponse), repeated individuals are not excluded from the sample in calculating the match rates. This was chosen as it difficult to reliably identify repeat parent-child pairs that are not successfully matched to their SSNs. Therefore, I include duplicate matched and unmatched individuals in each birth cohort in both the numerator and the denominator for the purpose of determining the match rate.

Table 2
Demographic Characteristics and Summary Statistics for Parent-Child Pairs

Variable	1990 Census	All Parent-Child Pairs (Matched and Unmatched)			Matched Parent-Child Pairs		
		CPS ASEC	SIPP	Total	CPS ASEC	SIPP	Total
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Parent Family Earnings					66,042	66,104	66,076
Individual Child Earnings					33,881	35,869	34,964
Share of Population (%)							
Black	14.0	14.5	14.3	14.4	13.4	13.0	13.2
Hispanic	11.7	11.5	10.7	11.1	10.1	9.7	9.9
Highest Educated Parent							
< High School	15.3	11.7	13.8	12.7	10.7	12.4	11.6
High School	26.7	32.1	33.6	32.8	32.6	33.2	32.9
Some College	31.6	27.8	28.5	28.1	28.2	29.2	28.7
College or Graduate	26.4	28.3	24.0	26.3	28.4	25.2	26.6
Teen Parent	6.9	7.0	8.1	7.5	6.9	6.8	6.8
Single Parent	24.9	26.0	35.4	30.4	29.6	33.2	31.5
Observations	10,147,768	39,977	33,059	73,036	24,562	24,997	49,559

This table shows the DER earnings and family demographic information for the survey samples. The first column shows the distribution of attributes for children in the 1990 Census Long Form sample. Columns (2)-(4) show the cohort weighted demographic information for children from all parent-child pairs in the CPS ASEC and SIPP samples. Columns (5)-(7) show the cohort weighted demographic information for the parent-child pairs that were successfully matched to the their SSNs. The parent family earnings are the average when the older parent is 40-44 years old. The individual child earnings are the average when the child is 29-30 years old.

Note that because of the sampling mechanism in the CPS ASEC where housing units are in the survey in consecutive years (subject to nonresponse), repeated individuals are not excluded from the All Parent-Child Pairs sample for the calculation of summary statistics. This was chosen as it difficult to reliably identify repeat parent-child pairs that are not successfully matched to their SSNs. In the Matched Parent-Child Pairs sample, duplicates were removed as is straightforward to exclude them by parent and child SSNs.

Table 3
Intergenerational Mobility and Family Characteristics Controlling for Spatial Heterogeneity

		Proxy for Location Effect							
		Chetty and Hendren Estimates							
	Baseline	Permanent Residents		Unadjusted Forecast		Raw Causal		Sorting-Adjusted Forecast	
Dependent Variable = Child Rank	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Parent Rank	0.215***	0.218***	0.374***	0.208***	0.287***	0.216***	0.260***	0.210***	0.289***
	(0.014)	(0.013)	(0.082)	(0.013)	(0.086)	(0.014)	(0.085)	(0.013)	(0.078)
Black	-16.19***	-15.27***	-16.26***	-16.05***	-17.16***	-16.04***	-17.29***	-15.63***	-14.57***
	(1.16)	(1.40)	(3.69)	(1.44)	(2.41)	(1.20)	(2.14)	(1.38)	(2.90)
Black*Female	15.48***	15.32***	15.62***	15.62***	13.77***	15.33***	14.81***	15.31***	12.63***
	(1.12)	(1.46)	(3.25)	(1.60)	(2.06)	(1.23)	(2.46)	(1.59)	(2.58)
Most Educated Parent									
< High School	-6.19***	-6.20***	-6.67***	-5.90***	-8.18***	-6.28***	-4.77**	-6.52***	-6.51***
	(1.04)	(1.04)	(2.30)	(1.13)	(1.73)	(1.03)	(2.00)	(1.06)	(2.32)
College+	8.42***	8.72***	9.81***	8.50***	9.33***	8.75***	8.42***	8.55***	8.27***
	(1.09)	(1.09)	(2.90)	(1.05)	(2.78)	(1.11)	(2.14)	(1.10)	(2.23)
Interacted with Parent Rank									
Black	0.061***	0.054**	0.120**	0.063***	0.106**	0.062***	0.095***	0.057**	0.061
	(0.021)	(0.024)	(0.054)	(0.023)	(0.049)	(0.021)	(0.034)	(0.023)	(0.042)
Most Educated Parent									
< High School	0.031	0.036	0.101*	0.037	0.154***	0.032	0.022	0.037	0.072
	(0.030)	(0.030)	(0.057)	(0.029)	(0.053)	(0.029)	(0.052)	(0.030)	(0.073)
College+	-0.039**	-0.042**	-0.075*	-0.041**	-0.041	-0.045**	-0.029	-0.039**	-0.047
	(0.017)	(0.018)	(0.045)	(0.017)	(0.039)	(0.018)	(0.031)	(0.018)	(0.032)
Location Effect		4.80		13.41**		-1.48		13.72*	
		(4.32)		(5.94)		(2.16)		(7.14)	
Interacted with Location Effect									
Parent Rank		0.147		0.215		0.015		0.073	
		(0.139)		(0.259)		(0.071)		(0.266)	
Black		-7.328		-7.267		-0.513		5.634	
		(7.980)		(13.778)		(5.709)		(14.708)	
Black*Female		13.989		-1.313		2.240		7.110	
		(10.377)		(19.475)		(7.739)		(19.292)	
Most Educated Parent									
< High School		4.711		5.001		1.804		-7.516	
		(6.477)		(14.906)		(4.213)		(13.632)	
College+		-5.080		-5.243		4.711		-3.389	
		(6.982)		(7.478)		(3.240)		(9.869)	
Constant	44.50***	44.17***	44.13***	45.06***	41.65***	44.52***	52.43***	44.79***	48.20***
	(0.87)	(0.86)	(4.25)	(0.80)	(4.27)	(0.88)	(4.46)	(0.83)	(4.14)
Causal Interacted with parent rank and baseline model dummies		X		X		X		X	
Causal quintile dummies (interacted with all baseline model variables, 3rd quintile excluded)			X		X		X		X
Other CZ Characteristics			X		X		X		X
R-Squared	0.11	0.11	0.12	0.12	0.12	0.11	0.12	0.11	0.12
Observations	49,559	49,102	49,102	49,102	49,102	48,277	48,277	49,073	49,073

These regressions test whether the spatial heterogeneity in mobility biases coefficients for individual and family characteristics using different proxies for location fixed effects. In Columns (2) and (3), location effects are proxied with outcomes of permanent residents, which includes the effects of sorting on observed and unobserved characteristics, as well as any heterogeneous location effects. In columns (4) and (5), the location proxy is the unadjusted forecast, which includes some sorting as well. In columns (6) and (7), the proxy is the imprecise raw causal estimates from Chetty and Hendren (2016a). In columns (8) and (9), the proxy is the sorting-adjusted location effects estimated in this paper. In the even column, the location effects are included as a continuous variable. Each regression uses the cohort weights discussed in Appendix A with errors clustered at the CZ level. The "Other CZ Characteristics" are the five primary ones found by CHKS to be most correlated with mobility: the spatial mismatch in access to jobs (fraction with < 15 minute commute), inequality (the Gini coefficient of the bottom 99%), school quality (measured by the high school dropout rate), social capital (index from Goetz and Rupasingha (2006)), and the fraction of single mothers. ***, **, * represent significance at the 0.01%, 0.05% and 0.10% level.

Table 4
Change in Causal Rank/Year of Exposure to Area with and without Sorting Adjustment

A. Census Region

	Unweighted						Weighted					
	25th Percentile			75th Percentile			25th Percentile			75th Percentile		
Region	**Un**	**Adj**	**Adj-Un**	**Un**	**Adj**	**Adj-Un**	**Un**	**Adj**	**Adj-Un**	**Un**	**Adj**	**Adj-Un**
Northeast	0.05	0.01	-0.04	0.05	0.05	-0.01	0.00	-0.02	-0.02	0.05	0.05	0.00
Midwest	0.16	0.12	-0.04	0.15	0.14	0.00	0.00	-0.01	-0.01	0.04	0.04	0.00
South	-0.03	0.00	0.03	0.01	0.04	0.03	-0.07	-0.05	0.02	-0.04	-0.02	0.02
West	0.08	0.02	-0.07	-0.02	-0.03	-0.01	-0.01	-0.04	-0.03	-0.11	-0.12	-0.01

B. Census Division

		Unweighted						Weighted					
		25th Percentile			75th Percentile			25th Percentile			75th Percentile		
Division	**Region**	**Un**	**Adj**	**Adj-Un**	**Un**	**Adj**	**Adj-Un**	**Un**	**Adj**	**Adj-Un**	**Un**	**Adj**	**Adj-Un**
New England	Northeast	0.02	-0.05	-0.06	-0.01	-0.03	-0.02	0.01	-0.02	-0.03	0.03	0.02	-0.02
Middle Atlantic	Northeast	0.06	0.04	-0.03	0.09	0.09	0.00	-0.01	-0.02	-0.01	0.06	0.06	0.00
East North Centra	Midwest	0.03	0.00	-0.03	0.06	0.06	0.01	-0.05	-0.05	0.00	0.02	0.02	0.00
West North Centr	Midwest	0.24	0.19	-0.05	0.20	0.19	-0.01	0.11	0.08	-0.03	0.10	0.09	-0.01
South Atlantic	South	-0.10	-0.06	0.04	-0.05	-0.01	0.04	-0.10	-0.07	0.02	-0.07	-0.05	0.02
East South Central	South	-0.08	-0.03	0.05	-0.01	0.03	0.04	-0.10	-0.06	0.04	-0.03	0.00	0.03
West South Centra	South	0.07	0.08	0.01	0.09	0.10	0.01	-0.01	0.00	0.01	0.02	0.02	0.00
Mountain	West	0.13	0.07	-0.07	0.03	0.01	-0.02	0.04	-0.01	-0.05	-0.06	-0.08	-0.02
Pacific	West	0.01	-0.05	-0.06	-0.08	-0.09	-0.01	-0.03	-0.05	-0.02	-0.13	-0.14	-0.01

This table compares two causal estimates for rank-rank intergenerational mobility, the 1) unadjusted forecast estimates and 2) forecast estimates adjusted for sorting by race, education, and family type. For each estimate, the causal impact of place (in terms of change in expected rank for each year of exposure) is shown for children from below and above-median income families, denoted as 25th and 75th percentile respectively. The unweighted columns show the estimates averaged across CZs by region or division without population weights and the weighted columns show the same CZ estimates averaged by 2000 population. The Census divisions (and regions) are 1) New England: Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont (Northeast), 2) Middle Atlantic: New Jersey, New York, and Pennsylvania (Northeast), 3) East North Central: Illinois, Indiana, Michigan, Ohio, and Wisconsin (Midwest), 4) West North Central: Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, and South Dakota (Midwest), 5) South Atlantic: Delaware, District of Columbia, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, and West Virginia (South), 6) East South Central: Alabama, Kentucky, Mississippi, and Tennessee (South), 7) West South Central: Arkansas, Louisiana, Oklahoma, and Texas (South), 8) Mountain: Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, and Wyoming (West), and 9) Pacific: Alaska, California, Hawaii, Oregon, and Washington (West).

Table 5
Impact of Sorting-Adjustment on Forecast Place Effects for 50 Largest CZs

	CZ	State	Forecast				Rank (of Top 50)		
			Unadjusted (U)	Sorting-Adjusted (SA)	Difference (SA-U)	% Difference in Income (20 Years Exposure)	Unadjusted (U)	Sorting-Adjusted (SA)	Rank Improvement (U-SA)
			(1)	(2)	(3)	(4)	(5)	(6)	(7)
1	Baltimore	MD	-0.083	-0.041	0.042	2.66	33	27	6
2	New Orleans	LA	-0.226	-0.194	0.032	2.00	50	49	1
3	St. Louis	MO	-0.077	-0.048	0.028	1.79	32	29	3
4	Jacksonville	FL	-0.043	-0.017	0.026	1.63	28	22	6
5	Milwaukee	WI	-0.034	-0.009	0.025	1.58	26	16	10
6	Cleveland	OH	-0.003	0.022	0.025	1.57	20	12	8
7	Charlotte	NC	-0.214	-0.192	0.022	1.36	49	48	1
8	Washington DC	DC	0.120	0.142	0.022	1.36	2	1	1
9	Cincinnati	OH	-0.077	-0.060	0.017	1.05	31	32	-1
10	Detroit	MI	-0.109	-0.093	0.016	1.00	38	36	2
11	Philadelphia	PA	-0.003	0.013	0.016	0.97	19	14	5
12	Nashville	TN	-0.091	-0.076	0.015	0.93	35	34	1
13	Raleigh	NC	-0.201	-0.187	0.014	0.89	48	46	2
14	Atlanta	GA	-0.113	-0.100	0.013	0.80	40	37	3
15	Indianapolis	IN	-0.117	-0.105	0.011	0.72	41	38	3
16	Dallas	TX	-0.035	-0.027	0.008	0.50	27	25	2
17	Houston	TX	-0.018	-0.012	0.006	0.38	23	18	5
18	Dayton	OH	-0.058	-0.052	0.006	0.37	30	31	-1
19	Fort Worth	TX	0.063	0.069	0.005	0.34	5	3	2
20	Miami	FL	-0.019	-0.014	0.005	0.33	24	19	5
21	Chicago	IL	-0.148	-0.144	0.005	0.29	44	44	0
22	Columbus	OH	-0.089	-0.085	0.003	0.21	34	35	-1
23	Las Vegas	NV	0.025	0.027	0.002	0.13	13	10	3
24	Kansas City	MO	-0.013	-0.012	0.001	0.06	21	17	4
25	Newark	NJ	0.026	0.025	-0.001	-0.09	12	11	1
26	Buffalo	NY	0.031	0.028	-0.002	-0.15	11	8	3
27	Port St. Lucie	FL	-0.185	-0.188	-0.003	-0.21	47	47	0
28	New York	NY	-0.111	-0.115	-0.004	-0.25	39	39	0
29	Tampa	FL	-0.122	-0.128	-0.006	-0.39	42	41	1
30	Orlando	FL	-0.149	-0.157	-0.008	-0.52	45	45	0
31	Los Angeles	CA	-0.133	-0.142	-0.009	-0.55	43	43	0
32	Phoenix	AZ	-0.015	-0.028	-0.013	-0.80	22	26	-4
33	San Diego	CA	0.059	0.044	-0.015	-0.97	6	6	0
34	San Francisco	CA	0.044	0.028	-0.016	-0.99	9	9	0
35	Seattle	WA	0.136	0.118	-0.019	-1.16	1	2	-1
36	Grand Rapids	MI	-0.032	-0.051	-0.019	-1.20	25	30	-5
37	Sacramento	CA	0.003	-0.016	-0.019	-1.21	18	21	-3
38	Bridgeport	CT	-0.053	-0.074	-0.020	-1.26	29	33	-4
39	Providence	RI	0.007	-0.015	-0.022	-1.41	17	20	-3
40	Boston	MA	0.058	0.036	-0.023	-1.42	7	7	0
41	Pittsburgh	PA	0.034	0.011	-0.023	-1.44	10	15	-5
42	Minneapolis	MN	0.085	0.060	-0.025	-1.59	4	4	0
43	San Jose	CA	0.045	0.015	-0.030	-1.86	8	13	-5
44	Austin	TX	-0.094	-0.127	-0.033	-2.07	36	40	-4
45	Fresno	CA	-0.185	-0.220	-0.036	-2.23	46	50	-4
46	San Antonio	TX	-0.104	-0.141	-0.037	-2.34	37	42	-5
47	Denver	CO	0.021	-0.018	-0.039	-2.41	16	23	-7
48	Portland	OR	0.024	-0.018	-0.042	-2.65	14	24	-10
49	Salt Lake City	UT	0.101	0.047	-0.055	-3.44	3	5	-2
50	Manchester	NH	0.021	-0.041	-0.062	-3.89	15	28	-13

This table shows the largest 50 CZs ordered by difference between the sorting-adjusted and unadjusted forecast estimate. Columns (1) and (2) report the unadjusted and sorting-adjusted estimates. Column (3) reports the difference. Column (4) shows the percent difference in expected income between the two forecasts. Columns (5) and (6) report the rank of the 50 largest CZs from the unadjusted and adjusted forecasts. Column (7) reports the difference in rank.

Table 6
Impact of Sorting-Adjustment on Forecast Place Effects for 100 Largest Counties

	County	State	Forecast				Rank (of Top 100)		
			Unadjusted (U)	Sorting-Adjusted (SA)	Difference (SA-U)	% Difference in Income (20 Years Exposure)	Unadjusted (U)	Sorting-Adjusted (SA)	Rank Improvement (U-SA)
			(1)	(2)	(3)	(4)	(5)	(6)	(7)
1	District Of Columt	DC	-0.033	0.096	0.129	8.09	53	17	36
2	Baltimore City	MD	-0.208	-0.122	0.086	5.42	97	80	17
3	Shelby	TN	-0.192	-0.127	0.065	4.06	92	81	11
4	Jefferson	AL	-0.085	-0.023	0.062	3.87	69	48	21
5	Prince Georges	MD	-0.037	0.024	0.061	3.80	55	35	20
6	Philadelphia	PA	-0.001	0.052	0.053	3.31	45	28	17
7	Essex	NJ	-0.121	-0.069	0.053	3.30	77	65	12
8	Fulton	GA	-0.165	-0.117	0.048	3.00	87	79	8
9	DeKalb	GA	-0.078	-0.039	0.039	2.46	66	58	8
10	Milwaukee	WI	-0.135	-0.098	0.037	2.34	81	72	9
11	Hamilton	OH	-0.106	-0.071	0.035	2.19	75	66	9
12	Wayne	MI	-0.168	-0.134	0.035	2.19	88	82	6
13	Duval	FL	0.022	0.056	0.034	2.12	37	27	10
14	Cuyahoga	OH	-0.062	-0.030	0.032	1.98	61	51	10
15	Davidson	TN	-0.104	-0.072	0.032	1.98	73	67	6
16	Jackson	MO	-0.031	-0.003	0.028	1.78	52	45	7
17	Hudson	NJ	0.119	0.144	0.025	1.58	14	10	4
18	Mecklenburg	NC	-0.217	-0.193	0.024	1.50	99	96	3
19	Marion	IN	-0.194	-0.173	0.021	1.31	93	90	3
20	Suffolk	MA	-0.099	-0.078	0.020	1.28	72	68	4
21	Jefferson	KY	-0.119	-0.099	0.019	1.22	76	75	1
22	Kings	NY	-0.049	-0.032	0.017	1.10	60	52	8
23	Montgomery	OH	-0.124	-0.106	0.017	1.10	79	77	2
24	Dallas	TX	-0.072	-0.061	0.011	0.71	63	61	2
25	Franklin	OH	-0.123	-0.114	0.009	0.56	78	78	0
76	Suffolk	NY	0.023	-0.002	-0.025	-1.58	35	44	-9
77	Bergen	NJ	0.297	0.272	-0.025	-1.58	1	1	0
78	Hennepin	MN	-0.037	-0.062	-0.026	-1.61	54	62	-8
79	Middlesex	MA	0.131	0.105	-0.026	-1.65	13	15	-2
80	Cobb	GA	-0.079	-0.105	-0.026	-1.66	67	76	-9
81	Santa Clara	CA	0.052	0.025	-0.027	-1.71	27	34	-7
82	Honolulu	HI	0.108	0.080	-0.028	-1.74	17	18	-1
83	Dupage	IL	0.275	0.247	-0.028	-1.76	2	2	0
84	Fresno	CA	-0.213	-0.242	-0.029	-1.81	98	99	-1
85	Fairfax	VA	0.267	0.238	-0.029	-1.82	3	3	0
86	Fairfield	CT	-0.105	-0.135	-0.030	-1.87	74	83	-9
87	Snohomish	WA	0.205	0.175	-0.030	-1.87	5	5	0
88	Worcester	MA	0.088	0.058	-0.030	-1.90	20	25	-5
89	Nassau	NY	0.016	-0.015	-0.031	-1.92	40	47	-7
90	Montgomery	MD	0.176	0.145	-0.031	-1.94	7	9	-2
91	Montgomery	PA	0.173	0.142	-0.031	-1.94	8	11	-3
92	Bexar	TX	-0.140	-0.173	-0.033	-2.10	82	91	-9
93	San Mateo	CA	0.113	0.078	-0.035	-2.17	16	19	-3
94	Multnomah	OR	-0.027	-0.063	-0.036	-2.27	49	63	-14
95	Gwinnett	GA	-0.048	-0.088	-0.040	-2.49	59	69	-10
96	Pima	AZ	-0.150	-0.190	-0.040	-2.53	84	94	-10
97	Essex	MA	0.007	-0.035	-0.041	-2.60	44	54	-10
98	Norfolk	MA	0.197	0.150	-0.047	-2.94	6	7	-1
99	Salt Lake	UT	0.061	0.014	-0.048	-2.98	25	40	-15
100	Bernalillo	NM	-0.080	-0.141	-0.061	-3.82	68	84	-16

This table shows the largest 100 counties ordered by difference between the sorting-adjusted and unadjusted forecast estimate. Columns (1) and (2) report the unadjusted and sorting-adjusted estimates. Column (3) reports the difference. Column (4) shows the percent difference in expected income between the two forecasts. Columns (5) and (6) report the rank of the largest 100 counties from the unadjusted and adjusted forecasts. Column (7) reports the difference in rank.

Appendix Table 1
Comparing CPS-SIPP/DER Earnings Mobility to CHKS

	CHKS Parent Family Income → Child Individual Earnings	CSD Parent Family Earnings → Child Individual Earnings	
		Parent Rank	CHKS Predicted Rank
	(1)	(2)	(3)
All Children	0.282	0.251	0.719
Sons	0.313	0.294	0.844
Daughters	0.249	0.208	0.592

All of the coefficients are significant at the 1% level. CHKS do not report the slope of a rank-rank regression of child individual earnings on parent family earnings. The most comparable reported coefficient is of child individual earnings regressed on parent family income in column (1). Column (3) is the regression of individual child earnings on the predicted child rank based on their parent earnings and the CHKS CZ-level mobility coefficients. The coefficient for all children is 0.717 which is nearly equal to the ratio of the CPS-SIPP/DER slope to the baseline CHKS slope ($0.251/0.341 = 0.736$). The regressions in columns (2) and (3) use the cohort weights discussed in Online Appendix A.

Appendix Table 2
Spatial Heterogeneity in CHKS and the CPS-SIPP/DER
A. Correlation Between CZ-Level Expected Rank at 25th and 75th Percentiles

Min Observations in CSDfor Inclusion	# of CZs	Unweighted 25th Percentile	Unweighted 75th Percentile	CSD Observation Weighted 25th Percentile	CSD Observation Weighted 75th Percentile
3	544	0.11	0.04	0.35	0.12
50	244	0.40	0.06	0.48	0.18
100	128	0.49	0.14	0.57	0.29
250	39	0.63	0.41	0.66	0.53
500	10	0.58	0.77	0.65	0.83
1000	5	0.90	0.87	0.87	0.90

B. Correlation Between Expected Rank at 25th and 75th Percentiles in Grouped CZs

Quantile Groups	25th Percentile	75th Percentile	Parent-Child Pairs in Smallest Quantile Group	Average Number of Parent-Child Pairs
5	1.00***	0.94***	3,597	9,815
	(0.01)	(0.20)		
10	0.98***	0.77***	1,454	4,907
	(0.02)	(0.16)		
20	0.95***	0.53***	643	2,454
	(0.02)	(0.15)		
25	0.96***	0.58***	487	1,963
	(0.03)	(0.14)		
50	0.90***	0.49***	141	982
	(0.04)	(0.11)		

Panel A reports the correlation between the expected child rank for children of parents at the 25th and 75th percentile of the national distribution in the CHKS and CPS-SIPP/DER baseline samples (from the intercept and slope of a CZ-level rank-rank regression). Given the baseline CHKS sample size of 9,867,736 over 741 CZs, there are nearly 13,500 observations per CZ. The CPS-SIPP/DER sample contains 49,559 observations over 573 CZs, or about 86 individuals per CZ. CHKS limits their regressions to CZs with at least 250 parent-child pairs, yielding a sample of 709. Due to the small number of CZs with reasonably large samples for the rank-rank regression, I also calculate another measure of the correlation between the CHKS spatial heterogeneity and the CPS-SIPP/DER in Panel B. I divide the CZs into k quantile groups from lowest to highest expected rank for 25th and 75th percentile children. For each group, I calculate the expected child rank in each quantile group for 25th and 75th percentile children in the CPS-SIPP/DER data and the observation weighted average of the expected child ranks from CHKS. I then calculated the correlation between the two sets of coefficients. The standard errors were calculated using a bootstrap with 100 replications.

Appendix Table 3
Correlation Between Family and Demographic Characteristics and CHKS Mobility

	CZ Groups						1990 Census	
	5		25		50			
CHKS Coefficient	**25^{th} Percentile**	**75^{th} Percentile**	**25^{th} Percentile**	**75^{th} Percentile**	**25^{th} Percentile**	**75^{th} Percentile**	**25^{th} Percentile**	**75^{th} Percentile**
Black	-0.92	-0.85	-0.87	-0.83	-0.85	-0.78	-0.84	-0.77
Hispanic	-0.10	-0.29	-0.13	-0.32	-0.13	-0.29	-0.12	-0.21
Parent Education								
< High School	0.39	0.27	0.13	0.06	-0.02	-0.06	0.04	0.09
High School	-0.93	-0.85	-0.87	-0.83	-0.85	-0.78	-0.84	-0.76
Some College	-0.75	-0.87	-0.74	-0.86	-0.67	-0.77	-0.67	-0.72
College +	-0.71	-0.55	-0.49	-0.32	-0.41	-0.27	-0.40	-0.20
Teen Parent	0.81	0.88	0.84	0.90	0.77	0.78	0.65	0.58
Single Parent	0.82	0.77	0.53	0.51	0.42	0.41	0.49	0.43

This table shows the spatial correlation between the baseline model family and demographic characteristics and CHKS CZ-level mobility. In the first six columns, the CZs are grouped into k quantiles by expected rank for children of 25^{th} percentile parents and the characteristics are averaged over all CSD observations in each group. In the last two columns, the family characteristics are averaged within each CZ for all children in the 1990 Long Form census. The correlations are population-weighted correlations between the share in each group with the given characteristics and the expected rank of children of 25^{th} and 75^{th} percentile parents.

Appendix Table 4
Variation Explained by Sorting on Family and Demographic Characteristics

Measure	CZ Quantile Groups 5	10	20	25	50	1990 Census Estimates
Regression Coefficient						
Intercept ($\alpha_{p,adj} = \gamma_\alpha + \delta_\alpha \alpha_p$)	0.59	0.62	0.65	0.67	0.70	0.61
Slope ($\beta_{p,adj} = \gamma_\beta + \delta_\beta \beta_p$)	0.42	0.39	0.58	0.65	0.74	0.72
Reduction in Dispersion						
Variance						
Intercept	0.63	0.57	0.52	0.51	0.44	0.50
Slope	0.79	0.82	0.58	0.51	0.33	0.36
Coefficient of Variation						
Intercept	0.45	0.40	0.37	0.36	0.32	0.41
Slope	0.50	0.53	0.29	0.23	0.11	-0.04
Mean Absolute Deviation						
Intercept	0.40	0.38	0.31	0.32	0.27	0.30
Slope	0.53	0.55	0.37	0.33	0.18	0.23

In this table, I test the variation explained by the demographic and family characteristics. In the first five columns, I divide the individuals into k CZ quantile groups based on the relative mobility in each CZ. In the sixth column, I use the 1990 decennial census Long Form and calculate the predicted rank for each child using the CHKS CZ-level estimates. For columns 1-5, I use the coefficients from the baseline model (model (1) in Table 3) to calculate a sorting-adjusted rank $y_{i,Adj}$. The $y_{i,adj}$ accounts for the relationship between the observable characteristics and child rank but not parent rank. I then calculate the CZ-group level (for the CZ quantile groups) and CZ level (for the 1990 census sample) slope and intercept from the regression of adjusted child rank and predicted rank on parent rank. I regress adjusted rank-rank slope on the unadjusted, and the adjusted rank-rank intercept on the unadjusted for each group or CZ. I also calculate a variety of dispersion measures for both intercept and slope coefficients: including variance, coefficient of variation, and mean absolute deviation. For each dispersion measure, I calculate the share of the variation explained by the observable characteristic as the reduction in dispersion in the adjusted measure compared to the unadjusted (1-adjusted/unadjusted).

Appendix Table 5
Intergenerational Earnings Mobility and Family Characteristics

Dependent Variable = Child Rank	Race and Parent Rank	Parent Rank Interactions	Baseline Model
Variable	(1)	(2)	(3)
Parent Rank	0.221***	0.219***	0.215***
	(0.010)	(0.016)	(0.014)
Black	-10.22***	-16.03***	-16.19***
	(0.97)	(1.35)	(1.16)
Hispanic	-0.90	2.29	2.28
	(1.31)	(1.47)	(1.47)
Female		-8.53***	-8.58***
		(0.86)	(0.82)
Black*Female		15.18***	15.48***
		(1.64)	(1.12)
Most Educated Parent			
< High School		-6.05***	-6.19***
		(1.07)	(1.04)
Some College		2.08**	1.75***
		(0.91)	(0.49)
College+		8.57***	8.42***
		(1.08)	(1.09)
Teen Parent		-3.17***	-3.17***
		(0.68)	(0.68)
Single Parent		2.28***	2.28***
		(0.60)	(0.60)
Interacted with Parent Rank			
Black	0.080***	0.057	0.061***
	(0.020)	(0.035)	(0.021)
Hispanic	-0.007	-0.025	-0.025
	(0.031)	(0.034)	(0.034)
Female		-0.042**	-0.041***
		(0.016)	(0.015)
Black*Female		0.009	
		(0.047)	
Most Educated Parent*Rank			
< High School		0.028	0.031
		(0.031)	(0.030)
Some College		-0.007	
		(0.019)	
College+		-0.042**	-0.039**
		(0.018)	(0.017)
Constant	41.48***	44.33***	44.50***
	(0.59)	(0.92)	(0.87)
R-Squared	0.07	0.11	0.11
Observations	49,559	49,559	49,559

In this table, I regress child rank on parent rank and a variety of other demographic and family characteristics using the cohort weights discussed in Appendix A. In, model (1), I include race dummies and race interacted with parent rank. In model (2), I add a richer set of family characteristics as dummies and interacted with parent rank. In model (3), the baseline model, I include the less than high school and college+ education interactions as both are significant in the either in the weighted or unweighted regressions (and nearly so in the other) and the point estimates for both are large in magnitude. The errors are clustered at the CZ level. ***, **, * represent significance at the 0.01%, 0.05% and 0.10% level.

Appendix Table 6
Intergenerational Mobility and Family Characteristics Controlling for Spatial Heterogeneity
More Complete Regression Results

		Proxy for Location Effect							
		Chetty and Hendren Estimates							
	Baseline	Permanent Residents		Unadjusted Forecast		Raw Causal		Sorting-Adjusted Forecast	
Dependent Variable = Child Rank	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Parent Rank	0.215***	0.218***	0.374***	0.208***	0.287***	0.216***	0.260***	0.210***	0.289***
	(0.014)	(0.013)	(0.082)	(0.013)	(0.086)	(0.014)	(0.085)	(0.013)	(0.078)
Black	-16.19***	-15.27***	-16.26***	-16.05***	-17.16***	-16.04***	-17.29***	-15.63***	-14.57***
	(1.16)	(1.40)	(3.69)	(1.44)	(2.41)	(1.20)	(2.14)	(1.38)	(2.90)
Hispanic	2.28	2.14	3.76*	2.10	-0.20	2.54*	-1.14	2.47*	-2.03
	(1.47)	(1.47)	(2.15)	(1.47)	(1.98)	(1.50)	(1.97)	(1.45)	(2.27)
Female	-8.58***	-8.40***	-8.30***	-8.30***	-7.66***	-8.58***	-9.20***	-8.86***	-6.63***
	(0.82)	(0.82)	(1.75)	(0.83)	(1.57)	(0.82)	(1.36)	(0.81)	(1.23)
Black*Female	15.48***	15.32***	15.62***	15.62***	13.77***	15.33***	14.81***	15.31***	12.63***
	(1.12)	(1.46)	(3.25)	(1.60)	(2.06)	(1.23)	(2.46)	(1.59)	(2.58)
Most Educated Parent									
< High School	-6.19***	-6.20***	-6.67***	-5.90***	-8.18***	-6.28***	-4.77**	-6.52***	-6.51***
	(1.04)	(1.04)	(2.30)	(1.13)	(1.73)	(1.03)	(2.00)	(1.06)	(2.32)
Some College	1.75***	1.71***	2.22**	1.64***	2.65***	1.71***	2.33***	1.72***	1.98**
	(0.49)	(0.48)	(0.90)	(0.47)	(0.90)	(0.49)	(0.89)	(0.49)	(0.84)
College+	8.42***	8.72***	9.81***	8.50***	9.33***	8.75***	8.42***	8.55***	8.27***
	(1.09)	(1.09)	(2.90)	(1.05)	(2.78)	(1.11)	(2.14)	(1.10)	(2.23)
Teen Parent	-3.175***	-3.334***	-4.901***	-3.408***	-3.790***	-3.220***	-5.138***	-3.380***	-4.599***
	(0.681)	(0.658)	(1.163)	(0.673)	(1.247)	(0.683)	(1.226)	(0.649)	(1.364)
Single Parent	2.280***	2.380***	3.209***	2.143***	2.922***	2.251***	0.843	2.435***	3.623***
	(0.600)	(0.590)	(1.089)	(0.571)	(0.920)	(0.598)	(0.940)	(0.584)	(1.031)
Interacted with Parent Rank									
Black	0.061***	0.054**	0.120**	0.063***	0.106**	0.062***	0.095***	0.057**	0.061
	(0.021)	(0.024)	(0.054)	(0.023)	(0.049)	(0.021)	(0.034)	(0.023)	(0.042)
Hispanic	-0.025	-0.018	-0.088	-0.018	0.007	-0.036	0.035	-0.030	0.096
	(0.034)	(0.035)	(0.062)	(0.039)	(0.053)	(0.036)	(0.043)	(0.038)	(0.076)
Female	-0.041***	-0.043***	-0.087**	-0.046***	-0.081**	-0.041***	-0.031	-0.038**	-0.063***
	(0.015)	(0.016)	(0.040)	(0.015)	(0.034)	(0.016)	(0.022)	(0.016)	(0.023)
Most Educated Parent									
< High School	0.031	0.036	0.101*	0.037	0.154***	0.032	0.022	0.037	0.072
	(0.030)	(0.030)	(0.057)	(0.029)	(0.053)	(0.029)	(0.052)	(0.030)	(0.073)
College+	-0.039**	-0.042**	-0.075*	-0.041**	-0.041	-0.045**	-0.029	-0.039**	-0.047
	(0.017)	(0.018)	(0.045)	(0.017)	(0.039)	(0.018)	(0.031)	(0.018)	(0.032)
Location Effect		4.80		13.41**		-1.48		13.72*	
		(4.32)		(5.94)		(2.16)		(7.14)	

These regressions test whether the spatial heterogeneity in mobility biases coefficients for individual and family characteristics using different proxies for location fixed effects. In Columns (2) and (3), location effects are proxied with outcomes of permanent residents, which includes the effects of sorting on observed and unobserved characteristics, as well as any heterogeneous location effects. In columns (4) and (5), the location proxy is the unadjusted forecast, which includes some sorting as well. In columns (6) and (7), the proxy is the imprecise raw causal estimates from Chetty and Hendren (2016a). In columns (8) and (9), the proxy is the sorting-adjusted location effects estimated in this paper. In the even column, the location effects are included as a continuous variable. Each regression uses the cohort weights discussed in Appendix A with errors clustered at the CZ level. The “Other CZ Characteristics” are the five primary ones found by CHKS to be most correlated with mobility: the spatial mismatch in access to jobs (fraction with < 15 minute commute), inequality (the Gini coefficient of the bottom 99%), school quality (measured by the high school dropout rate), social capital (index from Goetz and Rupasingha (2006)), and the fraction of single mothers. ***, **, * represent significance at the 0.01%, 0.05% and 0.10% level. The regressions report a more complete set of coefficients than Table 3.

Appendix Table 6, Cont.
Intergenerational Mobility and Family Characteristics Controlling for Spatial Heterogeneity
More Complete Regression Results

		Proxy for Location Effect							
		Chetty and Hendren Estimates							
	Baseline	Permanent Residents		Unadjusted Forecast		Raw Causal		Sorting-Adjusted Forecast	
Dependent Variable = Child Rank	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Interacted with Location Effect									
Parent Rank		0.147		0.215		0.015		0.073	
		(0.139)		(0.259)		(0.071)		(0.266)	
Black		-7.328		-7.267		-0.513		5.634	
		(7.980)		(13.778)		(5.709)		(14.708)	
Hispanic		14.574**		-0.500		2.183		3.625	
		(6.847)		(8.571)		(3.662)		(9.190)	
Most Educated Parent									
< High School		4.711		5.001		1.804		-7.516	
		(6.477)		(14.906)		(4.213)		(13.632)	
College+		-5.080		-5.243		4.711		-3.389	
		(6.982)		(7.478)		(3.240)		(9.869)	
Location Effect Quintile (3rd Omitted)									
1st Quintile			-2.259		-1.881		-2.348		-1.324
			(2.708)		(2.459)		(2.646)		(2.258)
2nd Quintile			-0.328		-2.753		-4.373*		1.703
			(2.335)		(2.391)		(2.253)		(2.308)
4th Quintile			-0.524		2.569		-5.209**		2.015
			(2.794)		(1.934)		(2.389)		(2.676)
5th Quintile			12.668***		8.714***		-6.399*		15.642***
			(4.341)		(3.088)		(3.831)		(3.757)
Constant	44.50***	44.17***	44.13***	45.06***	41.65***	44.52***	52.43***	44.79***	48.20***
	(0.87)	(0.86)	(4.25)	(0.80)	(4.27)	(0.88)	(4.46)	(0.83)	(4.14)
Other CZ Characteristics			X		X		X		X
R-Squared	0.11	0.11	0.12	0.12	0.12	0.11	0.12	0.11	0.12
Observations	49,559	49,102	49,102	49,102	49,102	48,277	48,277	49,073	49,073

These regressions test whether the spatial heterogeneity in mobility biases coefficients for individual and family characteristics using different proxies for location fixed effects. In Columns (2) and (3), location effects are proxied with outcomes of permanent residents, which includes the effects of sorting on observed and unobserved characteristics, as well as any heterogeneous location effects. In columns (4) and (5), the location proxy is the unadjusted forecast, which includes some sorting as well. In columns (6) and (7), the proxy is the imprecise raw causal estimates from Chetty and Hendren (2016a). In columns (8) and (9), the proxy is the sorting-adjusted location effects estimated in this paper. In the even column, the location effects are included as a continuous variable. Each regression uses the cohort weights discussed in Appendix A with errors clustered at the CZ level. The "Other CZ Characteristics" are the five primary ones found by CHKS to be most correlated with mobility: the spatial mismatch in access to jobs (fraction with < 15 minute commute), inequality (the Gini coefficient of the bottom 99%), school quality (measured by the high school dropout rate), social capital (index from Goetz and Rupasingha (2006)), and the fraction of single mothers. ***, **, * represent significance at the 0.01%, 0.05% and 0.10% level. The regressions report a more complete set of coefficients than Table 3.

Appendix Table 7
Change in Causal Rank/Year of Exposure to State with and without Sorting Adjustment

	Unweighted						Weighted					
	25th Percentile			75th Percentile			25th Percentile			75th Percentile		
State	Unadj	Adj	Adj-Un	Unadj	Adj	Adj-Un	Unadj	Adj	Adj-Un	Unadj	Adj	Unadj
Alabama	-0.08	-0.01	0.08	0.00	0.05	0.05	-0.09	-0.03	0.06	-0.01	0.02	0.03
Alaska	-0.07	-0.14	-0.07	-0.14	-0.13	0.01	0.06	-0.01	-0.06	-0.02	-0.03	0.00
Arizona	-0.06	-0.10	-0.04	-0.11	-0.13	-0.02	-0.04	-0.07	-0.02	-0.08	-0.10	-0.02
Arkansas	-0.02	0.01	0.03	0.01	0.04	0.03	-0.03	-0.01	0.02	0.01	0.03	0.03
California	0.01	-0.04	-0.04	-0.10	-0.11	-0.01	-0.05	-0.07	-0.02	-0.16	-0.16	0.00
Colorado	0.14	0.06	-0.08	0.01	-0.02	-0.03	0.04	-0.01	-0.05	-0.06	-0.09	-0.03
Connecticut	-0.05	-0.07	-0.02	0.04	0.03	-0.01	-0.05	-0.07	-0.02	0.04	0.03	-0.01
Delaware	-0.13	-0.12	0.02	-0.03	-0.01	0.03	-0.13	-0.11	0.02	-0.03	-0.01	0.02
District of Columbia	0.12	0.14	0.02	0.10	0.10	0.00	0.12	0.14	0.02	0.10	0.10	0.00
Florida	-0.10	-0.09	0.00	-0.11	-0.11	0.01	-0.09	-0.09	0.00	-0.14	-0.14	0.01
Georgia	-0.17	-0.08	0.09	-0.10	-0.03	0.07	-0.14	-0.09	0.05	-0.08	-0.04	0.04
Hawaii	0.03	-0.04	-0.08	-0.13	-0.14	-0.01	0.07	0.02	-0.05	-0.11	-0.12	-0.02
Idaho	0.15	0.09	-0.06	-0.01	-0.01	0.00	0.09	0.02	-0.07	-0.06	-0.08	-0.02
Illinois	0.05	0.02	-0.03	0.12	0.12	0.00	-0.09	-0.10	-0.01	0.02	0.02	0.00
Indiana	-0.02	-0.04	-0.02	0.03	0.05	0.02	-0.05	-0.06	-0.01	0.00	0.02	0.01
Iowa	0.27	0.23	-0.04	0.23	0.23	0.00	0.21	0.17	-0.04	0.19	0.18	-0.01
Kansas	0.22	0.17	-0.05	0.19	0.18	-0.01	0.08	0.04	-0.05	0.08	0.07	-0.02
Kentucky	-0.02	-0.02	0.00	-0.01	0.02	0.02	-0.04	-0.03	0.01	-0.02	0.00	0.01
Louisiana	-0.02	0.06	0.08	0.12	0.16	0.04	-0.10	-0.04	0.06	0.04	0.07	0.03
Maine	0.00	-0.06	-0.06	-0.03	-0.04	-0.01	0.03	-0.03	-0.06	-0.02	-0.04	-0.01
Maryland	-0.06	-0.05	0.01	0.07	0.09	0.02	-0.08	-0.04	0.04	0.06	0.08	0.01
Massachusetts	0.01	-0.07	-0.07	-0.03	-0.06	-0.03	0.04	0.01	-0.03	0.05	0.03	-0.02
Michigan	0.01	-0.04	-0.05	0.00	0.00	-0.01	-0.07	-0.07	-0.01	-0.04	-0.03	0.01
Minnesota	0.27	0.23	-0.04	0.20	0.20	0.00	0.15	0.11	-0.04	0.12	0.10	-0.02
Mississippi	-0.13	-0.02	0.11	0.02	0.08	0.06	-0.14	-0.05	0.09	0.00	0.04	0.05
Missouri	0.07	0.04	-0.03	0.09	0.09	0.00	-0.01	-0.02	0.00	0.03	0.03	0.00
Montana	0.16	0.08	-0.08	0.06	0.04	-0.03	0.14	0.05	-0.09	0.01	-0.02	-0.03
Nebraska	0.31	0.26	-0.05	0.23	0.22	-0.01	0.16	0.11	-0.05	0.12	0.10	-0.02
Nevada	0.10	0.06	-0.03	-0.05	-0.03	0.02	0.03	0.02	-0.01	-0.15	-0.14	0.01
New Hampshire	0.03	-0.04	-0.08	-0.03	-0.05	-0.02	0.02	-0.04	-0.06	0.01	-0.01	-0.02
New Jersey	0.05	0.03	-0.02	0.09	0.08	-0.01	0.03	0.03	-0.01	0.09	0.08	-0.01
New Mexico	0.02	-0.04	-0.06	-0.05	-0.07	-0.03	-0.03	-0.09	-0.07	-0.09	-0.13	-0.04
New York	0.03	0.00	-0.03	0.06	0.05	-0.01	-0.06	-0.07	-0.01	0.03	0.03	0.00
North Carolina	-0.14	-0.12	0.03	-0.09	-0.05	0.04	-0.18	-0.16	0.02	-0.11	-0.08	0.03
North Dakota	0.42	0.38	-0.04	0.33	0.31	-0.02	0.36	0.30	-0.06	0.27	0.24	-0.03
Ohio	-0.02	-0.03	-0.01	0.04	0.06	0.02	-0.04	-0.03	0.01	0.04	0.04	0.00
Oklahoma	0.12	0.10	-0.02	0.13	0.13	0.00	0.05	0.03	-0.02	0.07	0.07	-0.01
Oregon	0.06	-0.01	-0.07	-0.05	-0.04	0.00	0.00	-0.06	-0.05	-0.08	-0.09	-0.02
Pennsylvania	0.09	0.07	-0.02	0.12	0.12	0.01	0.04	0.04	-0.01	0.08	0.08	0.00
Rhode Island	0.01	-0.02	-0.02	0.02	0.02	0.00	0.01	-0.02	-0.02	0.02	0.02	0.00
South Carolina	-0.17	-0.09	0.09	-0.11	-0.04	0.07	-0.17	-0.11	0.06	-0.11	-0.06	0.05
South Dakota	0.15	0.09	-0.06	0.15	0.12	-0.02	0.22	0.16	-0.06	0.15	0.13	-0.02
Tennessee	-0.10	-0.08	0.01	-0.05	-0.01	0.03	-0.12	-0.10	0.02	-0.06	-0.04	0.02
Texas	0.10	0.10	0.00	0.10	0.10	0.00	0.01	0.01	0.00	0.01	0.00	-0.01
Utah	0.22	0.15	-0.07	0.10	0.09	-0.01	0.14	0.07	-0.07	0.03	0.00	-0.03
Vermont	0.06	-0.01	-0.07	0.01	0.00	-0.01	0.06	-0.02	-0.07	0.00	-0.02	-0.02
Virginia	-0.06	-0.02	0.03	0.01	0.05	0.04	-0.08	-0.04	0.03	0.00	0.02	0.03
Washington	0.06	-0.01	-0.07	-0.03	-0.04	-0.02	0.10	0.07	-0.03	-0.01	-0.03	-0.02
West Virginia	0.09	0.08	-0.01	0.10	0.11	0.01	0.06	0.04	-0.01	0.08	0.08	0.00
Wisconsin	0.13	0.09	-0.04	0.10	0.11	0.00	0.08	0.06	-0.02	0.08	0.08	0.00
Wyoming	0.24	0.17	-0.07	0.13	0.12	-0.02	0.24	0.17	-0.07	0.14	0.12	-0.01

This table compares two causal estimates for rank-rank intergenerational mobility, the 1) unadjusted forecast estimates and 2) forecast estimates adjusted for sorting by race, education, and family type. For each estimate, the causal impact of place (in terms of change in expected rank for each year of exposure) is shown for children from below and above-median income families, denoted as 25th and 75th percentile respectively. The unweighted columns show the estimates averaged across CZs by state without population weights and the weighted columns show the same CZ estimates averaged by 2000 population.

Appendix Table 8
Change in Expected Rank/Year of Exposure to Area with and without Sorting Adjustment
(Using Chetty and Hendren Permanents Residents at 26)

A. Census Region

	Unweighted						Weighted					
	25th Percentile			75th Percentile			25th Percentile			75th Percentile		
Region	**Un**	**Adj**	**Adj-Un**	**Un**	**Adj**	**Adj-Un**	**Un**	**Adj**	**Adj-Un**	**Un**	**Adj**	**Adj-Un**
Northeast	0.05	0.00	-0.05	0.04	0.03	-0.01	-0.01	-0.02	-0.02	0.03	0.02	-0.01
Midwest	0.20	0.19	-0.01	0.19	0.17	-0.02	0.01	0.00	-0.01	0.05	0.05	0.00
South	-0.02	0.03	0.05	0.07	0.09	0.02	-0.07	-0.04	0.03	-0.02	0.00	0.02
West	0.13	0.06	-0.07	0.03	0.01	-0.02	0.01	-0.03	-0.04	-0.10	-0.11	-0.01

B. Census Division

		Unweighted						Weighted					
		25th Percentile			75th Percentile			25th Percentile			75th Percentile		
Division	**Region**	**Un**	**Adj**	**Adj-Un**	**Un**	**Adj**	**Adj-Un**	**Un**	**Adj**	**Adj-Un**	**Un**	**Adj**	**Adj-Un**
New England	Northeast	0.04	-0.06	-0.09	-0.02	-0.03	-0.02	0.02	-0.02	-0.04	0.02	0.00	-0.02
Middle Atlantic	Northeast	0.06	0.04	-0.02	0.08	0.07	-0.01	-0.02	-0.02	-0.01	0.03	0.02	-0.01
East North Centra	Midwest	0.04	0.02	-0.03	0.08	0.08	0.00	-0.05	-0.06	-0.01	0.02	0.02	0.00
West North Centr	Midwest	0.29	0.29	0.00	0.24	0.21	-0.03	0.14	0.13	-0.01	0.13	0.11	-0.02
South Atlantic	South	-0.09	-0.04	0.05	-0.01	0.04	0.04	-0.09	-0.06	0.03	-0.05	-0.03	0.03
East South Central	South	-0.07	0.00	0.06	0.05	0.09	0.04	-0.09	-0.05	0.04	0.01	0.04	0.03
West South Centra	South	0.08	0.13	0.04	0.15	0.15	0.00	-0.01	0.01	0.02	0.03	0.03	0.00
Mountain	West	0.19	0.12	-0.07	0.09	0.05	-0.04	0.07	0.02	-0.05	-0.02	-0.04	-0.02
Pacific	West	0.04	-0.04	-0.08	-0.06	-0.06	0.00	-0.02	-0.05	-0.03	-0.14	-0.14	-0.01

This table compares two causal estimates for rank-rank intergenerational mobility, the 1) Chetty and Hendren forecast estimates and 2) forecast estimates adjusted for sorting by race, education, and family type. For each estimate, the causal impact of place (in terms of change in expected rank for each year of exposure) is shown for children from below and above-median income families, denoted as 25th and 75th percentile respectively. The unweighted columns show the estimates averaged across CZs by region or division without population weights and the weighted columns show the same CZ estimates averaged by 2000 population. This table differs from Table 4 in how the adjustment was applied. In Table 4, the adjustment was made to CHKS mobility estimates as those were used to construct the adjustment. In this table, the adjustment was made to Chetty and Hendren permanent resident mobility at 26 years old as that is the group used to create the forecast in their paper.

Appendix Table 9
Change in Causal Rank/Year of Exposure to State with and without Sorting Adjustment (Using Chetty and Hendren Permanents Residents at 26)

	Unweighted						Weighted					
	25th Percentile			75th Percentile			25th Percentile			75th Percentile		
State	Unadj	Adj	Adj-Un	Unadj	Adj	Adj-Un	Unadj	Adj	Adj-Un	Unadj	Adj	Unadj
Alabama	-0.08	0.03	0.10	0.07	0.11	0.04	-0.08	-0.01	0.08	0.04	0.07	0.03
Alaska	-0.03	-0.13	-0.10	-0.07	-0.06	0.01	0.13	0.08	-0.05	0.04	0.03	-0.01
Arizona	-0.06	-0.13	-0.07	-0.05	-0.06	-0.01	-0.03	-0.07	-0.04	-0.05	-0.06	-0.01
Arkansas	-0.01	0.04	0.05	0.10	0.12	0.03	-0.01	0.02	0.03	0.07	0.09	0.02
California	0.01	-0.04	-0.06	-0.10	-0.11	-0.01	-0.05	-0.07	-0.02	-0.17	-0.17	0.00
Colorado	0.23	0.15	-0.07	0.10	0.06	-0.04	0.08	0.01	-0.06	-0.03	-0.06	-0.04
Connecticut	-0.05	-0.07	-0.02	0.03	0.01	-0.02	-0.05	-0.07	-0.02	0.03	0.01	-0.02
Delaware	-0.12	-0.09	0.02	0.03	0.05	0.02	-0.11	-0.09	0.02	0.02	0.04	0.02
District of Columbia	0.10	0.14	0.04	0.06	0.07	0.01	0.10	0.14	0.04	0.06	0.07	0.01
Florida	-0.08	-0.08	0.00	-0.08	-0.07	0.01	-0.09	-0.09	0.00	-0.13	-0.12	0.01
Georgia	-0.17	-0.06	0.10	-0.04	0.03	0.07	-0.14	-0.09	0.05	-0.08	-0.02	0.05
Hawaii	0.03	-0.08	-0.11	-0.12	-0.13	0.00	0.05	-0.03	-0.08	-0.14	-0.15	-0.01
Idaho	0.22	0.18	-0.03	0.03	0.03	0.00	0.14	0.07	-0.06	-0.02	-0.04	-0.02
Illinois	0.06	0.04	-0.02	0.15	0.14	-0.01	-0.09	-0.10	0.00	0.02	0.01	0.00
Indiana	0.03	0.02	-0.01	0.10	0.11	0.01	-0.02	-0.03	-0.01	0.06	0.07	0.01
Iowa	0.32	0.33	0.01	0.27	0.25	-0.02	0.25	0.25	0.00	0.22	0.19	-0.03
Kansas	0.32	0.33	0.01	0.26	0.23	-0.03	0.15	0.13	-0.02	0.14	0.11	-0.03
Kentucky	0.02	0.03	0.01	0.05	0.07	0.02	-0.02	-0.02	0.00	0.01	0.03	0.01
Louisiana	-0.04	0.07	0.11	0.17	0.19	0.02	-0.11	-0.02	0.09	0.05	0.08	0.03
Maine	0.01	-0.08	-0.09	0.00	-0.01	-0.01	0.04	-0.05	-0.09	-0.03	-0.04	-0.01
Maryland	-0.04	-0.02	0.02	0.12	0.13	0.01	-0.09	-0.04	0.05	0.08	0.09	0.01
Massachusetts	0.04	-0.11	-0.15	-0.07	-0.10	-0.04	0.04	0.01	-0.03	0.03	0.00	-0.03
Michigan	-0.01	-0.08	-0.07	-0.02	-0.02	-0.01	-0.09	-0.11	-0.02	-0.07	-0.05	0.02
Minnesota	0.31	0.33	0.02	0.23	0.22	-0.01	0.17	0.15	-0.02	0.13	0.10	-0.03
Mississippi	-0.16	-0.02	0.14	0.07	0.13	0.05	-0.16	-0.05	0.11	0.04	0.08	0.05
Missouri	0.15	0.15	0.01	0.17	0.16	-0.01	0.00	0.01	0.00	0.06	0.06	-0.01
Montana	0.20	0.08	-0.12	0.12	0.04	-0.08	0.15	0.06	-0.10	0.02	-0.03	-0.04
Nebraska	0.35	0.36	0.01	0.28	0.24	-0.03	0.19	0.16	-0.02	0.16	0.12	-0.04
Nevada	0.17	0.16	-0.01	0.08	0.10	0.01	0.06	0.05	-0.02	-0.07	-0.05	0.02
New Hampshire	0.06	-0.03	-0.09	-0.01	-0.03	-0.02	0.05	-0.02	-0.07	0.02	0.00	-0.02
New Jersey	0.03	0.01	-0.02	0.05	0.03	-0.01	0.02	0.01	0.00	0.05	0.04	-0.01
New Mexico	0.04	-0.04	-0.08	-0.04	-0.07	-0.02	-0.01	-0.11	-0.10	-0.09	-0.12	-0.03
New York	0.02	-0.02	-0.04	0.03	0.02	-0.01	-0.07	-0.08	-0.01	-0.01	-0.01	0.00
North Carolina	-0.13	-0.10	0.03	-0.03	0.02	0.04	-0.17	-0.15	0.02	-0.07	-0.03	0.04
North Dakota	0.42	0.43	0.01	0.32	0.25	-0.07	0.36	0.36	-0.01	0.24	0.18	-0.06
Ohio	-0.01	-0.03	-0.02	0.06	0.08	0.01	-0.05	-0.05	-0.01	0.03	0.04	0.01
Oklahoma	0.17	0.20	0.02	0.20	0.18	-0.02	0.07	0.07	-0.01	0.11	0.10	-0.01
Oregon	0.09	0.02	-0.07	-0.01	0.00	0.01	0.02	-0.07	-0.09	-0.08	-0.09	-0.01
Pennsylvania	0.10	0.09	0.00	0.12	0.12	-0.01	0.03	0.04	0.00	0.08	0.07	-0.01
Rhode Island	0.01	-0.02	-0.02	0.02	0.01	-0.01	0.01	-0.02	-0.02	0.02	0.01	-0.01
South Carolina	-0.18	-0.07	0.11	-0.05	0.02	0.07	-0.17	-0.09	0.08	-0.06	-0.01	0.05
South Dakota	0.20	0.14	-0.06	0.16	0.12	-0.04	0.27	0.25	-0.02	0.16	0.11	-0.04
Tennessee	-0.06	-0.04	0.02	0.03	0.06	0.03	-0.11	-0.09	0.02	-0.02	0.00	0.03
Texas	0.11	0.14	0.03	0.15	0.14	-0.01	0.00	0.00	0.00	0.01	0.00	-0.01
Utah	0.32	0.31	-0.01	0.19	0.16	-0.03	0.22	0.16	-0.05	0.11	0.07	-0.04
Vermont	0.10	0.02	-0.08	0.01	0.00	-0.01	0.09	0.00	-0.08	0.00	-0.03	-0.02
Virginia	-0.03	0.03	0.06	0.07	0.11	0.03	-0.07	-0.02	0.05	0.03	0.06	0.03
Washington	0.10	0.02	-0.08	0.00	-0.02	-0.02	0.12	0.07	-0.05	0.00	-0.02	-0.02
West Virginia	0.09	0.11	0.01	0.10	0.10	0.00	0.05	0.04	-0.01	0.05	0.05	0.00
Wisconsin	0.16	0.14	-0.02	0.12	0.11	-0.01	0.09	0.09	-0.01	0.09	0.07	-0.01
Wyoming	0.29	0.26	-0.03	0.19	0.15	-0.04	0.29	0.27	-0.02	0.20	0.16	-0.03

This table compares two causal estimates for rank-rank intergenerational mobility, the 1) unadjusted forecast estimates and 2) forecast estimates adjusted for sorting by race, education, and family type. For each estimate, the causal impact of place (in terms of change in expected rank for each year of exposure) is shown for children from below and above-median income families, denoted as 25th and 75th percentile respectively. The unweighted columns show the estimates averaged across CZs by state without population weights and the weighted columns show the same CZ estimates averaged by 2000 population.

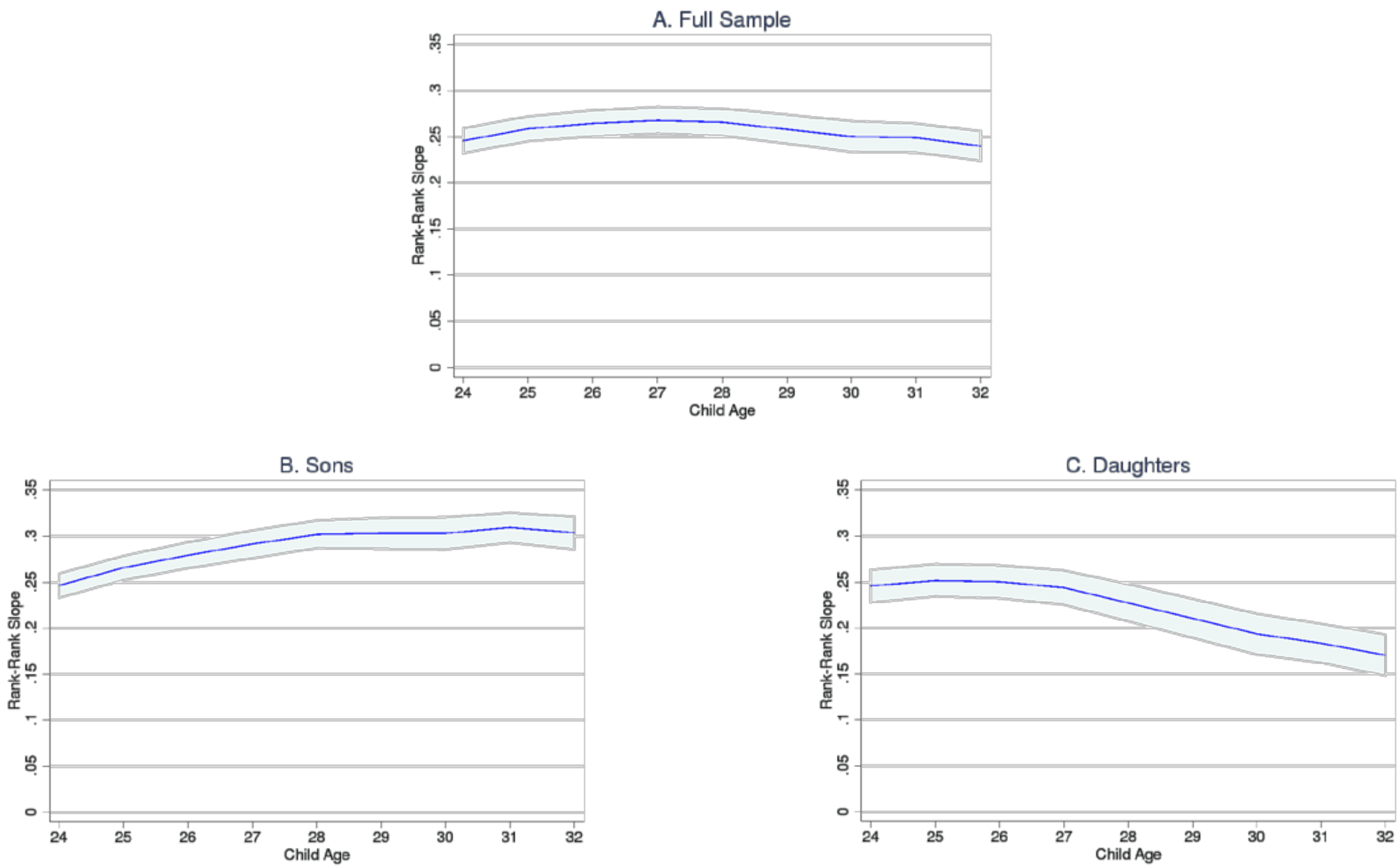


Figure 1
Intergenerational Mobility by Age of Child Earnings Measurement

These figures plot the rank-rank slope of intergenerational mobility. The parent family earnings are the average when the older parent is 40-44 years old. The child earnings are the average of earnings for age t and $t + 1$ where t varies from 24 to 32. It should be noted that as t varies, so does the size of the sample because more children in the CPS ASEC and SIPP from 1991 on reach $t + 1$ by 2012, the last available year of DER earnings data. On average for each year younger of t, the sample increases by about 18%. For example, at $t = 32$, there are 28,918 parent-child pairs and at $t = 24$, there are 106,766 parent-child pairs. Panel A shows the rank-rank slope by age for the full sample, and Panels B and C show the slope by age for sons and daughters respectively.

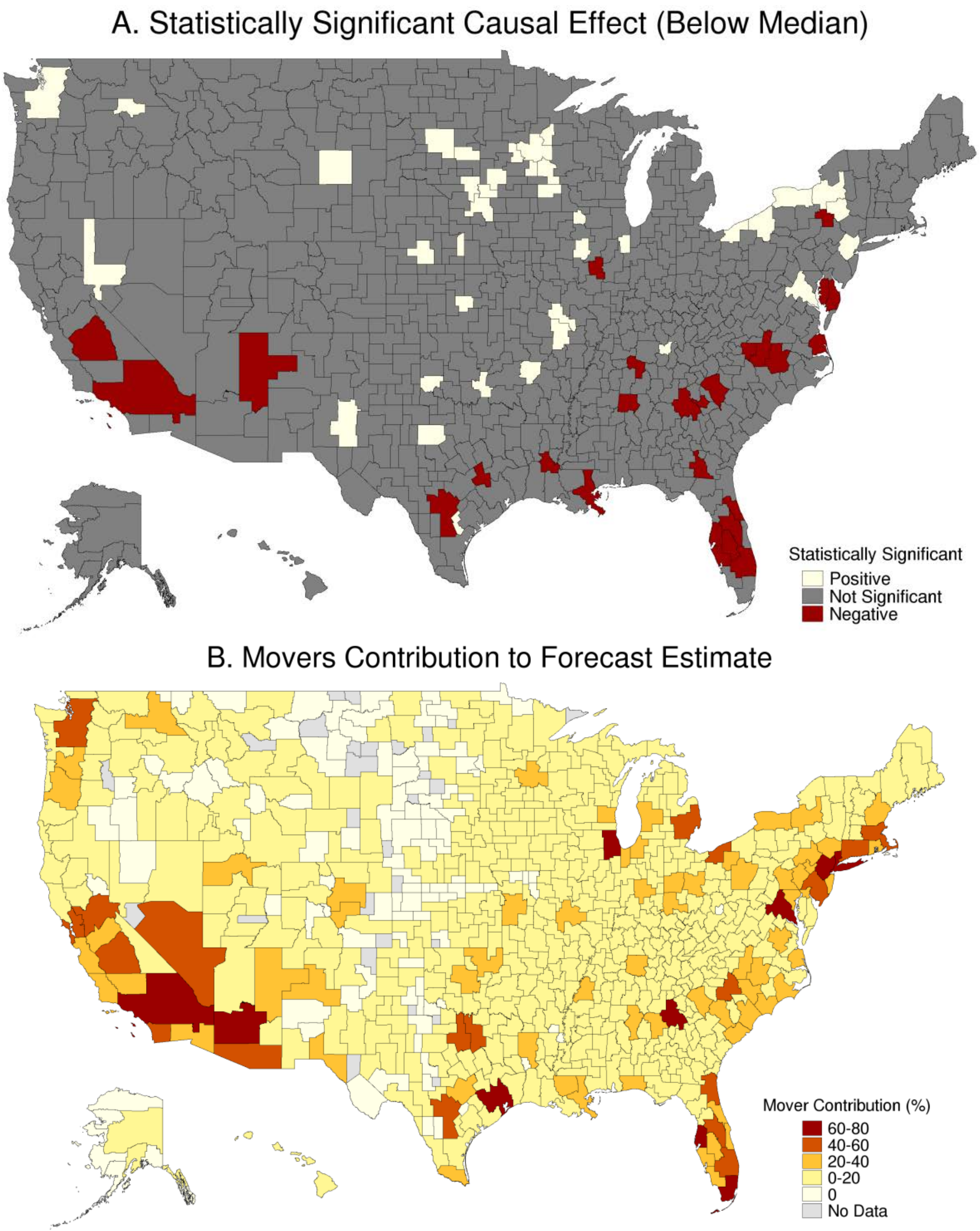


Figure 2
Chetty and Hendren Causal Estimates and Causal Weights in Forecasts

Panel A shows the CZs that Chetty and Hendren estimate have statistically significant impacts on children from below-median income families (positive in light yellow, negative in red). Because of the low signal-to-noise ratio they observe (71 percent of variation across CZs is sampling variation), only 8.8 percent of CZs, representing 23.8 percent of the population, have statistically significant effects on mobility. To address this, they create a mean-square error minimizing forecast that is a weighted average of: 1) the unbiased but imprecise causal estimate and 2) the biased but precisely estimated mobility experienced by permanent residents. The weight given to each term in each CZ is a function of the uncertainty in their causal estimate. Panel B shows the weights for each CZ in the US. The weight on the biased permanent resident estimate is greater than 0.5 in 98 percent of commuting zones.

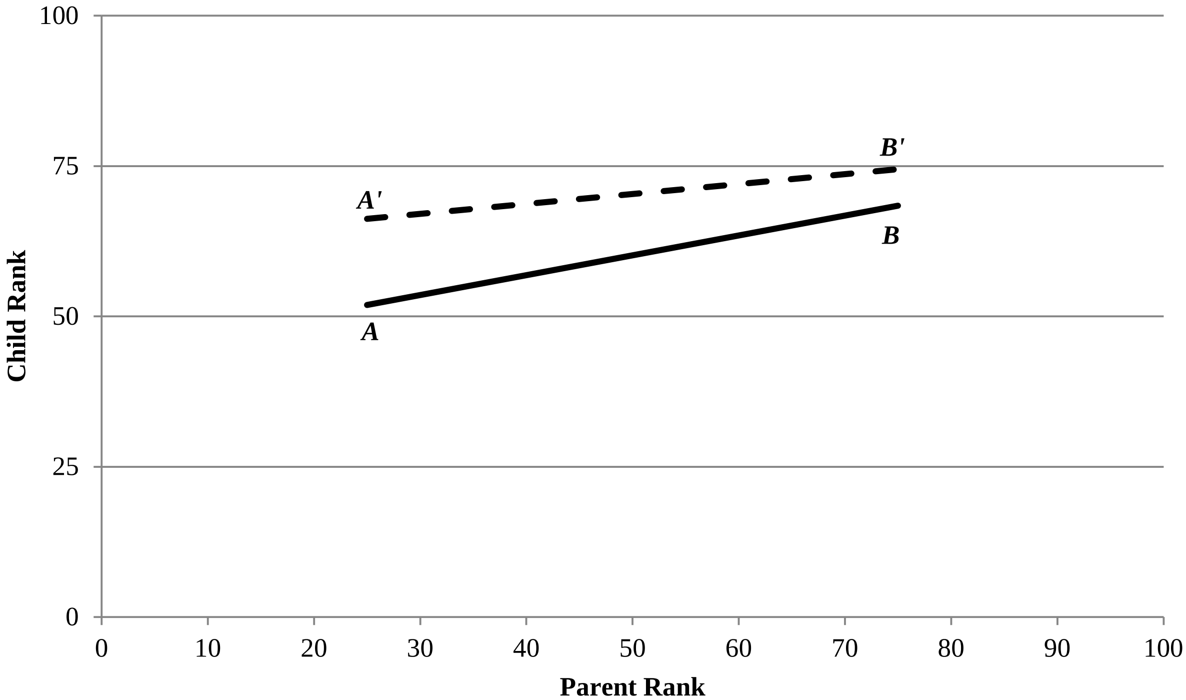
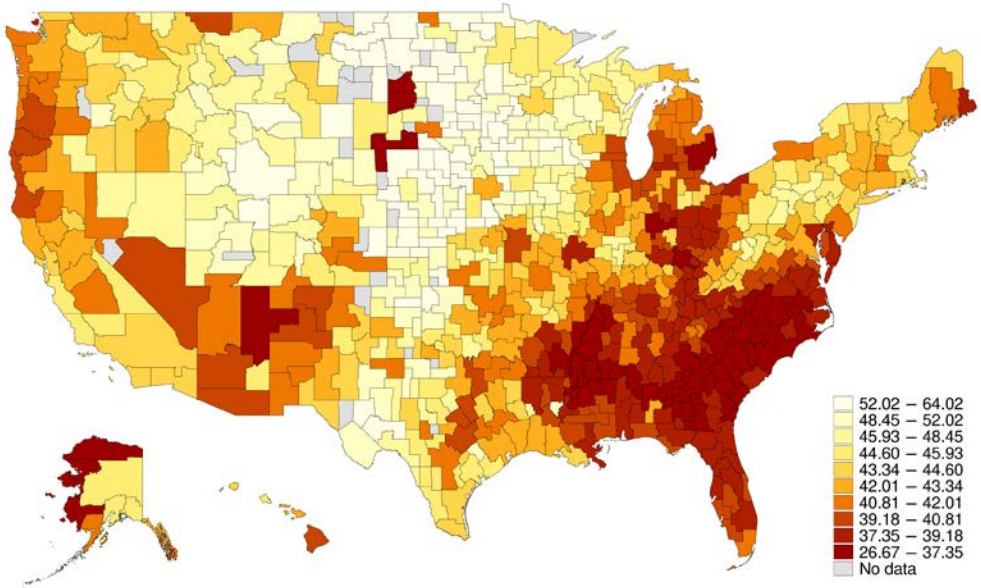


Figure 3
Example of the Sorting Adjustment

The adjustment is calculated using the baseline model coefficients model (1) in Table 3 and using microdata from the 1990 long-orm census. For each child, the parent rank was estimated from the national distribution of parents in the 1990 census by age cohort of the older parent. The child was assigned an expected child rank ($\hat{y}_i$) from the CHKS location slope and intercept terms (CZ or county). From the characteristics in the baseline model observed in the census, I calculated $\hat{y}_{i,Adj} = \hat{y}_i - \hat{\beta}_O X_i^O$ and conducted the rank-rank regression of the adjusted child rank on the estimated parent rank. Each individual was adjusted to the model baseline group of White sons of married, high school educated parents. In the New York CZ, the CHKS intercept and slope are 43.67 and 33.00 respectively. Suppose there are only two children in New York, A) a Black son of high school graduates at the 25th percentile and B) a White daughter of college graduates at the 75th percentile. For each, I assign a predicted rank based on the CHKS coefficients, for A: $43.67 + 33(0.25) = 51.92$ and for B: $43.67 + 33(0.75) = 68.42$. I adjust the predicted rank for child A based on his characteristics as follows: 1) Black: $+$ 15.64 and 2) Black*parent rank: $-0.052(25)$. The total adjustment for A is $15.64 - 0.052(25) = 14.34$, to get an adjusted rank A' of 66.26. For B, the adjustments are 1) female: $+8.39$, 2) female*parent rank: $+0.045(75)$, 3) college graduates: -8.18, and 4) college graduates*parent rank: $+0.033(75)$. The total adjustment for B is $8.39 + 0.045(75) - 8.18 + 0.033(75) = 6.06$ to get an adjusted rank B' of 74.48. The adjusted slope for New York would be $(74.48 - 66.26)/(0.75 - 0.25) = 16.44$ and the adjusted intercept would be $66.26 - 16.44(0.25) = 62.15$. An sorting-adjusted expected child rank at each percentile in the parent distribution can be calculated from the adjusted slope and intercept.

A. CHKS Estimate



B. Sorting Adjustment

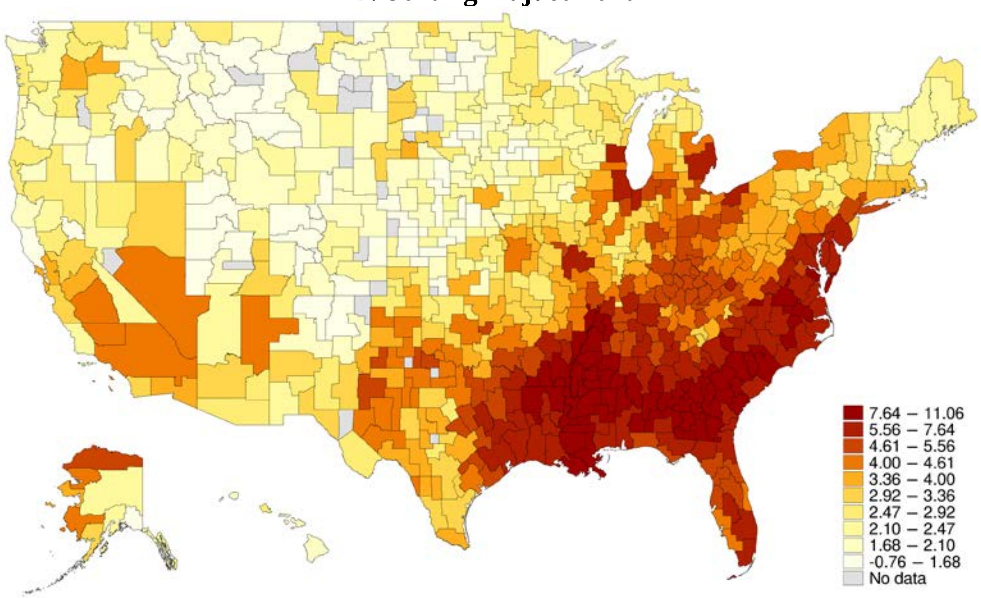
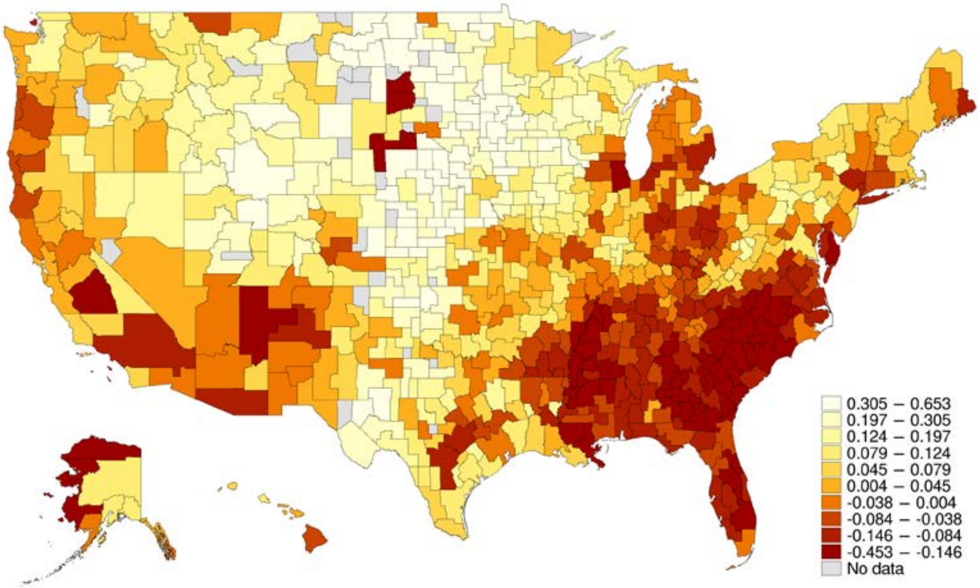


Figure 4
Expected Child Outcomes and the Contribution of Sorting for 25th Percentile Children

Panel A shows the expected income rank of a child from parents with income at the 25th percentile, from CHKS. Panel B shows the effect of controlling for observable characteristics, such as race and parent education, has on the expected child rank. The sorting adjustment is calculated using the coefficients from the baseline model (1) in Table 3 and microdata from the 1990 Long Form census. I regressed the adjusted child rank on the imputed parent rank, adjusting each CZ to the model baseline group of White sons of married, high school educated parents. The correlation between the expected child outcome and the sorting adjustment is -0.69.

A. Forecast Estimate



B. Forecast Sorting Adjustment

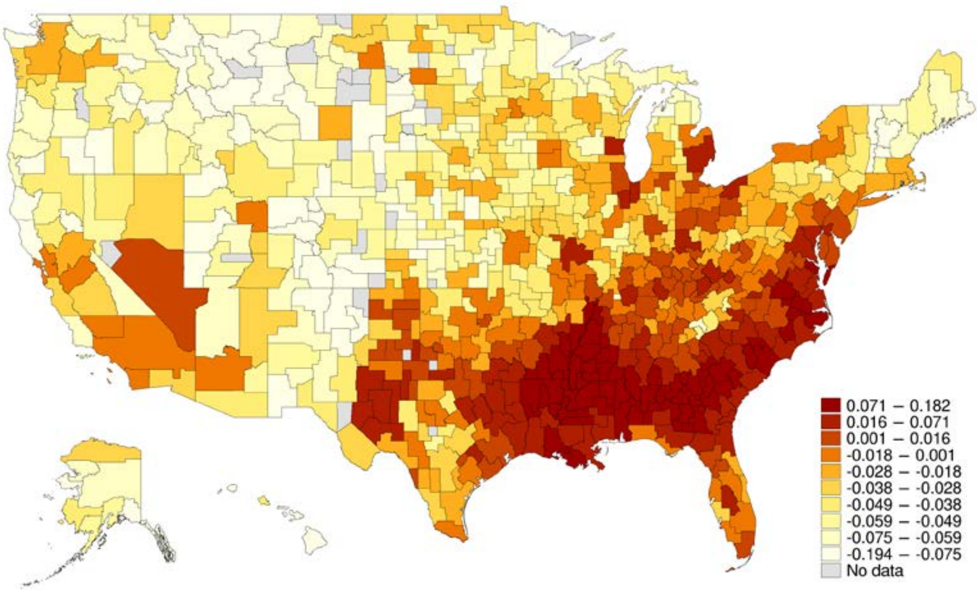


Figure 5
Causal Effect of Place and the Contribution of Sorting for 25th Percentile Children

Panel A shows the Chetty and Hendren forecast causal estimate of the effect of place for a child from parents with income at the 25th percentile. Panel B shows the effect on the forecast of controlling for observable characteristics, such as race and parent education, has on the expected child rank. The sorting adjustment is calculated using the coefficients from the baseline model (1) in Table 3 and microdata from the 1990 Long Form census. I regressed the adjusted child rank on the imputed parent rank, adjusting each CZ to the model baseline group of White sons of married, high school educated parents. The correlation between the forecast causal effect of place and the sorting adjustment is -0.46. In Panel B, areas in dark orange and red have unadjusted forecast effects that are biased downward by sorting and areas in light orange and yellow are biased upward by sorting.

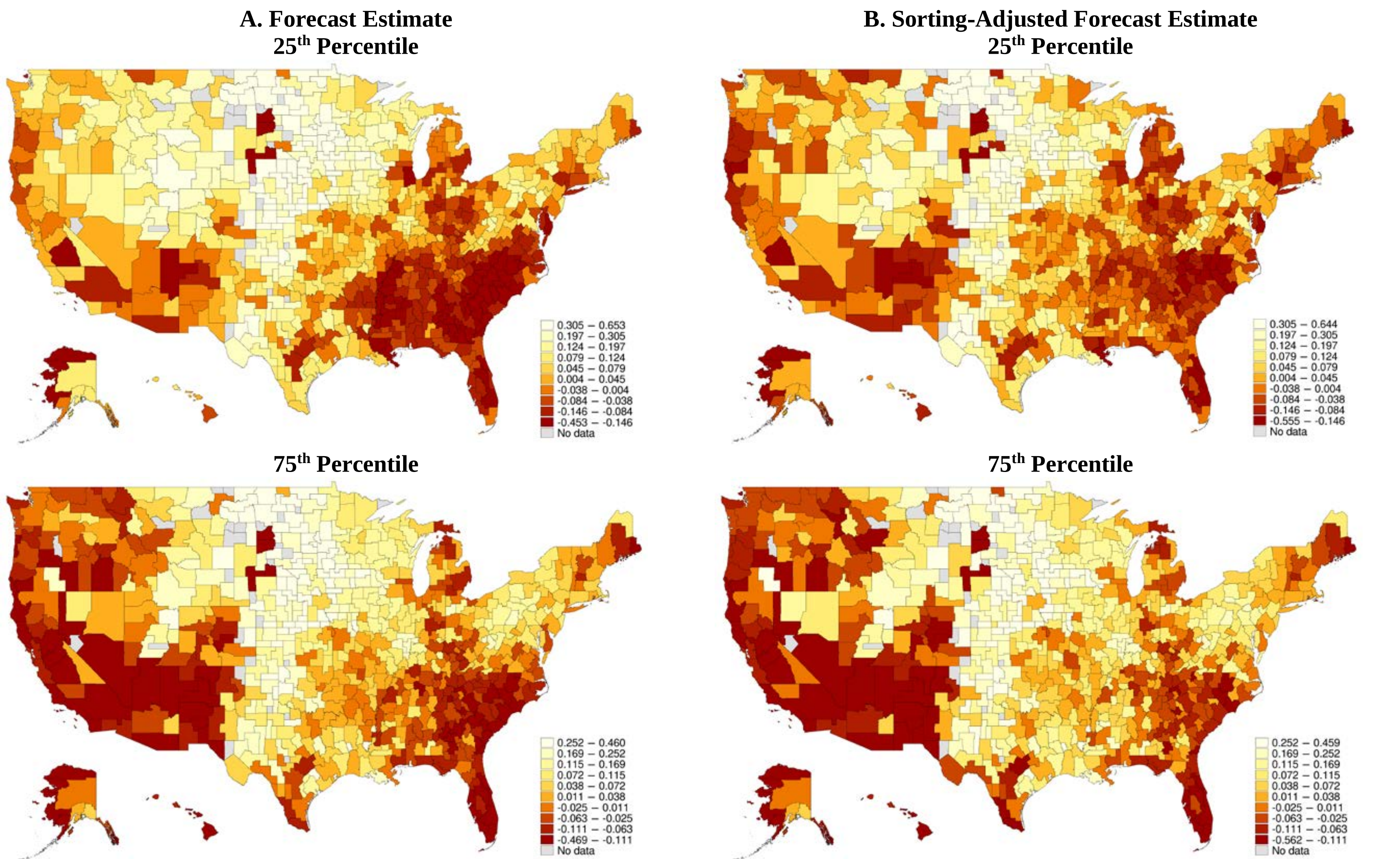


Figure 6

Comparison of Causal Effect of Place Before and After Sorting Adjustment by CZ

Panel A shows the unadjusted forecast causal effect for a child from parents with income at the 25th and 75th percentile without adjusting for sorting. Panel B shows the causal forecast controlling for observable characteristics, such as race and parent education. The sorting adjustment is calculated using the coefficients from the baseline model (1) in Table 3 and microdata from the 1990 Long Form census.

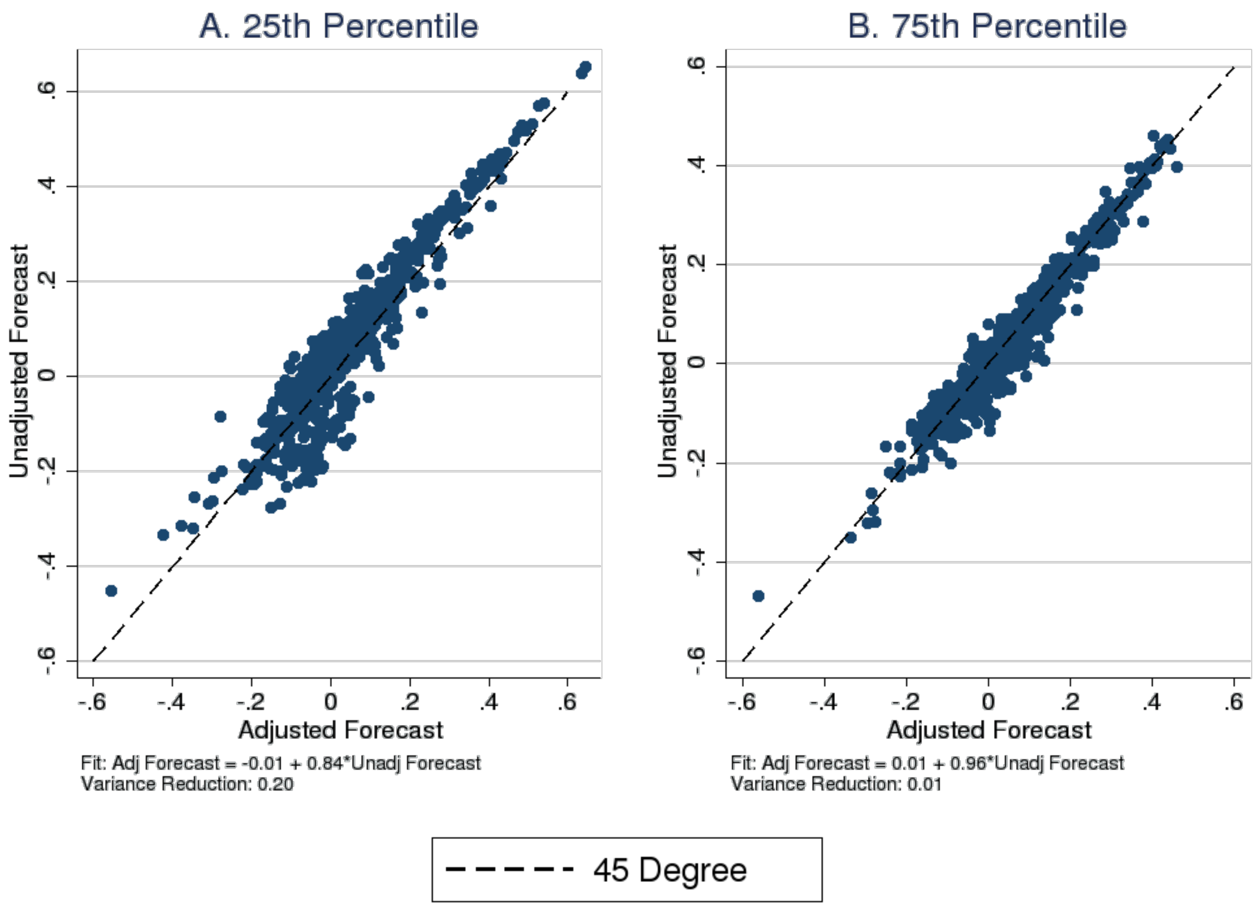


Figure 7
Unadjusted and Sorting-Adjusted Forecast Estimates

This figure compares the forecast causal estimates with and without the sorting adjustment to permanent resident mobility. The adjustment is calculated using the baseline model coefficients model (1) in Table 3 and using microdata from the 1990 census Long Form. I regressed the adjusted child rank on the imputed parent rank, adjusting each CZ to the model baseline group of White sons of married, high school educated parents. From the sorting-adjusted slope and intercept, I calculated the sorting-adjusted permanent resident mobility to be used in the forecast.

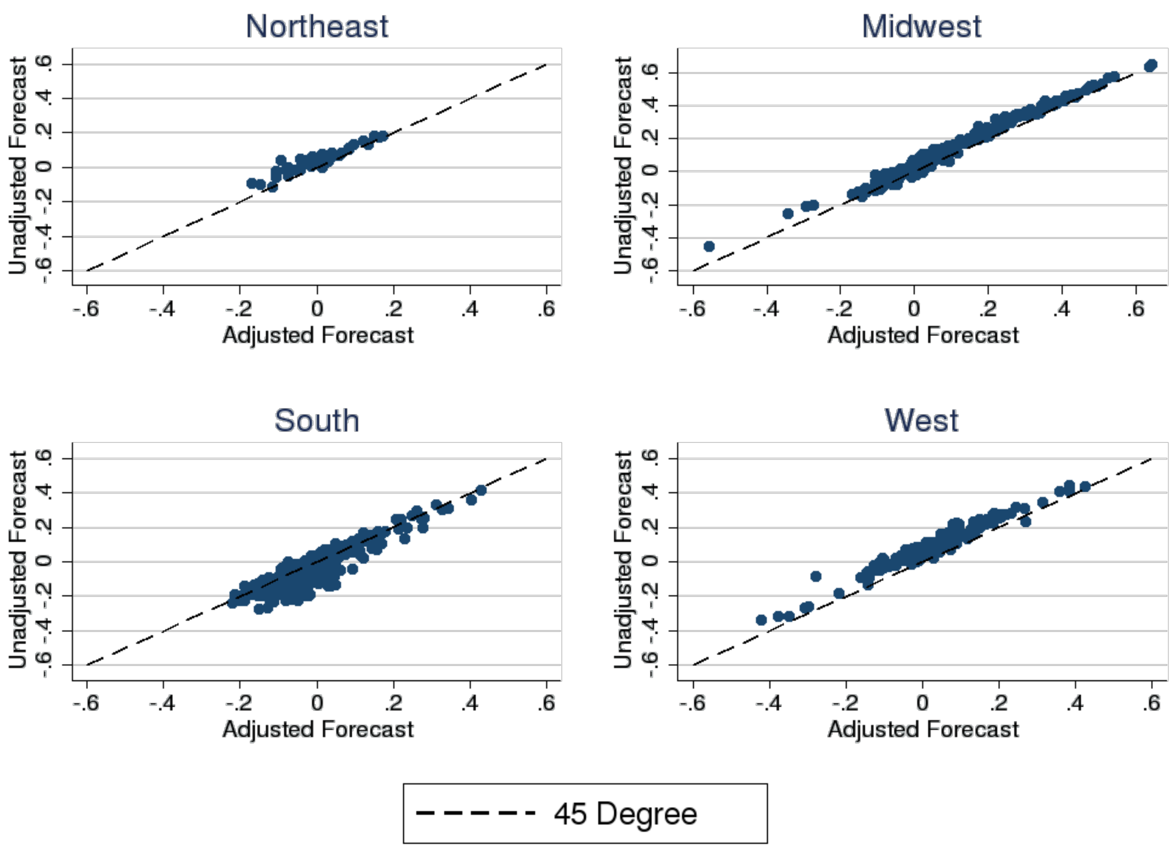
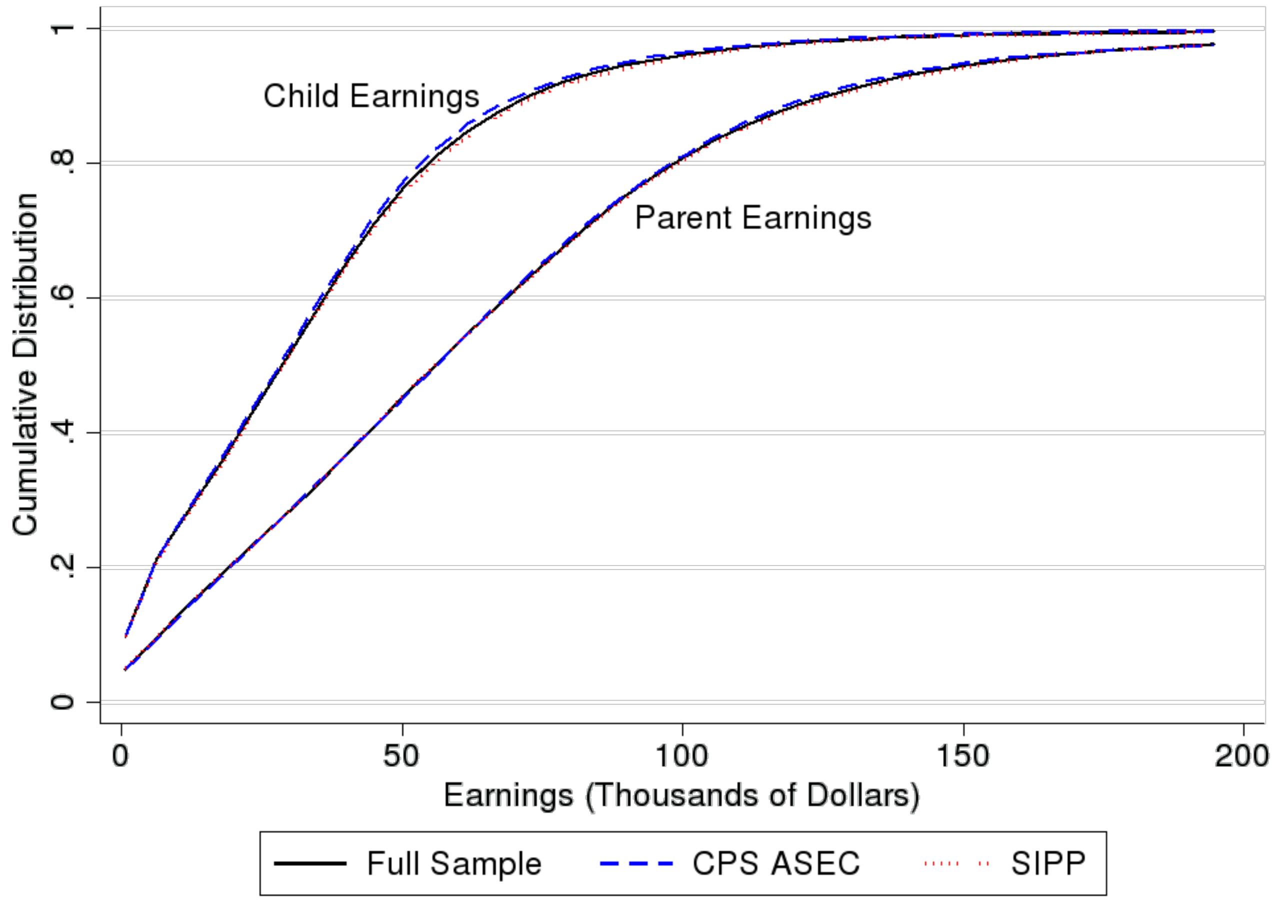


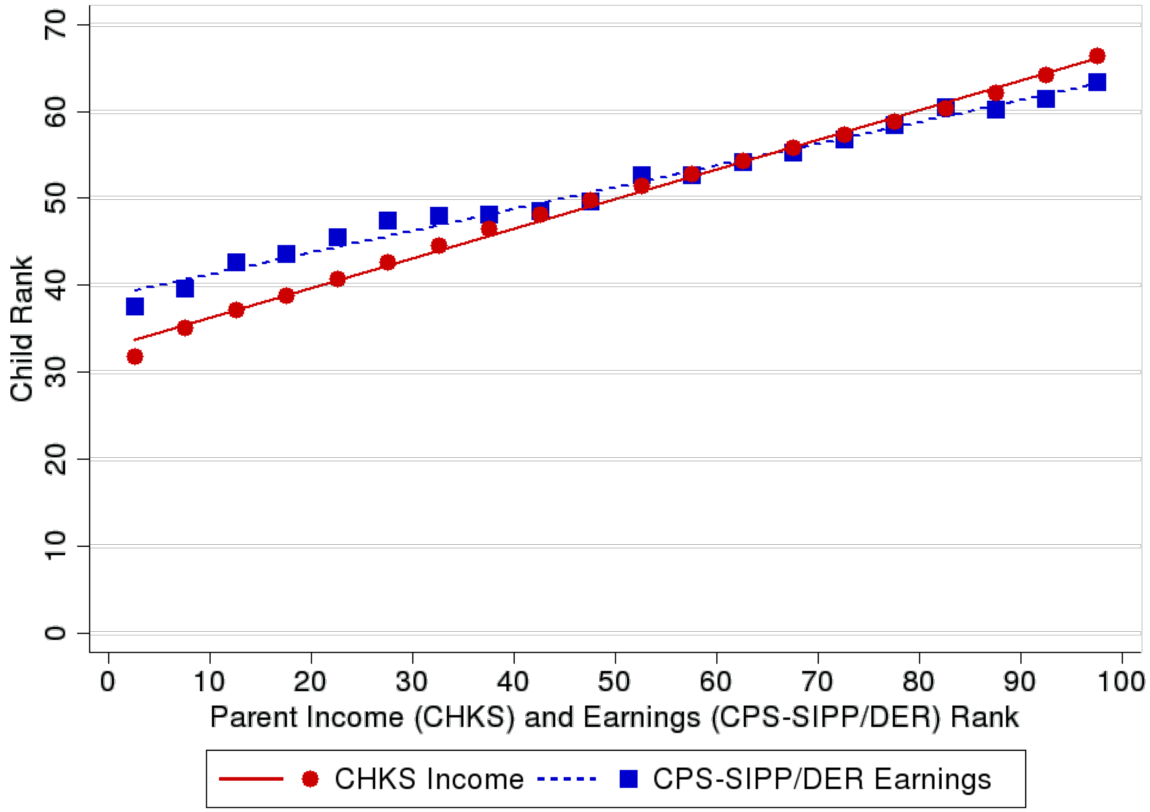
Figure 8
Regional Differences in Unadjusted and Sorting-Adjusted Forecast Estimates for 25th Percentile Children

This figure compares the unadjusted and adjusted forecast causal estimates by Census Region. The South is the only region with a large number of CZs below the diagonal, indicating sorting is related to lower upward mobility there. In the other regions, the majority of CZs are above the diagonal, which means that sorting increases mobility in them. The adjustment is calculated using the coefficients from the baseline model (1) in Table 3 and using microdata from the 1990 census Long Form. I regressed the adjusted child rank on the imputed parent rank, adjusting each CZ to the model baseline group of White sons of married, high school educated parents. From the sorting-adjusted slope and intercept, I calculated the sorting-adjusted permanent resident mobility to be used in the forecast.



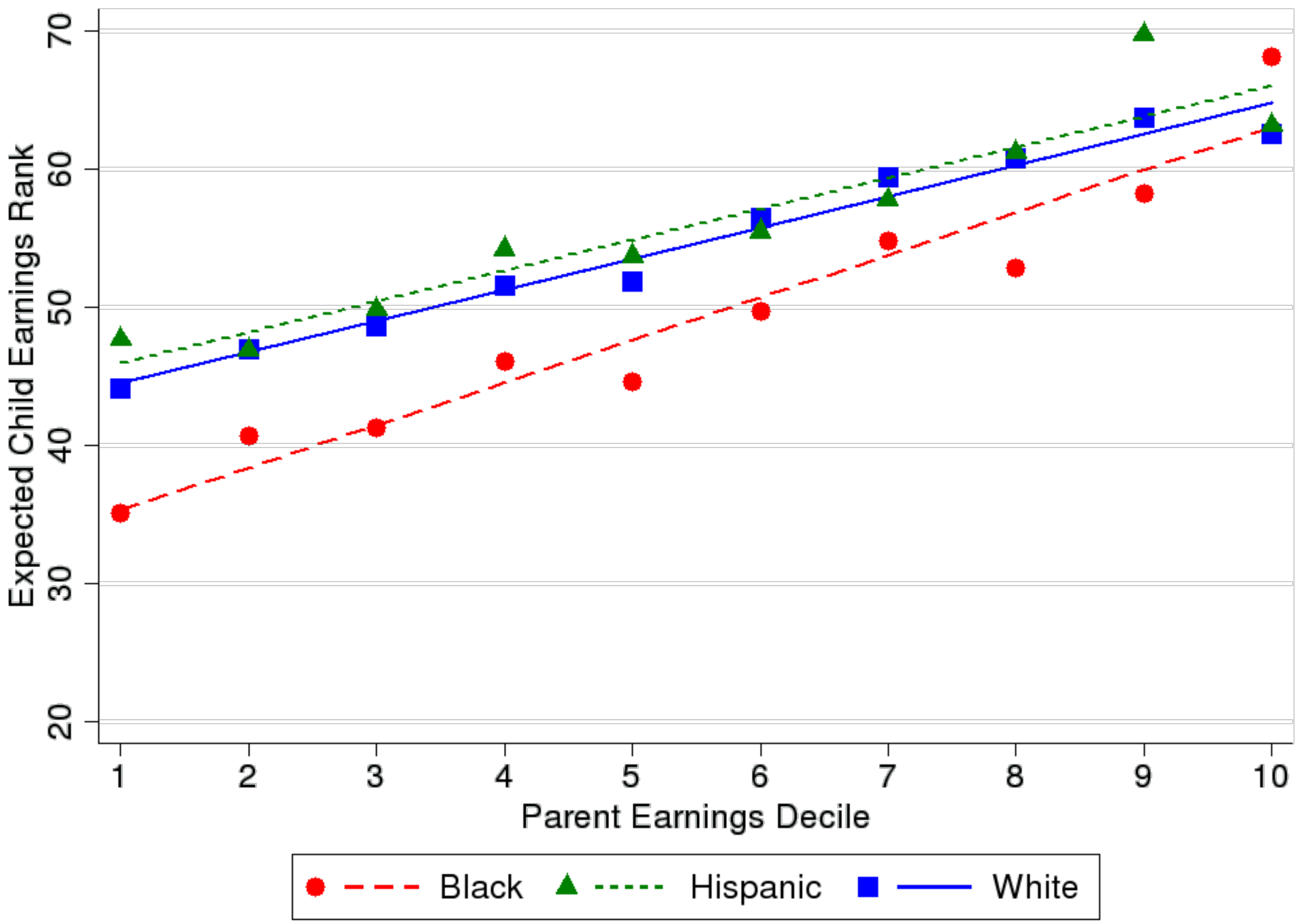
Appendix Figure 1
Parent Family and Child Individual Earnings Distribution in the CPS-SIPP/DER

The parent family earnings and child individual DER earnings are plotted for the CPS ASEC, SIPP, and combined full sample. Each line plots kernel density of the earnings in the relevant sample (in 2012 dollars). Parent earnings are much higher than child earnings for at least two reasons. First, parent earnings include the earnings of both spouses or partners whereas child earnings are for the individual children (as martial and partner data is not available for the children). Second, parent earnings are from later in their lifecycle as they are averaged when the older parent is between 40-44 years old, whereas child earnings are calculated when the children are 29-30.



Appendix Figure 2
Association between Parent and Child Rank in CHKS and CPS-SIPP/DER

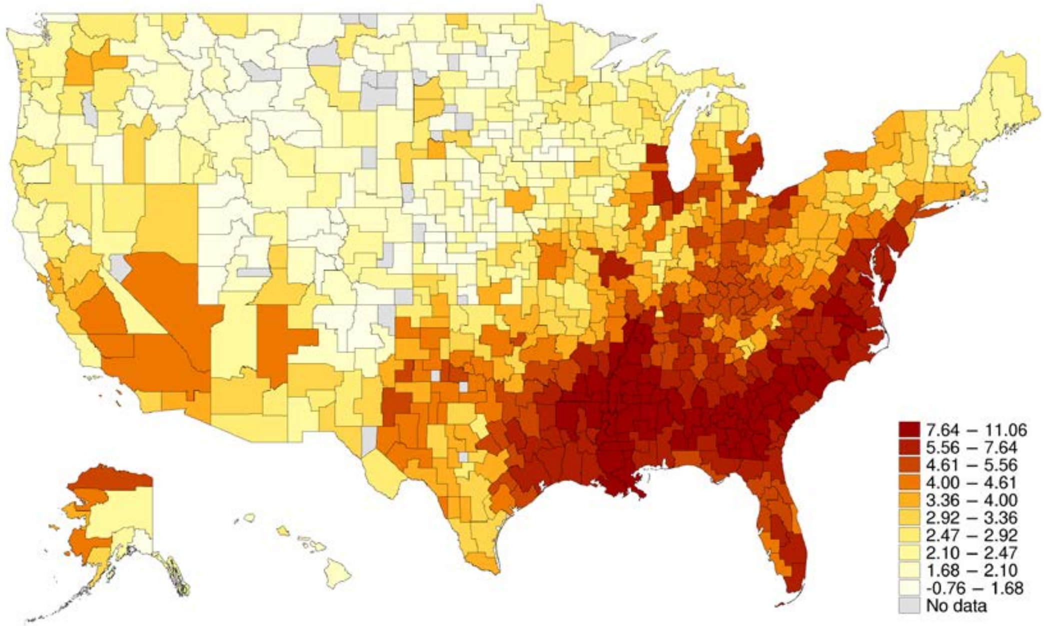
This figure plots the average child rank for 20 parent rank bins. In both the CPS-SIPP/DER and the CHKS data, the relationship between parent rank and average child rank is very well represented by the linear regression slope and intercepts on the individual observations. The CHKS parent ranks are determined by parent income rank from 1996-2000 and child ranks in 2011-2012 (child ages 29-32, depending on the birth year of 1980-1982). The CPS-SIPP/DER ranks are determined by ranking the earnings of each parent family against all parent families in the same age cohort (of the older parent) at ages 40-44. The CSD child ranks are determined by ranking each individual child against all individuals in the same age cohort, with earnings measured at 29-30 years old.



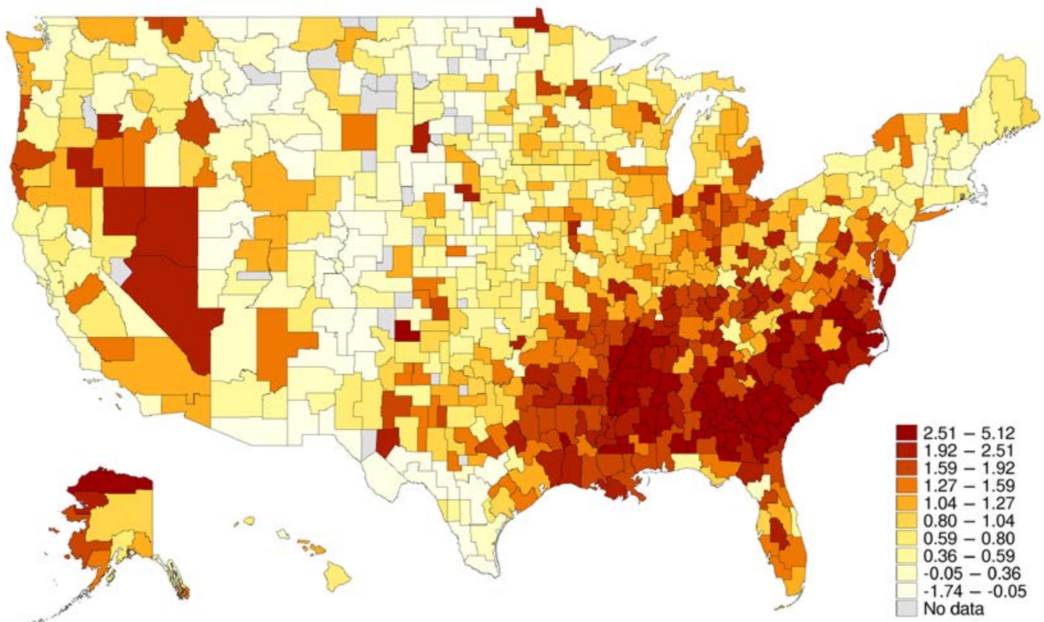
Appendix Figure 3
Race and Mobility by Decile Controlling for Parent Education

This figure plots the results of an OLS regression with dummies for each parent earnings decile interacted with race and highest parent education level (less than high school, some college, and college and above with high school as the default category). The three categories plotted by decile are white (and other), black, and Hispanic.

A. 25th Percentile



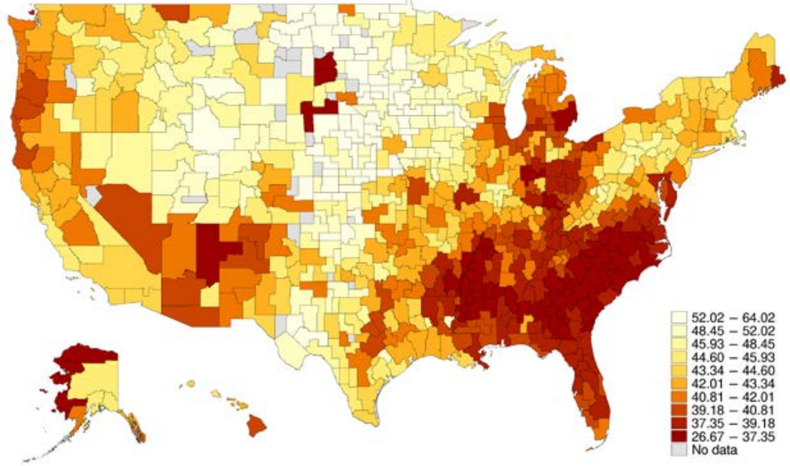
B. 75th Percentile



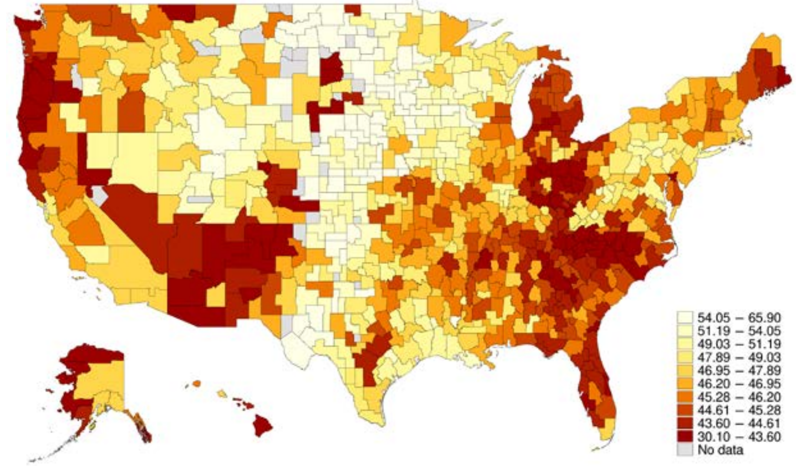
Appendix Figure 4
Impact of Sorting Adjustment on Child Rank at 25th and 75th Percentile by CZ

This figure shows how the expected child rank is affected by sorting on family and demographic characteristics. Panel A shows the adjustment to the expected rank for a child with parents at the 25th percentile and Panel B shows the adjustment for a child with parents at the 75th percentile of the income distribution The adjustment is calculated using the coefficients from the baseline model (1) in Table 3 and using microdata from the 1990 census Long Form. I regressed the adjusted child rank on the imputed parent rank, adjusting each CZ to the model baseline group of White sons of married, high school educated parents. In both panels, the adjustment is largest (dark red) in the Southeast and parts of the East Coast. A larger adjustment means that the family and demographic characteristics of children living there are associated with lower mobility. Each map is divided into ten equally sized quantiles.

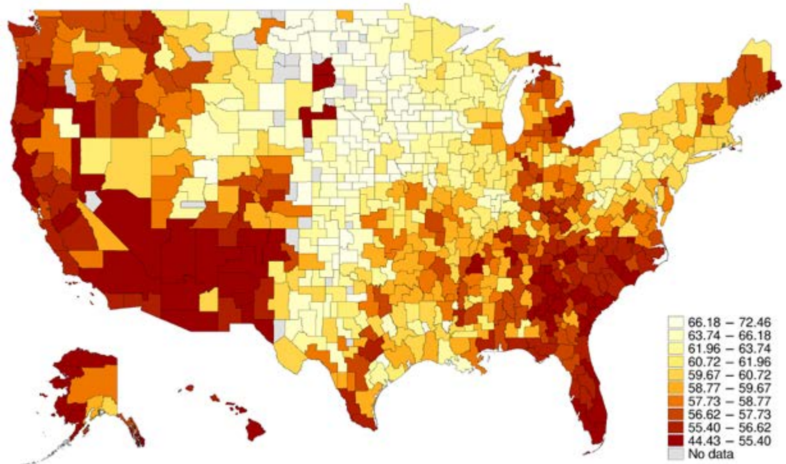
A. Expected Child Rank Without Sorting Adjustment
25^{th} Percentile



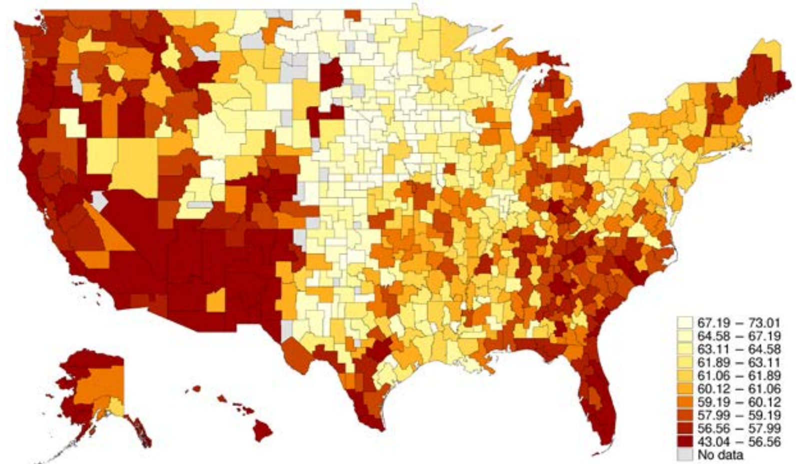
B. Sorting-Adjusted Expected Child Rank
25^{th} Percentile



75^{th} Percentile



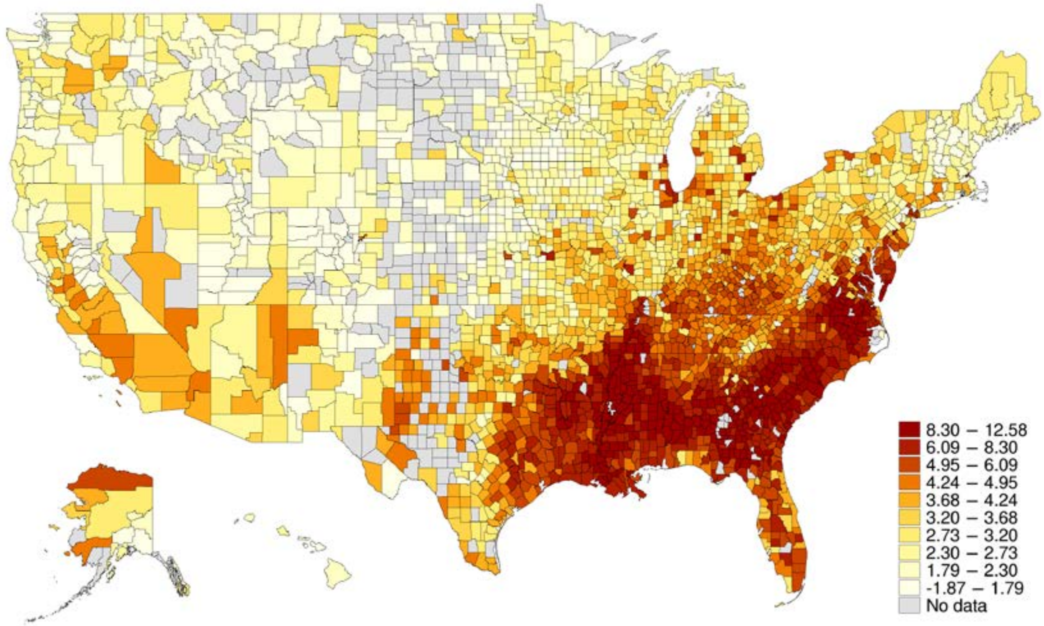
75^{th} Percentile



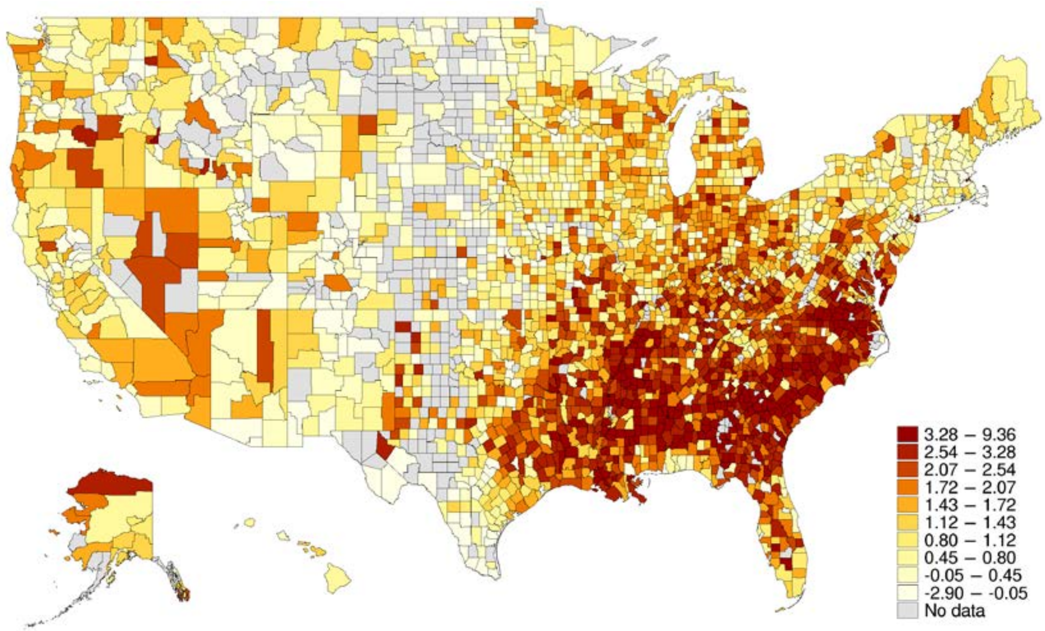
Appendix Figure 5
Comparison of Expected Rank Before and After Sorting Adjustment by CZ

Panel A shows the expected income rank of a child from parents with income at the 25^{th} and 75^{th} percentile without adjusting for sorting, from CHKS. Panel B shows the expected rank controlling for observable characteristics, such as race and parent education. The sorting adjustment is calculated using the coefficients from the baseline model (1) in Table 3 and microdata from the 1990 Long Form census. Each map is divided into ten equally sized quantiles.

A. 25^{th} Percentile

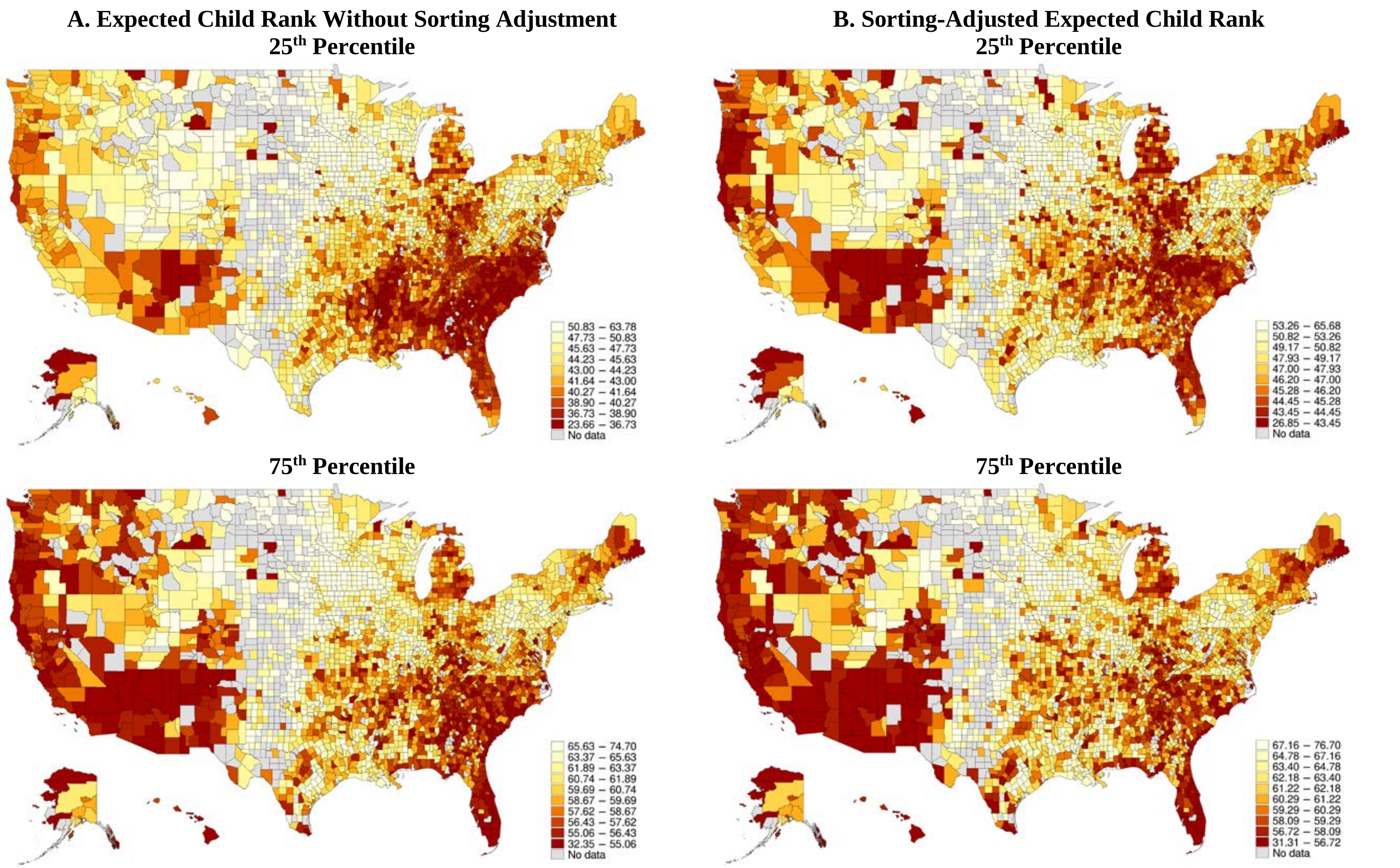


B. 75^{th} Percentile



Appendix Figure 6
Impact of Sorting Adjustment on Expected Child Rank at 25^{th} and 75^{th} Percentile by County

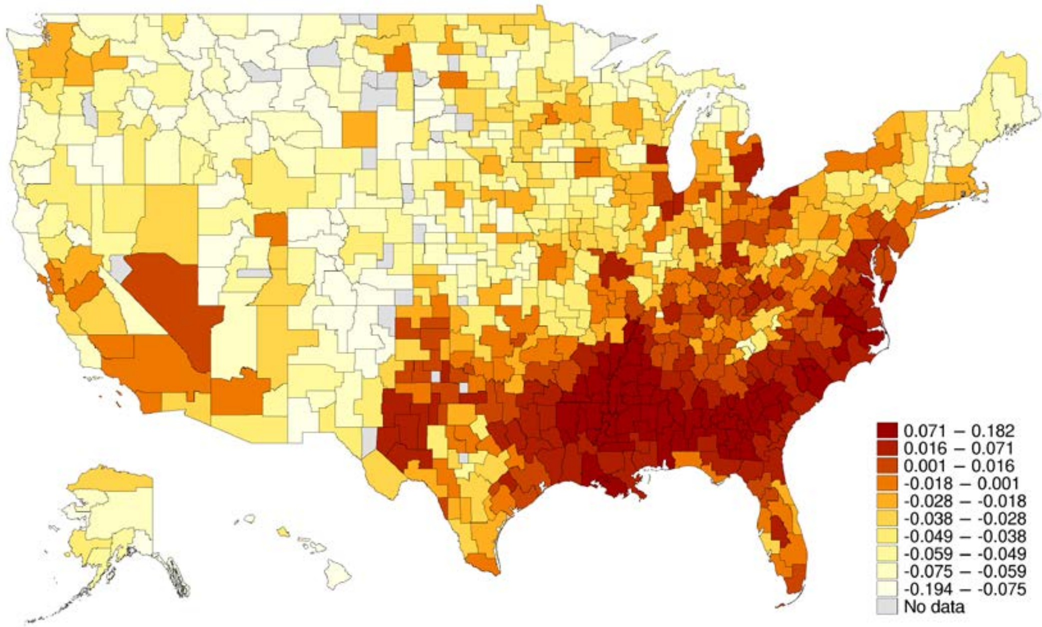
This figure shows how the expected child rank is affected by sorting on family and demographic characteristics. Panel A shows the adjustment to the expected rank for a child with parents at the 25^{th} percentile and Panel B shows the adjustment for a child with parents at the 75^{th} percentile of the income distribution The adjustment is calculated using the coefficients from the baseline model (1) in Table 3 and using microdata from the 1990 census Long Form. I regressed the adjusted child rank on the imputed parent rank, adjusting each county to the model baseline group of White sons of married, high school educated parents. Each map is divided into ten equally sized quantiles. Areas in dark orange and red have unadjusted forecast effects that are biased downward by sorting and areas in light orange and yellow are biased upward by sorting.



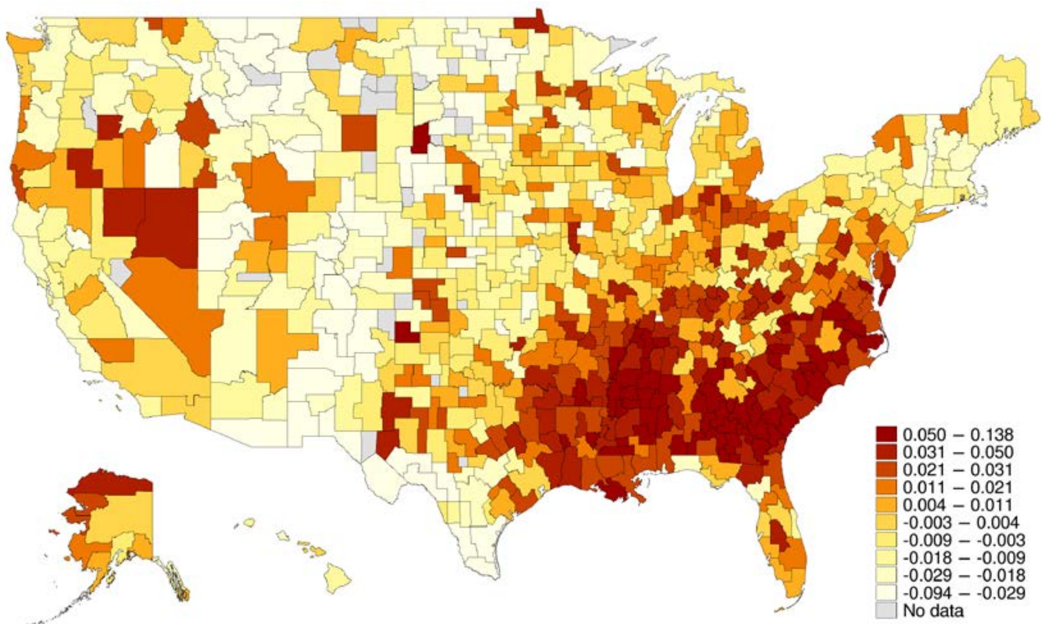
Appendix Figure 7
Comparison of Expected Rank Before and After Sorting Adjustment by County

Panel A shows the expected income rank of a child from parents with income at the 25th and 75th percentile without adjusting for sorting, from CHKS. Panel B shows the expected rank controlling for observable characteristics, such as race and parent education. The sorting adjustment is calculated using the coefficients from the baseline model (1) in Table 3 and microdata from the 1990 Long Form census. Each map is divided into ten equally sized quantiles.

A. 25th Percentile



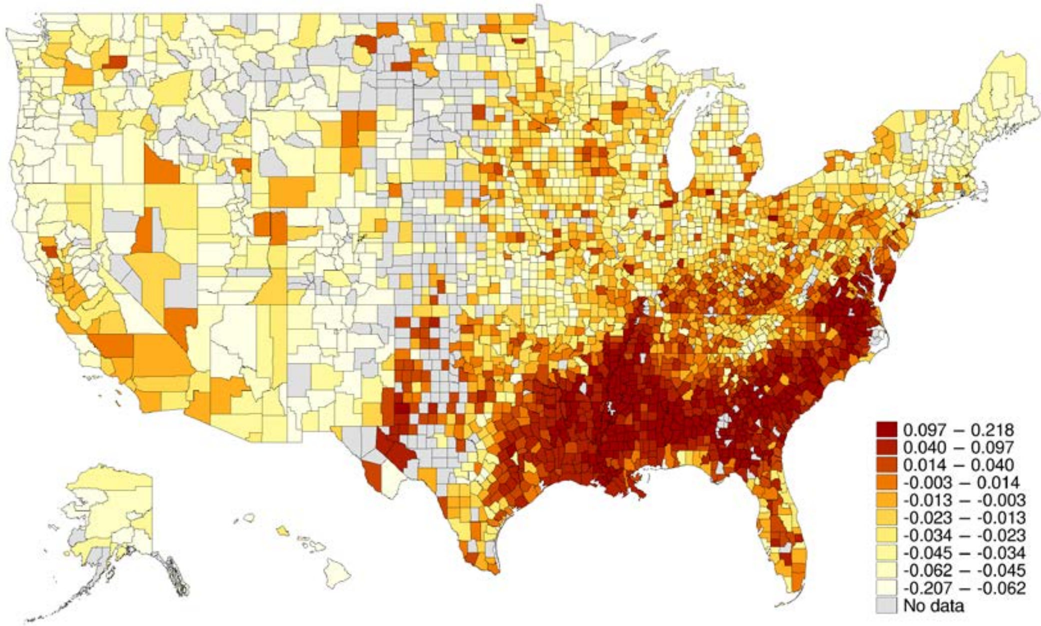
B. 75th Percentile



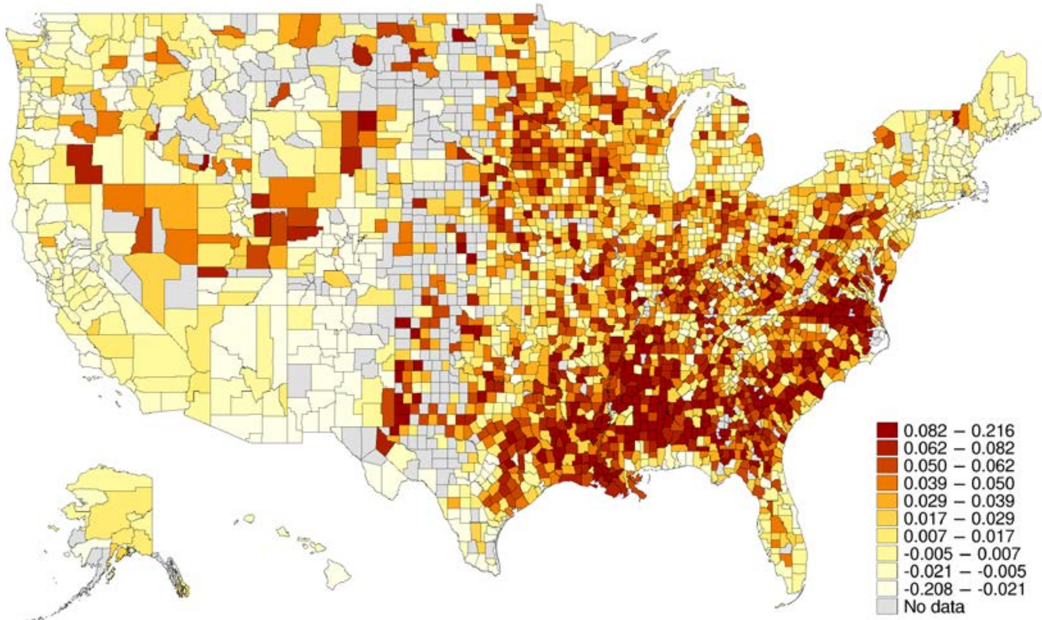
Appendix Figure 8
Impact of Sorting on Causal Mobility Estimates by CZ

This figure shows how the forecast causal estimates are affected by replacing their permanent resident mobility with estimates adjusted for sorting on demographic and family characteristics. The adjustment is calculated using the coefficients from the baseline model (1) in Table 3 and using microdata from the 1990 census Long Form. I regressed the adjusted child rank on the imputed parent rank, adjusting each CZ to the model baseline group of White sons of married, high school educated parents. From the sorting-adjusted slope and intercept, I calculated the sorting-adjusted permanent resident mobility to be used in the forecast. Each map is divided into ten equally sized quantiles. Areas in dark orange and red have unadjusted forecast effects that are biased downward by sorting and areas in light orange and yellow are biased upward by sorting.

A. 25th Percentile

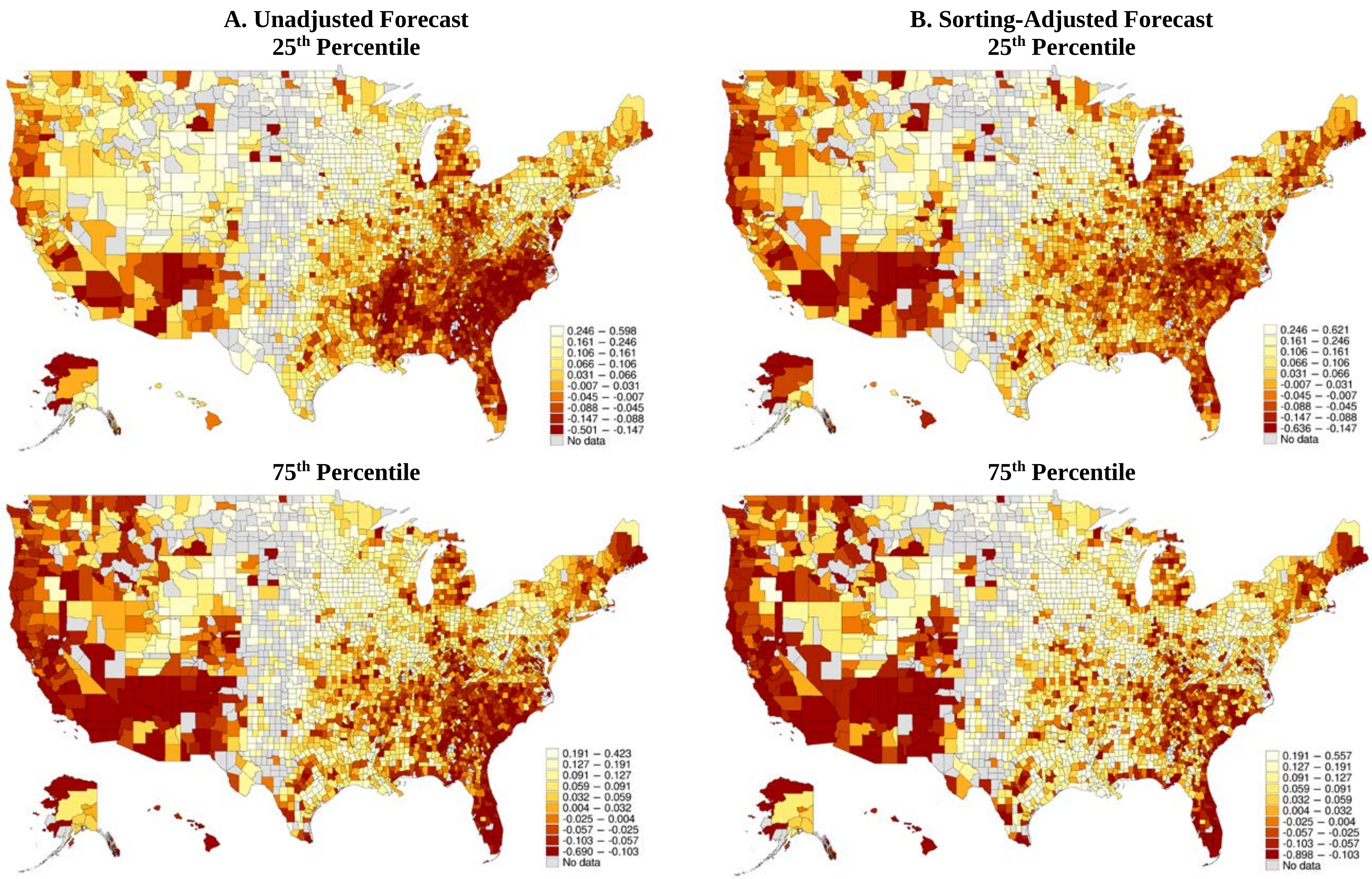


B. 75th Percentile



Appendix Figure 9
Impact of Sorting on Causal Mobility Estimates by County

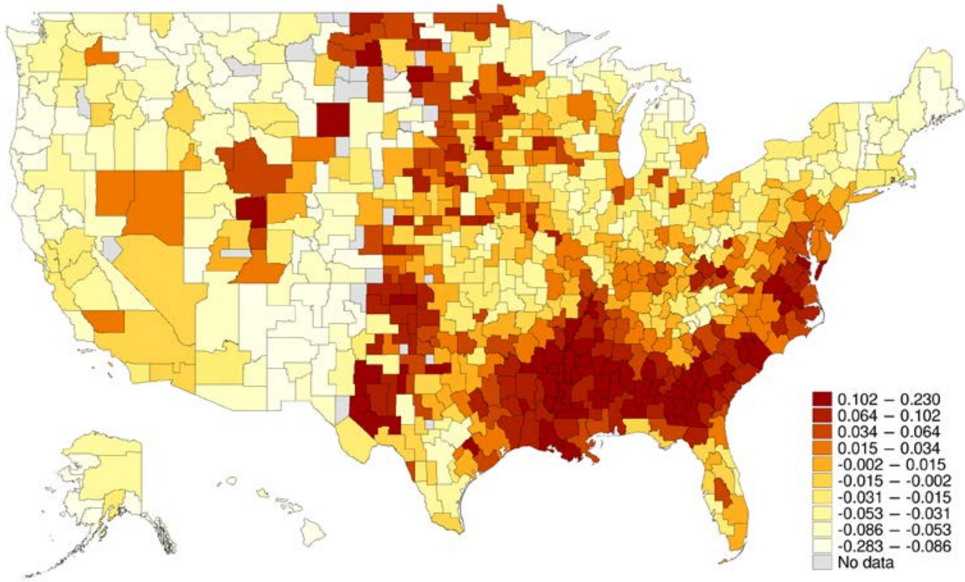
This figure shows how the forecast causal estimates are affected by replacing their permanent resident mobility with estimates adjusted for sorting on demographic and family characteristics. The adjustment is calculated using the coefficients from the baseline model (1) in Table 3 and using microdata from the 1990 census Long Form. I regressed the adjusted child rank on the imputed parent rank, adjusting each county to the model baseline group of White sons of married, high school educated parents. From the sorting-adjusted slope and intercept, I calculated the sorting-adjusted permanent resident mobility to be used in the forecast. Each map is divided into ten equally sized quantiles. Areas in dark orange and red have unadjusted forecast effects that are biased downward by sorting and areas in light orange and yellow are biased upward by sorting.



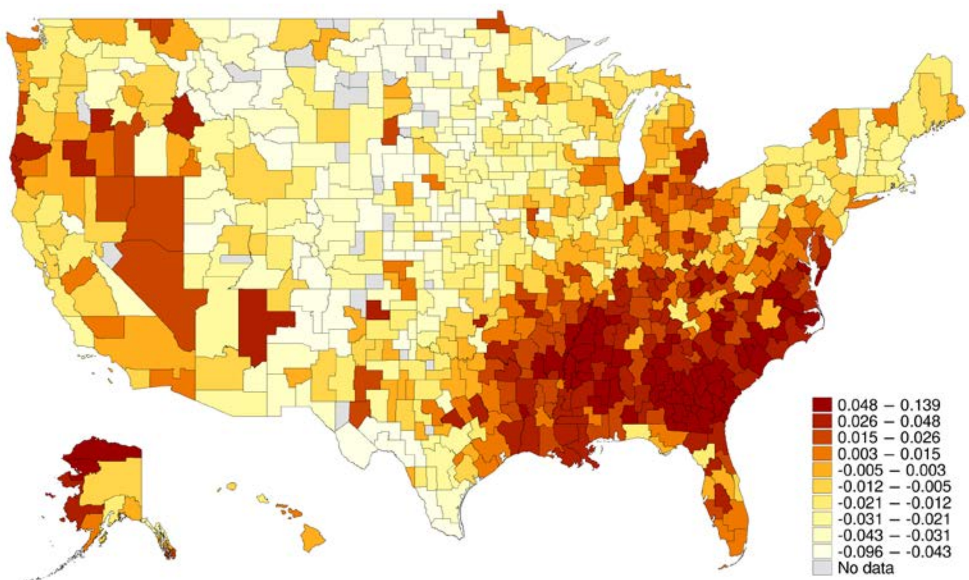
Appendix Figure 10
Comparison of Causal Effect of Place Before and After Sorting Adjustment by County

Panel A shows the unadjusted forecast causal effect for a child from parents with income at the 25th and 75th percentile without adjusting for sorting. Panel B shows the causal forecast controlling for observable characteristics, such as race and parent education. The sorting adjustment is calculated using the coefficients from the baseline model (1) in Table 3 and microdata from the 1990 Long Form census.

A. 25th Percentile

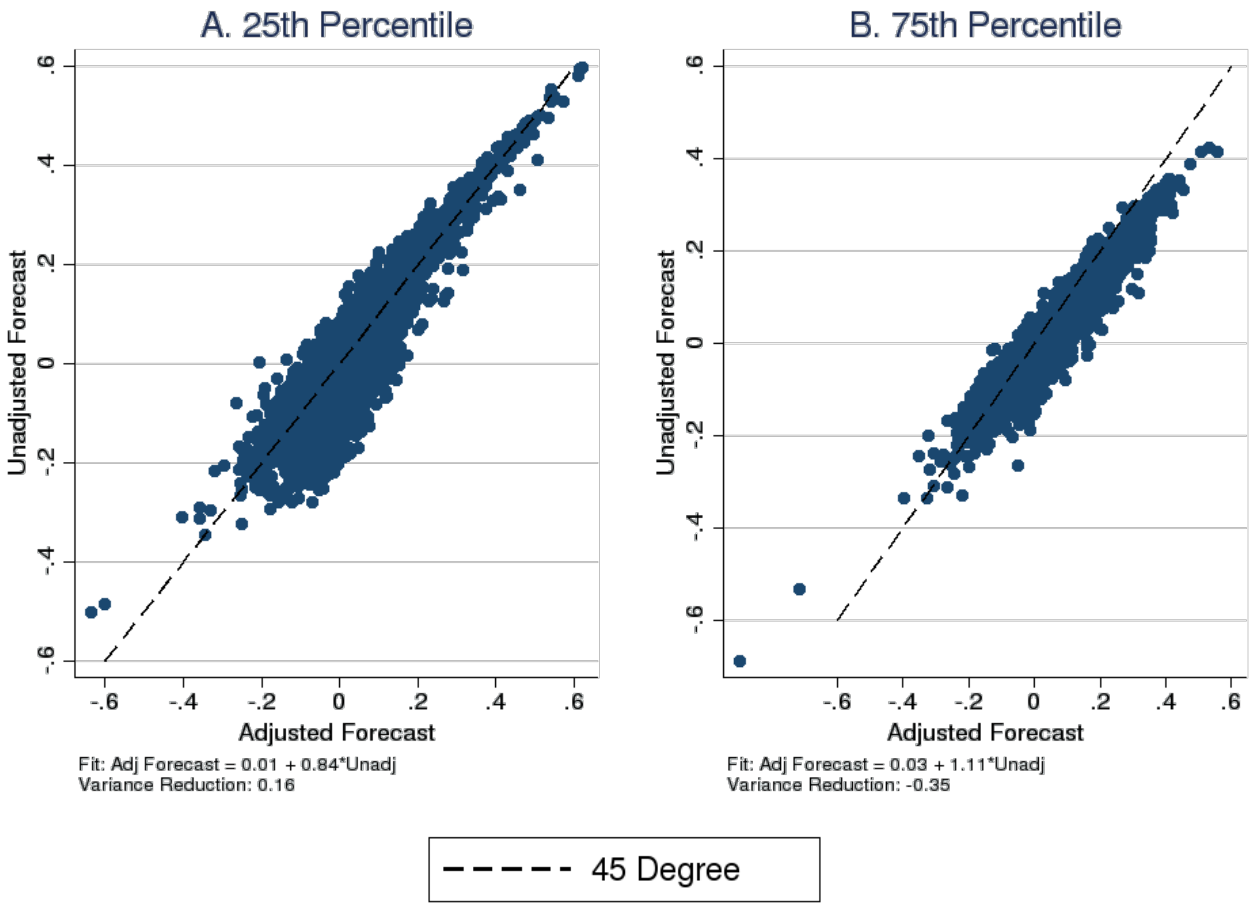


B. 75th Percentile



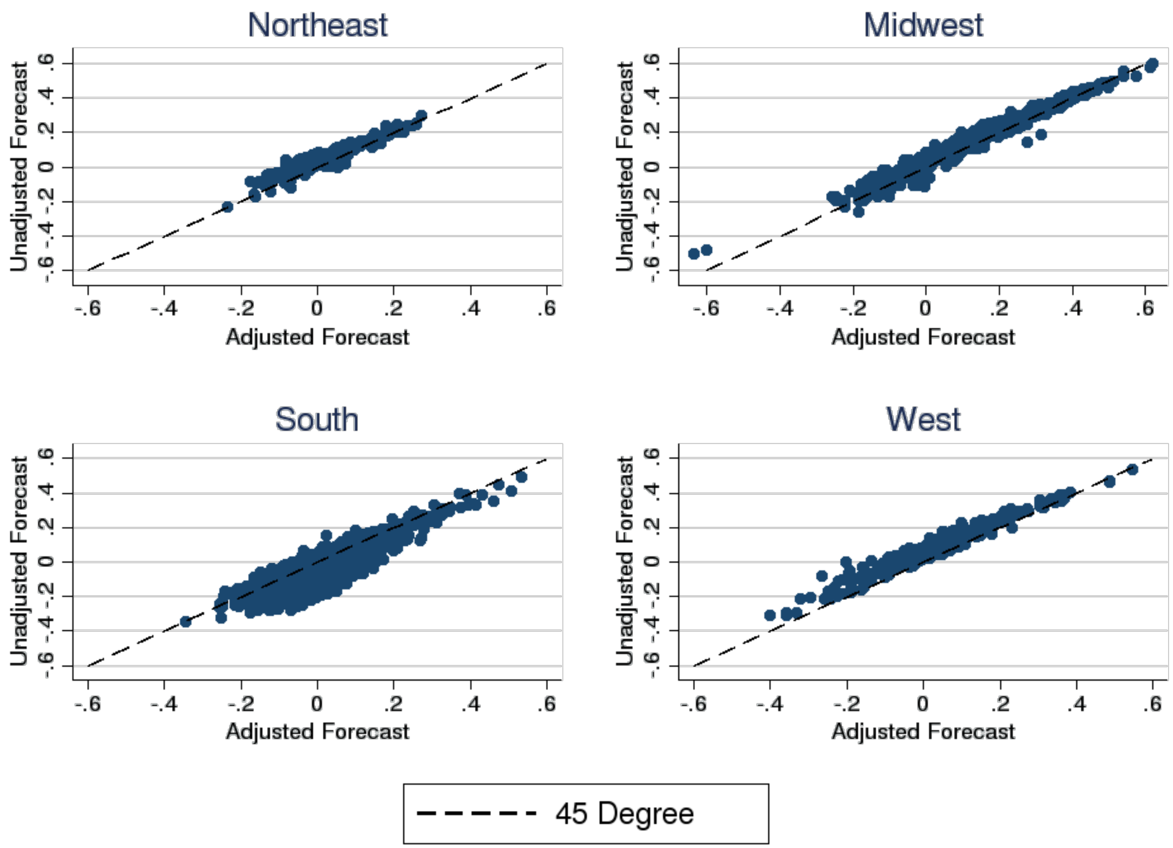
Appendix Figure 11
Impact of Sorting Adjustment on Causal Mobility Estimates using Chetty and Hendren Permanents Residents at 26

This figure shows how the forecast causal estimates from Chetty and Hendren for children from below median (Panel A) and above median (Panel B) families are affected by the sorting adjustment. The forecasts were created by taking the raw causal estimates and combining them with data on mobility of non-movers to address the fact that 71% of the variation in the raw causal estimates was due to sampling variation and not the causal effects of place. The weight given to non-movers in the forecast for each CZ is based on the precision of the raw causal estimate. Both maps are divided into ten equally sized quantiles. This figure differs from Appendix Figure 8 in the construction of the adjustment. In Appendix Figure 8, the adjustment is based on the CHKS estimates of mobility in each CZ (as that was the data used to construct the adjustment). In this figure, the magnitude of the adjustment is calculated from the CHKS values and applied to the permanent residents at 26 as in Chetty and Hendren. In both cases, the magnitude of adjustment to the permanent residents is the same, but the initial permanent resident value and forecast regression coefficient differ. Areas in dark orange and red have unadjusted forecast effects that are biased downward by sorting and areas in light orange and yellow are biased upward by sorting.



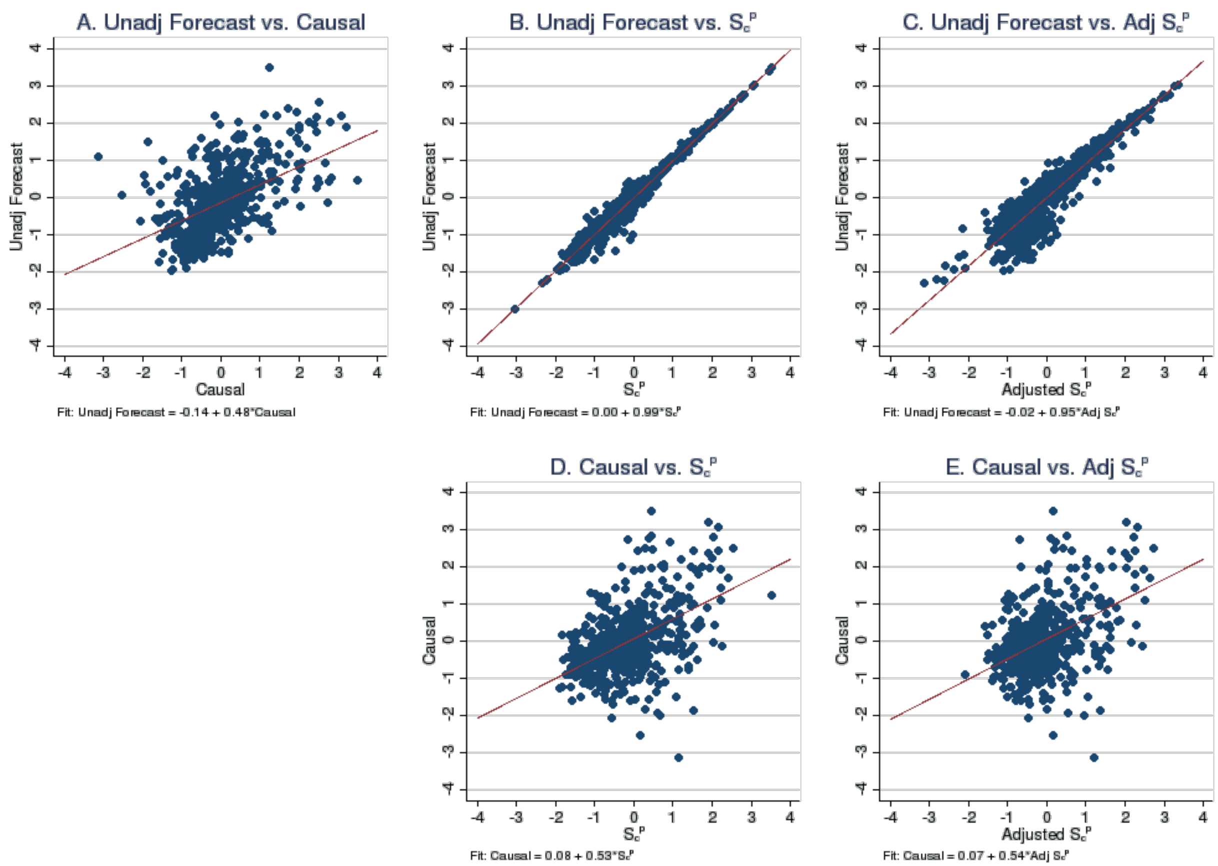
Appendix Figure 12
Unadjusted and Sorting-Adjusted Forecast Estimates by County

This figure compares the forecast causal estimates with and without the sorting adjustment to permanent resident mobility. The adjustment is calculated using the baseline model coefficients model (1) in Table 3 and using microdata from the 1990 census Long Form. I regressed the adjusted child rank on the imputed parent rank, adjusting each county to the model baseline group of White sons of married, high school educated parents. From the sorting-adjusted slope and intercept, I calculated the sorting-adjusted permanent resident mobility to be used in the forecast.



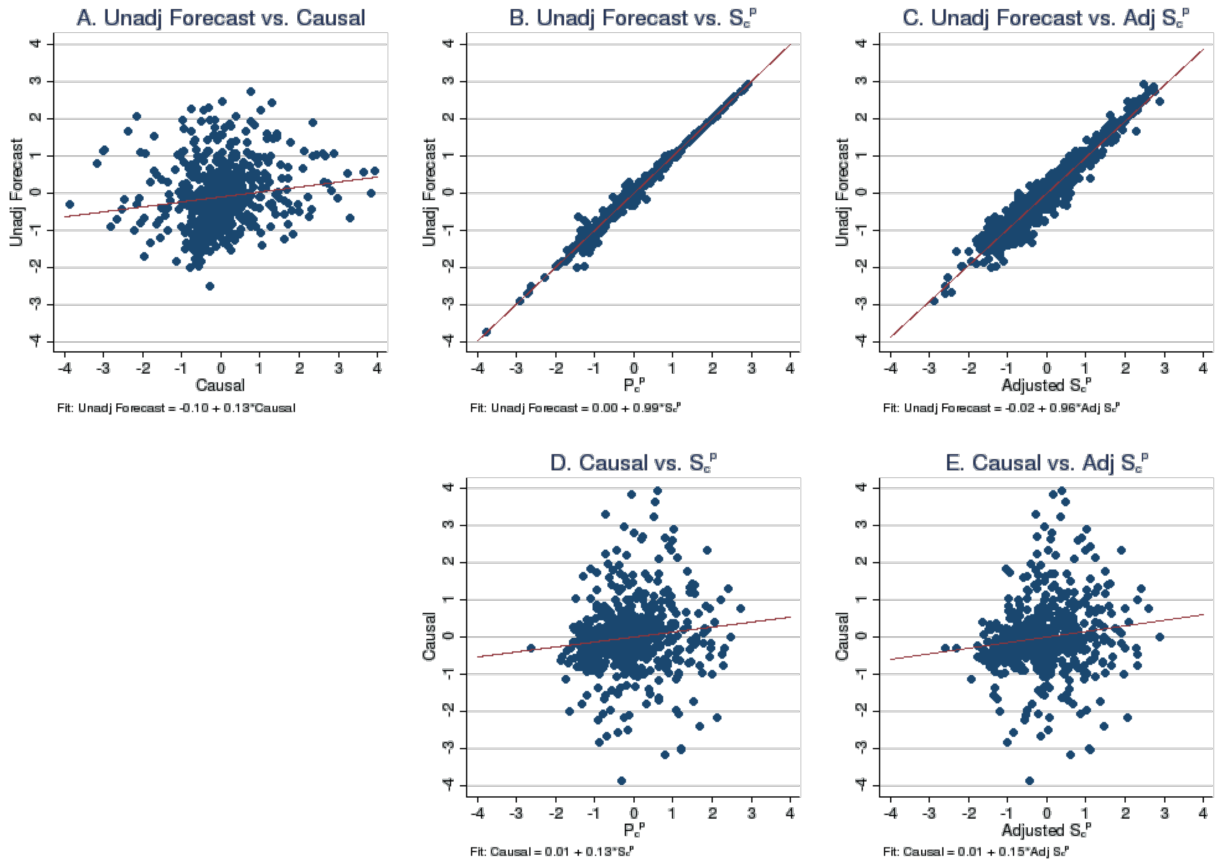
Appendix Figure 13
Regional Differences in Unadjusted Mobility Estimates and Sorting-Adjusted Estimates for 25th Percentile Children by County

This figure compares the unadjusted and adjusted forecast causal estimates by Census Region. The South is the only region with a large number of counties below the diagonal, indicating sorting is related to lower upward mobility there. In the other regions, the majority of counties are above the diagonal, which means that sorting increases mobility in them. The adjustment is calculated using the coefficients from the baseline model (1) in Table 3 and using microdata from the 1990 census Long Form. I regressed the adjusted child rank on the imputed parent rank, adjusting each county to the model baseline group of White sons of married, high school educated parents. From the sorting-adjusted slope and intercept, I calculated the sorting-adjusted permanent resident mobility to be used in the forecast.



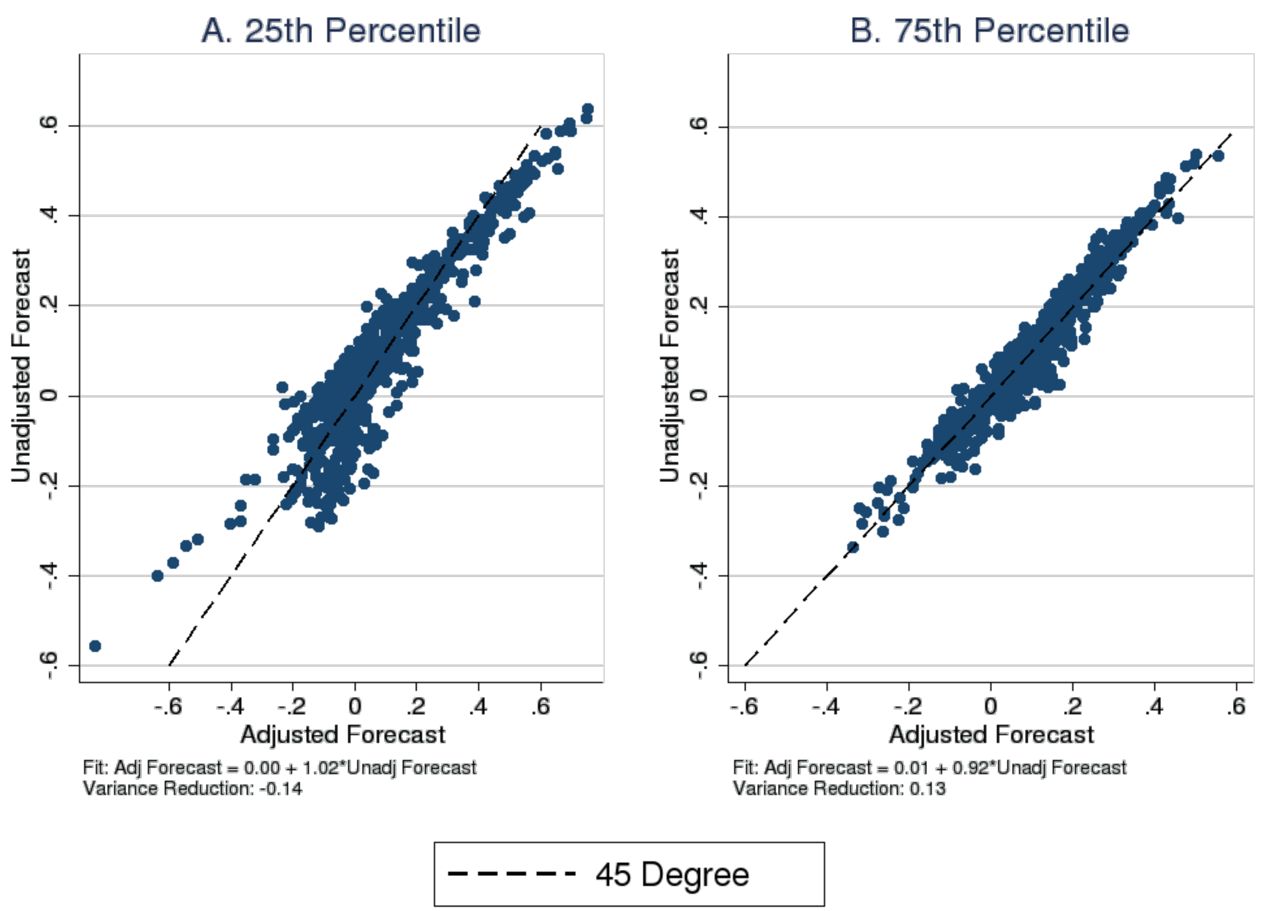
Appendix Figure 14
Comparing 25th Percentile Causal Estimates with S_c^p and Adjusted S_c^p

This figure shows how the correlation between the standardized causal/forecast estimates and unadjusted/adjusted permanent resident outcomes by CZ for children from below-median income families. In Panel A, the Chetty and Hendren causal estimates are compared to the unadjusted forecasts that use results from permanent residents to increase the precision of the estimates based on movers only. The unadjusted forecast is nearly perfectly correlated with outcomes of permanent residents (B), and less so with sorting-adjusted permanent resident outcomes (C). However, the causal estimate based on movers is not any more correlated with one or the other (D and E).



Appendix Figure 15
Comparing 75th Percentile Causal Estimates with S_c^p and Adjusted S_c^p

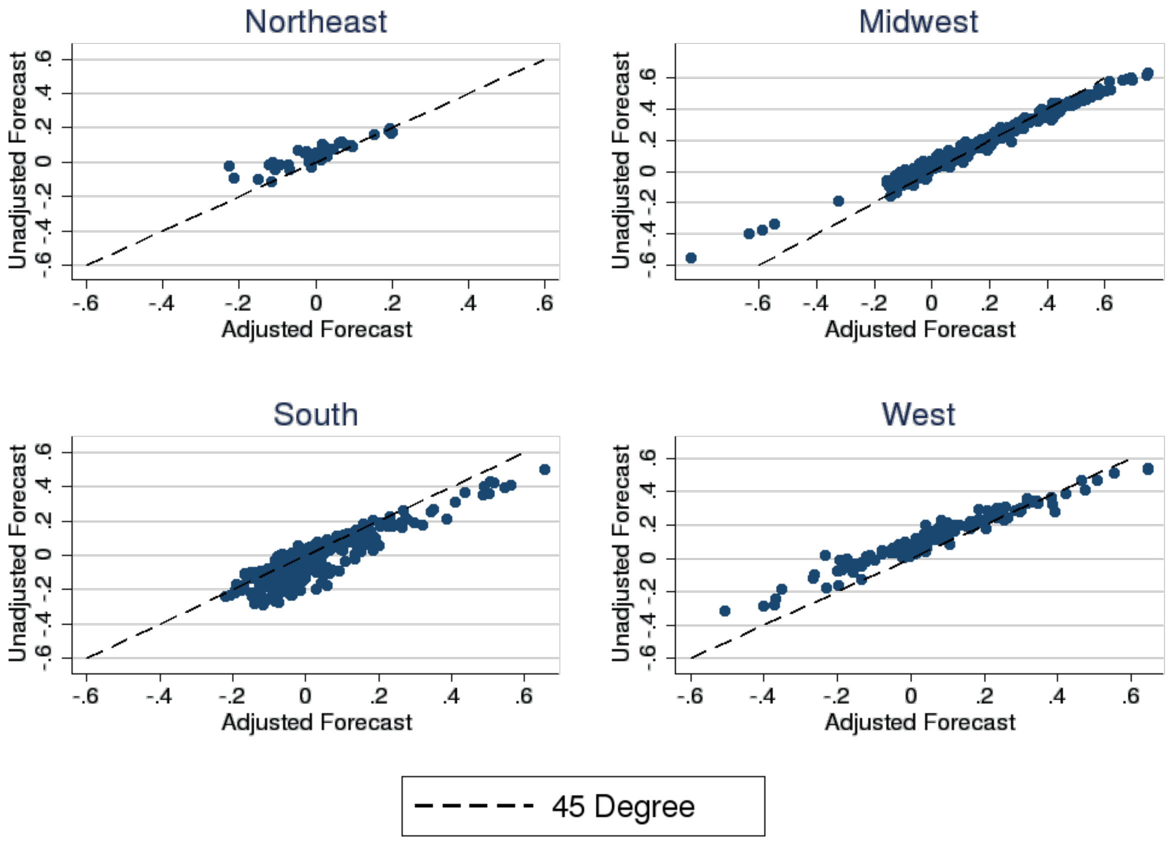
This figure shows how the correlation between the standardized causal/forecast estimates and unadjusted/adjusted permanent resident outcomes by CZ for children from below-median income families. In Panel A, the Chetty and Hendren causal estimates are compared to the unadjusted forecasts that use results from permanent residents to increase the precision of the estimates based on movers only. The unadjusted forecast is nearly perfectly correlated with outcomes of permanent residents (B), and less so with sorting-adjusted permanent resident outcomes (C). However, the causal estimate based on movers is not highly correlated with either (D and E).



Appendix Figure 16

Comparing Chetty and Hendren Causal Mobility Estimates to Sorting-Adjusted Estimates using Chetty and Hendren Permanents Residents at 26

This figure compares the forecast causal estimates from Chetty and Hendren with and without the sorting adjustment to permanent resident mobility. The adjustment is calculated using the baseline model coefficients model (1) in Table 3 and using microdata from the 1990 census Long Form. I regressed the adjusted child rank on the imputed parent rank, adjusting each CZ to the model baseline group of White sons of married, high school educated parents. From the sorting-adjusted slope and intercept, I calculated the sorting-adjusted permanent resident mobility to be used in the forecast.



Appendix Figure 17
Regional Differences in Chetty and Hendren Causal Mobility Estimates and Sorting-Adjusted Estimates for 25th Percentile Children using Chetty and Hendren Permanents Residents at 26

This figure compares the forecast causal estimates from Chetty and Hendren with and without the sorting adjustment to permanent resident mobility by Census Region. The South is the only region with a large number of CZs below the diagonal, indicating sorting is related to lower upward mobility there. In the other regions, the majority of CZs are above the diagonal, which means that sorting increases mobility in them. The adjustment is calculated using the baseline model coefficients model (1) in Table 3 and using microdata from the 1990 census Long Form. I regressed the adjusted child rank on the imputed parent rank, adjusting each CZ to the model baseline group of White sons of married, high school educated parents. From the sorting-adjusted slope and intercept, I calculated the sorting-adjusted permanent resident mobility to be used in the forecast. This corresponds to Figure 8 but with the baseline non-mover mobility replaced with permanent residents at 26 (as opposed to the adjusted CHKS estimate). In this figure, the magnitude of the adjustment is calculated from the CHKS values and applied to the permanent residents at 26 as in Chetty and Hendren. In both cases, the magnitude of adjustment to the permanent residents is the same, but the initial permanent resident value and forecast regression coefficient differ.

Appendix A: Data

A. Data Construction and Weighting

This paper uses survey data to construct a large sample of parents and children linked with administrative longitudinal earnings data. The parent-child links and information on parent family characteristics come from two surveys conducted by the US Census Bureau, the Current Population Survey Annual Social and Economic Supplement (CPS ASEC) and the Survey of Income and Program Participation (SIPP). The earnings data comes from W-2 records and 1040-SE forms filed with the Social Security Administration (SSA) and the Internal Revenue Service (IRS) and shared with the Census Bureau in the Detailed Earnings Record (DER) extract from the SSA Master Earnings File. Individuals are linked between the Census surveys and the DER by matching survey respondents to their Social Security Numbers (SSN).[41] Prior to the construction of the Census survey-administrative data set, the SSNs are removed from the data and individuals are given a Personal Identification Key (PIK) to enable the linkage.

While the CPS ASEC has been conducted annually since 1948, the links between the SSNs and respondents are currently available for the following survey years: 1991, 1994, 1996-present. The data in this paper uses the linked CPS ASEC files up to 2009. The SIPP data used in this study comes from an internal data product at the US Census Bureau, the SIPP Gold Standard File (GSF). It contains all SIPP respondents from the 1984, 1990, 1991, 1992, 1993, 1996, 2001, 2004, and 2008 panels. However, in this paper, I do not include observations from the 1984 panel of the SIPP as the family relationships were not gathered until the Wave 8 topical module conducted from January to March of 1986 and are therefore not available for families that attritted out of the

[41] The process by which CPS ASEC and SIPP individuals are linked to the DER file is described in Wagner and Layne (2014).

sample. In the CPS ASEC only children aged 15 and older were given a PIK to allow matching to the DER, and I only include children observed in their parent household up to age 18 in my sample. The DER earnings file contains annual W-2 earnings information from 1978 to 2012.

I estimate children living in families with unmarried partners using a modified Persons of Opposite Sex Sharing Living Quarters (POSSLQ) method, as cohabiting partners was not an option on either survey in the years studied. I classify two adults as partners if in the household: 1) a child of one adult is present, 2) there are only two opposite sex, unrelated adults, and 3) the potential partner is at least 15 years older than the child. All results are robust to excluding potential partner matches from the sample.

A.1. Weights

The CPS ASEC and SIPP both provide weights for individual observations in each round of the survey based on their probability of selection and response. However, as I am combining parent-child pairs over two dimensions: 1) across multiple survey rounds for the same survey and 2) between the two surveys, I have chosen to adjust the within survey-year weights to more accurately reflect the child population.

To weight observations across multiple survey rounds, I group children by age cohort. For example, a child who is 16 in the 1994 CPS ASEC would be in the 1978 cohort, as would a child who is 15 in the 1993 SIPP panel. Because the number of parent-child pairs varies by child age cohort, I normalize across cohorts so that the sum of the weights is one for each child age cohort.

This normalization is done for the CPS ASEC and SIPP samples separately before combining the samples. To combine the two samples, I adjust the weights by the share of the total number of observations for a given child age cohort that comes from that survey. So if share $\alpha \in [0,1]$ (of the unweighted number of observations) of the 1978 cohort comes from the SIPP and $1 - \alpha$ from the

CPS ASEC, then the SIPP observation weights are multiplied by α (and sum to α) and the CPS ASEC weights by $1 - \alpha$ so that the sum of the weights for the combined sample is again 1 for the child age cohort. In this way, the average weight of an observation is the same whether it comes from the CPS ASEC or SIPP sample.

To be included in the CSD sample, each parent-child pair must be matched to their SSNs. A pair is successfully matched if the child and all parents (both parents in two-parent families and the individual parent in one-parent families) are successfully matched. The match rates for the CPS ASEC and SIPP samples by child age cohort is reported in Table 1. For all cohort groups, the average match rate across the two surveys is above 70%.

A.2. Ages of Earnings Observation

The next step is to determine at what ages to measure parent and child earnings for the intergenerational mobility comparison. For parents, I average family earnings over the 5 years when the older parent is 40-44 years old. This was chosen for two reasons. First, the literature on life-cycle bias in estimates of intergenerational mobility suggests measuring income around 40 (Haider and Solon 2006). Second, this choice allows me to better compare my results to CHKS as they use a 5-year average of parent income in their analysis.

For children, the issue is complicated by sample size concerns. Because the earliest available surveys that can be matched to the DER are from 1991 for the CPS ASEC and 1990 for the SIPP, there is a tradeoff between observing children at later ages and reducing the sample size. For example, the oldest possible child in my sample is 18 years old in the 1990 SIPP. This child would be 39 in 2011, the final year of the available DER earnings data. However, if I restrict my sample to only those who are 39 by 2011, my sample would include only 533 parent-child pairs.[42] Instead, I follow CHKS in focusing on children around the age of 30. They show that there is little lifecycle bias in rank-rank income mobility by age 30 in child income. To test for lifecycle bias in the CSD sample, I plot the rank-rank slope of intergenerational earnings mobility with child earnings measured over two years starting from age 24 to 32, shown in Figure 1.[43] Panel A shows the effect of measuring earnings by age for the full sample. The general trend is similar to that in CHKS with increases at younger ages and potentially slight decreases at higher ages, but few of the differences are statistically significant. Panel B shows the trend for male children, which is increasing up to about 29 and flat above. The slight downward trend in Panel A is due to a decrease in the rank-rank slope for female children.

I have chosen to use average child earnings at 29 and 30 for the baseline sample to more closely match the period used in CHKS, where income was measured starting at 29-32 years old depending on the child's age cohort and to maximize the sample size.

A.3. Assigning Parent and Child Ranks

In order to proceed, I must assign ranks to each parent family and child individual earnings level. The sample comes from a wide variety of parent and child age cohorts. If I use earnings from the same calendar years, then I am comparing individuals at different stages in their life cycle. However, if I use earnings at the same age, then the comparisons will be over vastly different stages in the business cycle or even as far apart as three decades. For example, there are parents in my baseline sample who turn 40 in 1978 and others who turn 40 in 2007. Instead, I have chosen to compare parents and children to samples of all matched parents and children in their age cohort

[42] This includes the restriction that the older parent turns 40 between 1978 and 2007.
[43] The method for converting earnings to ranks is discussed in Appendix A.

in the CPS ASEC and SIPP. The parent that turns 40 in 1978 would be compared to all parents that turn 40 in 1978 regardless of the age of their children or the survey and year in which they were observed.[44]

To construct the parent comparison groups, I create a sample of all parent families from any year in either survey where all parents have PIKs, indicating a successful match to the SSN database. To be in this comparison group, a child must be present in the household, but the child need not be matched (either because a match was not available or because the child was 14 or under in the CPS ASEC and no match was attempted).

For the child comparison sample, I make a simplifying assumption, which vastly increases the size of the comparison group. I include all adults in the child's age cohort observed in any survey year as part of the comparison group, thereby assuming that in- and out-migration are sufficiently small between the year the child was observed in the CPS ASEC and SIPP and the year the adult cohort was observed in the later survey. In this way, a child born in 1980 and observed at 16 in the 1996 CPS ASEC would be compared to all matched individuals born in 1980 from either survey, including a 29 year-old adult observed in the 2009 CPS ASEC or a 24 year-old adult observed in the 2004 SIPP.

For the baseline sample of children at 29-30 and parents at 40-44, the earnings distributions are shown in Appendix Figure 1 for the full CSD sample and separately for the CPS ASEC and SIPP subsamples. Because the parent earnings are for families and the child earnings are for individuals as well as due to the later age of parent observation, parents earn much more than children in the sample. There are also more children than parents with zero earnings (as in CHKS with income).

[44] For two parent households, I use the age of the older parent.

Appendix B: Comparing CHKS and CSD Data

In the CSD data, I estimate rank-rank mobility using the basic regression model:

$$y_i = \alpha + \beta x_i + e_i \tag{15}$$

where y_i is the income/earnings rank for the child and x_i is the rank for the parents in parent-child pair i. Unfortunately, CHKS do not report any coefficient for mobility of child individual earnings regressed on parent family earnings, which corresponds to what I can estimate with the CSD data. Therefore, I compare my results to the closest analogue in their paper, child individual earnings regressed on parent family income.

Measuring mobility using a rank-rank specification has a number of advantages over the intergenerational elasticity of income (IGE). First, the relationship is linear, which CHKS show is not true for log income. Second, the inclusion and treatment of zeroes is straightforward, whereas with log income and the IGE, the coefficient is highly sensitive to these decisions. Appendix Figure 2 shows a binned scatter plot of average child and parent rank from CHKS and the CSD sample. The linear relationship between parent rank and average child rank holds in both data sets. The CHKS slope is steeper than in the CSD earnings data, which is reflected in the regression coefficients as well, reported in Appendix Table 1.

The CHKS coefficient for child individual earnings regressed on parent family income is 0.282 compared to 0.251 for individual child earnings regressed on parent family earnings in the CSD sample. In both datasets, the coefficient of rank-rank mobility for sons is higher and for daughters is lower than in the combined samples.

CHKS and Chetty and Hendren divide the United States into 741 CZs. For each CZ with at least 250 children in their sample, CHKS estimate the slope (α_c) and intercept (β_c) of the parent-child rank-rank mobility regression using their baseline sample and income definitions. Using this information for each parent-child pair i, I create a predicted child rank ($\hat{y}_{ic}$) based on the parent earnings rank (x_{ic}) and the parent commuting zone (at the time of first survey observation) so that:

$$\hat{y}_{ic} = \alpha_c + \beta_c x_{ic}. \tag{16}$$

This predicted child rank accounts for both the parent earnings and the spatial variation in mobility. I regress the child earnings rank on the CHKS predicted rank, with the slope coefficients reported in Column (3) of Appendix Table 1.

Next, I confirm that the spatial variation in mobility found by CHKS is also present in the CSD data. I estimate CZ-level rank-rank regression coefficients:

$$y_{ic} = \alpha_c + \beta_c x_{ic} + e_{ic}. \tag{17}$$

However, given the CSD sample of 49,559 parent-child pairs across 573 CZs, there are only 86 children per CZ on average. CHKS only includes CZs in their analysis with at least 250 children. In Appendix Table 2 Panel A, I vary the minimum number of CSD observations required in a CZ for it to be included in the analysis and calculate the correlation between the CHKS and CSD expected rank at the 25^{th} and 75^{th} percentiles for the included areas. At one extreme, including CZs with at least 1,000 observations leaves only five in the analysis and a CSD observation-weighted correlation coefficients of 0.87 and 0.90 for the 25^{th} and 75^{th} percentiles respectively. At the other extreme, including places with three observations and therefore extremely imprecisely estimated mobility coefficients, leaves 544 CZs and weighted correlations of 0.35 and 0.12 for the 25^{th} and 75^{th} percentiles. There are 39 CZs in the CSD samples with at least 250 observations (the CHKS minimum), with weighted correlations of 0.66 and 0.53.

While the correlations for CZs with 250 or more observations suggest that the spatial heterogeneity found in CHKS is present in the survey-linked data, the small number of included locations leaves room for doubt. It would be preferable to include more children in the analysis while avoiding the statistical noise from small samples that is apparent in Panel A.

To more precisely estimate the coefficients using the CSD data, I create CZ groups that combine areas with similar levels of mobility in CHKS. I order the 709 CZs from most to least mobile by their CHKS expected rank for children of 25th percentile parents. The CZs are then divided into k quantile groups. For example with $k = 50$, the first group contains the 14 CZs with the lowest expected rank, the second contains the 14 with the next lowest expected rank, etc. By decreasing the number of groups, I can increase the minimum number of parent-child pairs in each to get more precise estimates at the cost of combining CZs with a wider range of expected outcomes. I vary k from 5 to 50.

For each group, I estimate the benchmark the expected 25th and 75th percentile ranks by averaging the CHKS CZ values across the individual CSD observations.[45] I calculate the correlation between the CHKS and CSD expected ranks, shown in Appendix Table 2 Panel B. The standard errors were estimated using a bootstrap with 100 replications of this entire process from the initial CSD sample. With five CZ groups (and about 142 CZs per group), the smallest group has 3,597 children and the correlation between both the CHKS benchmark and CSD 25th and 75th percentile expected ranks is 1.00 and 0.94 respectively. At 25 groups, there are at least 487 observations in each, and the correlations are 0.96 for the 25th percentile and 0.58 for the 75th. At

[45] For example, if there are three equally-weighted individuals in the CSD samples in a given group and they live in CZs with slopes of 0.20, 0.21, and 0.28 and intercepts of 0.39, 0.36, and 0.30. The CHKS benchmark slope would be $(0.20 + 0.21 + 0.28)/3 = 0.23$, and the intercept would be $(0.39 + 0.36 + 0.30)/3 = 0.35$.

50 groups, there are at least 141 children in each group and the correlations are 0.90 and 0.49 for the 25th and 75th percentiles.

Taken together, the results in Appendix Table 2 indicate that a very high correlation between the spatial heterogeneity found by CHKS and in the CSD sample, especially for children of low-income/earning parents. Low mobility places in CHKS are also likely to be low mobility in the CSD data, with the same true for high mobility ones.