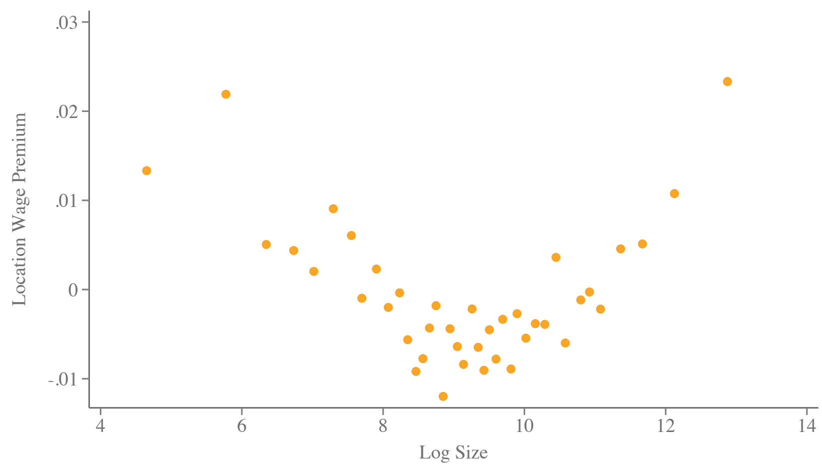
Online Appendix for

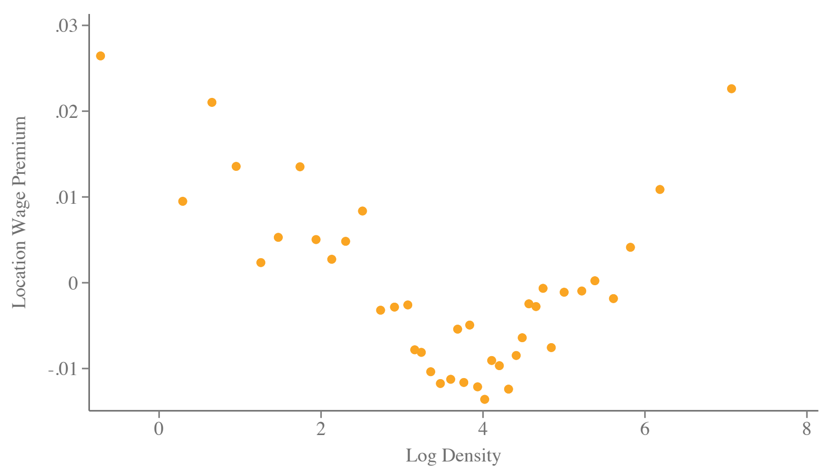
"The Geography of Lifecycle Human Capital Accumulation"

APPENDIX FIGURE 1: Location Wage Premia by CZ Characteristics

A. Log Size



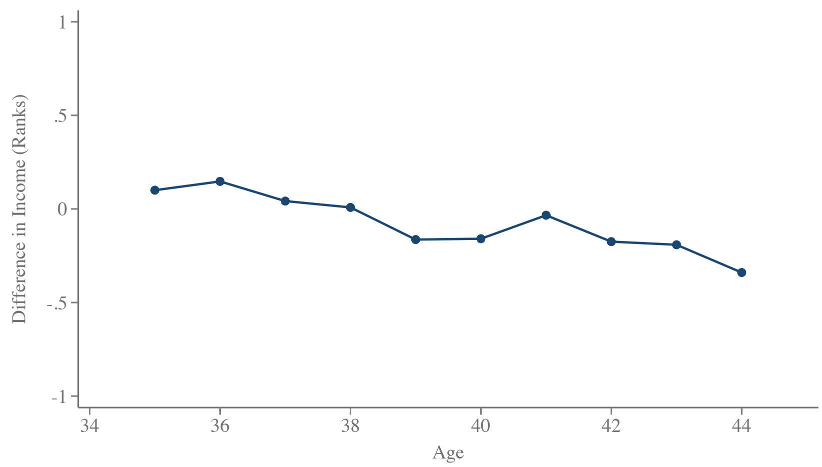
B. Log Density



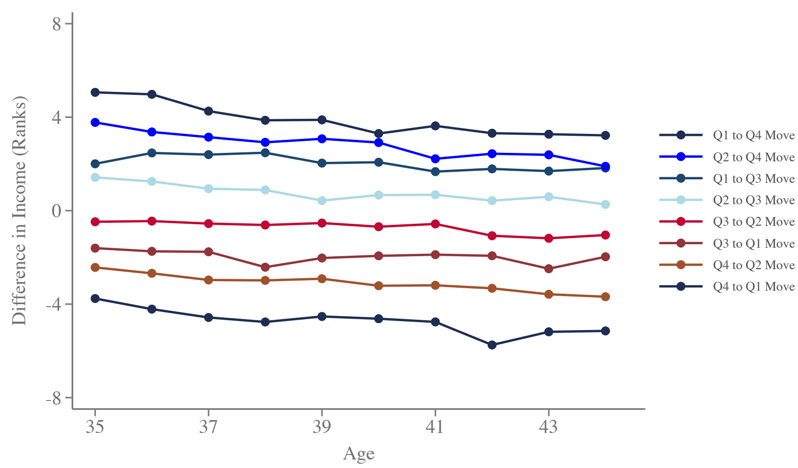
Notes: This figure plots the relationship between our estimates of location wage premia and CZ-level characteristics. Panel A presents a binned scatterplot that plots location wage premia against log CZ size, where size is measured by the population of children born in the 1978-1983 cohorts born in each CZ. Panel B plots location wage premia against log CZ density, where density is measured as the density of the densest county in the CZ in 2010.

APPENDIX FIGURE 2: Roy Sorting By Age

A. Similar CZ Moves



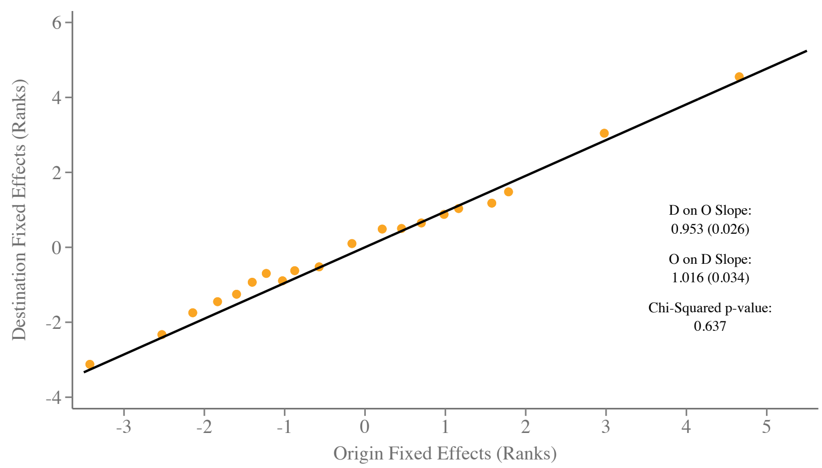
B. Moves Across CZ Quartiles



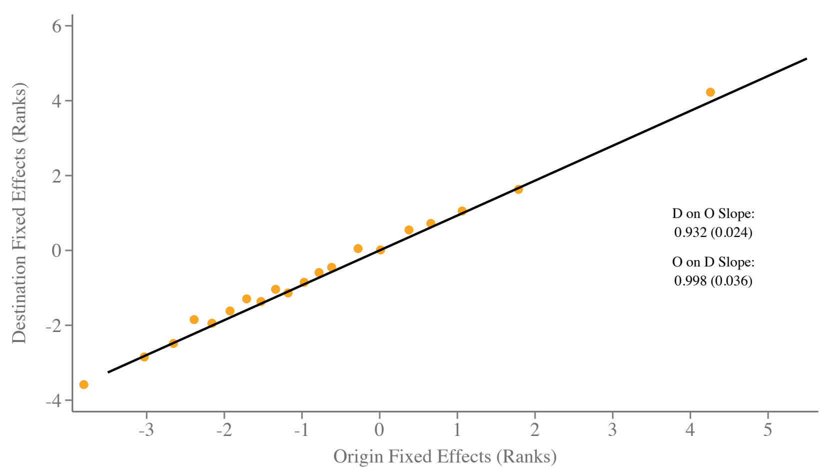
Notes: This figure examines the extent of Roy sorting in moves by age. Panel A examines the wage changes for a set of individuals who migrate across CZs but move to locations with similar location wage premia, as measured by an absolute value of the difference of less than 0.5 ranks. This is calculated using a split sample so the that the location wage premia are constructed using one half of the sample and the differences in wages across movers are constructed using the other half of the sample. This figure plots the wage changes among those movers by age. In order to construct Panel B, we separate locations into quartiles of the distribution of location wage premia. Panel B shows the wage changes of individuals as they move across those various quartiles. These means are reported by individual ages in the year prior to the move.

APPENDIX FIGURE 3: Location Wage Premia Symmetry Tests

A. Aligned Sample



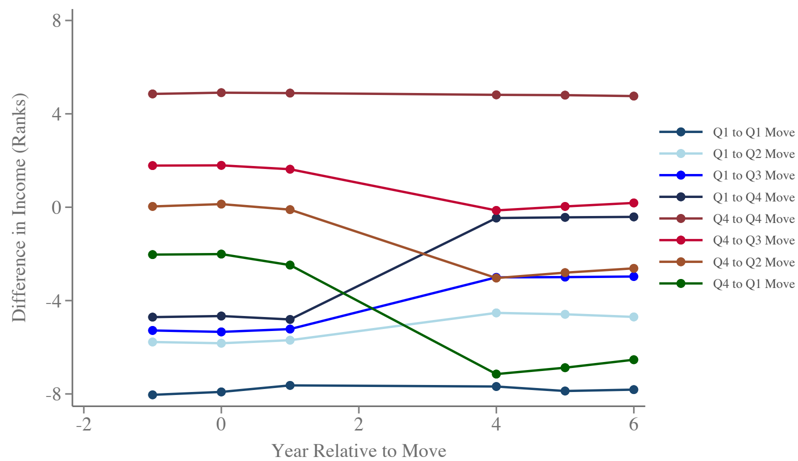
B. Full Sample



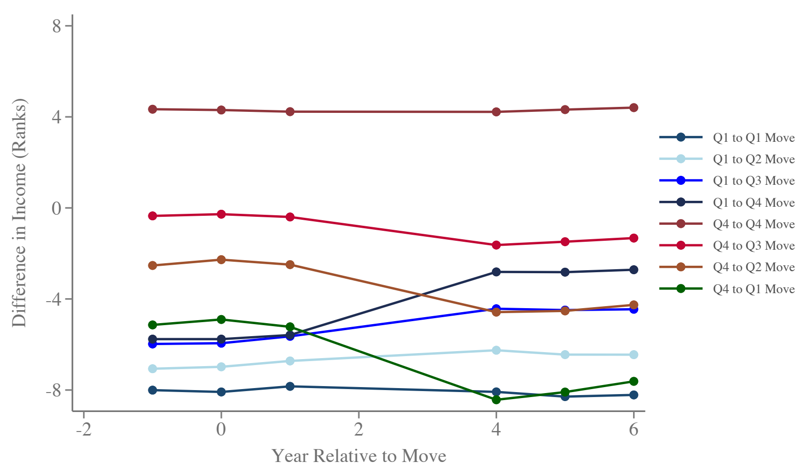
Notes: This figure conducts the location wage premia symmetry tests outlined in Section 4.2. In each CZ, an origin fixed effect and a destination fixed effect are calculated in order to estimate the location wage premia in those CZs. Both Panels A and B showed the binned scatterplot of the destination fixed effect regressed on the origin fixed effect. The panels also report the regression coefficient from the micro-data corresponding to the regression of the destination fixed effect on the origin fixed effect and the regression of the origin fixed effect on the destination fixed effects. These regressions use a split sample IV (with two-fold cross fitting) to account for measurement error. Both sets of estimates are constructed on a sample of individuals who are ages 35-44 in the years before their move. Panels A is constructed using an “aligned sample” where the origin fixed effects and destination fixed effects are measured in the same calendar years, 2012. This alignment is done by estimating those effects on two distinct samples of movers. This panel also reports the p-value from a Chi-squared test of equality across the coefficients. Panel B shows the symmetry tests for a full sample of individuals who move between 2010-2016.

APPENDIX FIGURE 4: Location Wage Premia Quartile Event Study Test

A. AKM Quartiles

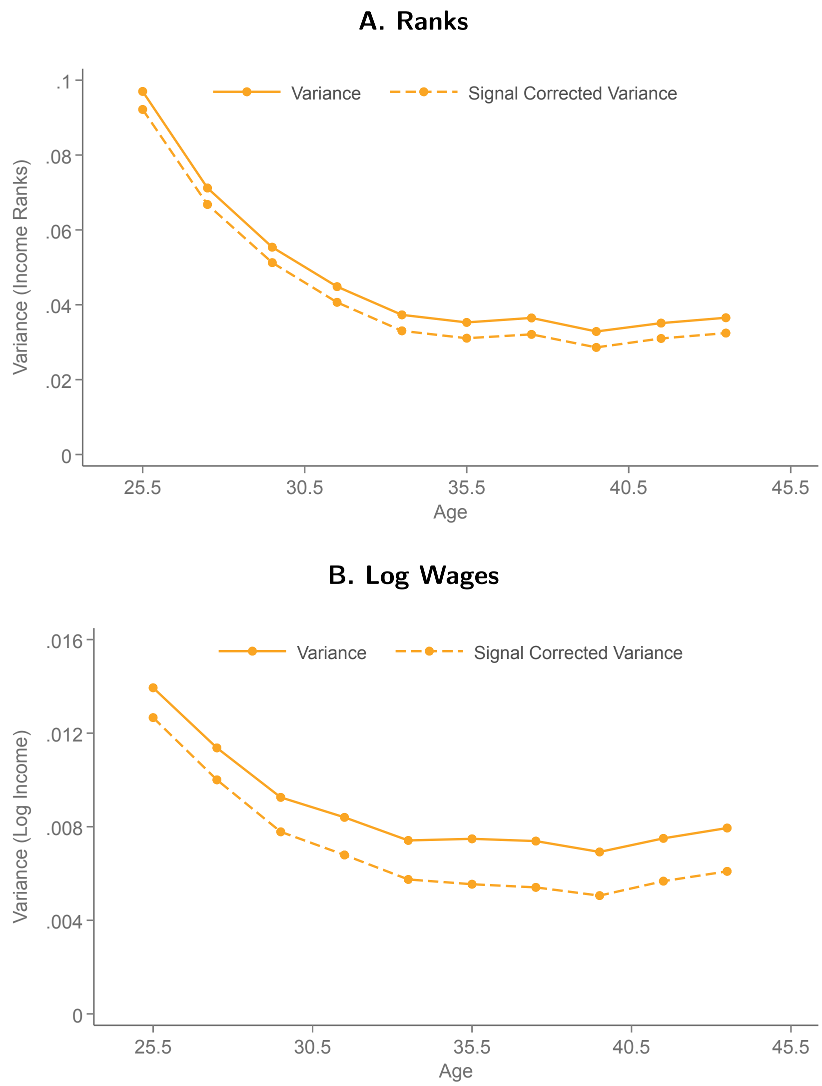


B. CZ Wage Quartiles



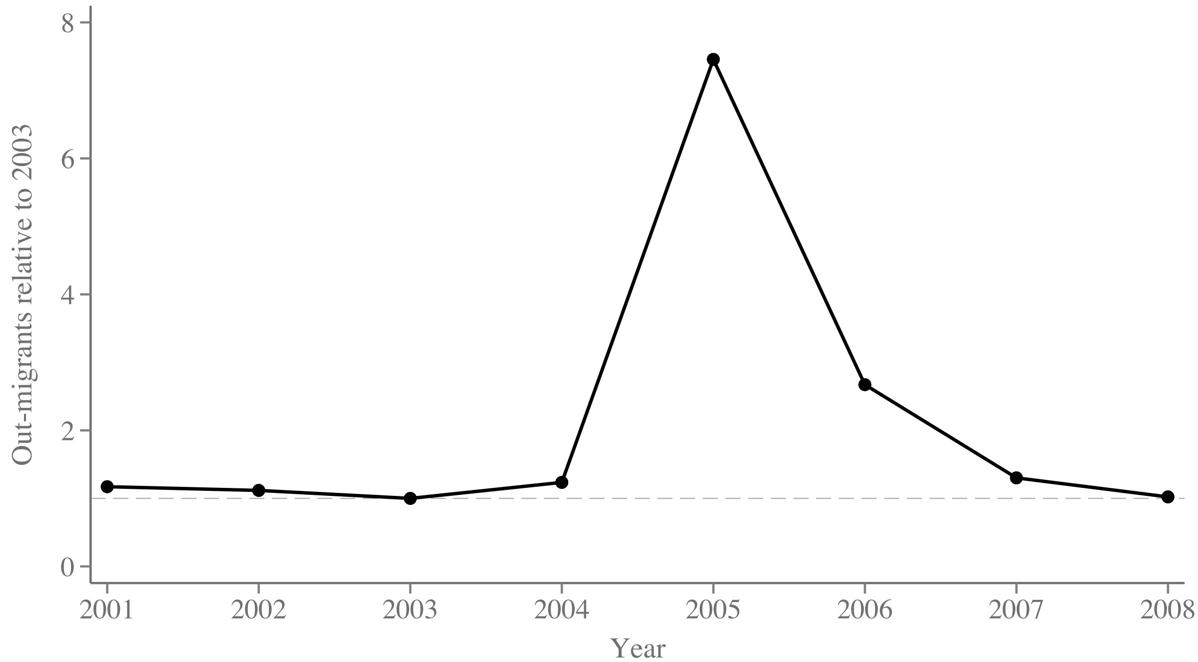
Notes: This figure examines the wage changes of movers as determined by their origin and destination locations. Panel A splits locations into quartiles based on mean wages. Panel B splits locations into quartiles by their location wage premia. For Panel B the sample is split so the location wage premia are calculated on a different sample from the population of movers used to estimate wage changes. The graphs report moves from the first and fourth quartiles of wages (or wage premia). All movers are ages 35-44 in the year prior to the move.

APPENDIX FIGURE 5: Variance of Location Wage Premia by Age



Notes: This figure plots the variance of location wage premia estimated among movers of different ages. In Panel A, the wage outcome of interest is individual income ranks and in Panel B the outcome of interest is log income. Individuals are categorized by their age before their move occurred and they are grouped into 2-year groupings of ages. The average of aged 25 and 26 moves is reported here as 25.5. In both panels we plot the variance of the initial estimates and we plot a signal corrected variance. That signal corrected variance is constructed by using the mean of the square of the standard errors of the individual estimates in order to calculate the noise in the estimates. Estimates are adjusted using the resulting signal to noise ratio.

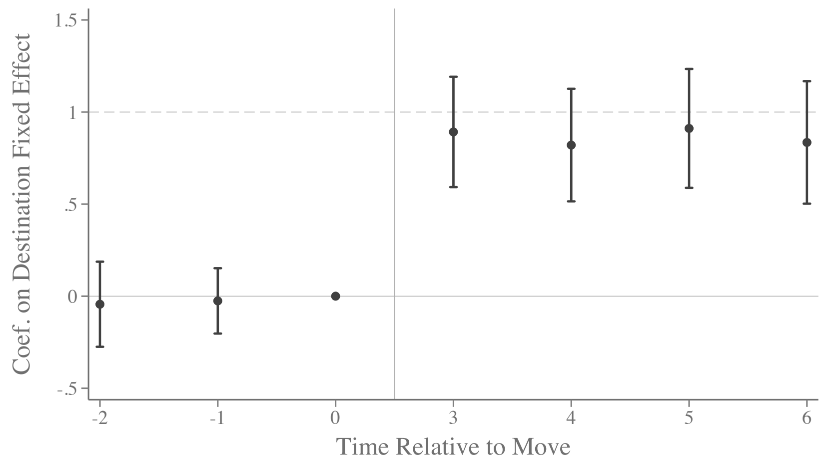
APPENDIX FIGURE 6: New Orleans Out-Migration Rates using W-2 Location Information



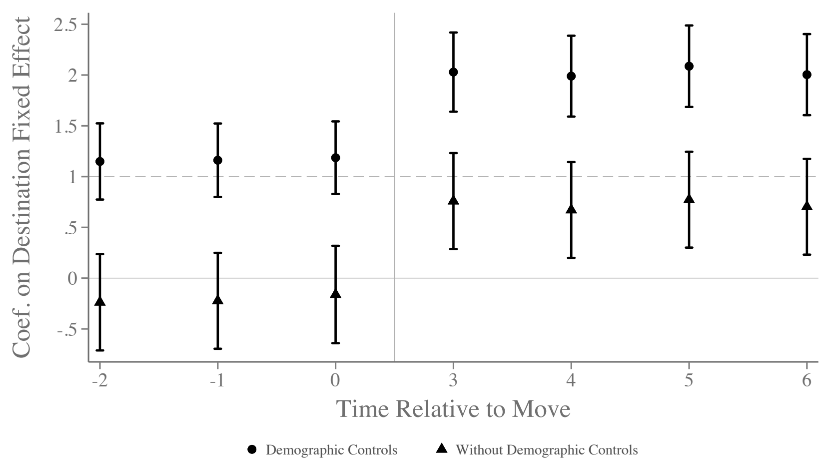
Notes: Just as in Figure 3 Panel A, this figure plots the rate of out-migration from New Orleans in each year around the Hurricane Katrina. In this case migration rates are calculated using location information from information returns alongside location information from tax form 1040 filings. This sample is calculated among individuals who are ages 35-44 in the years before their move.

APPENDIX FIGURE 7: Hurricane Katrina Out-Migration Event Studies, Alternate Specifications

A. Single Destination Fixed Effect

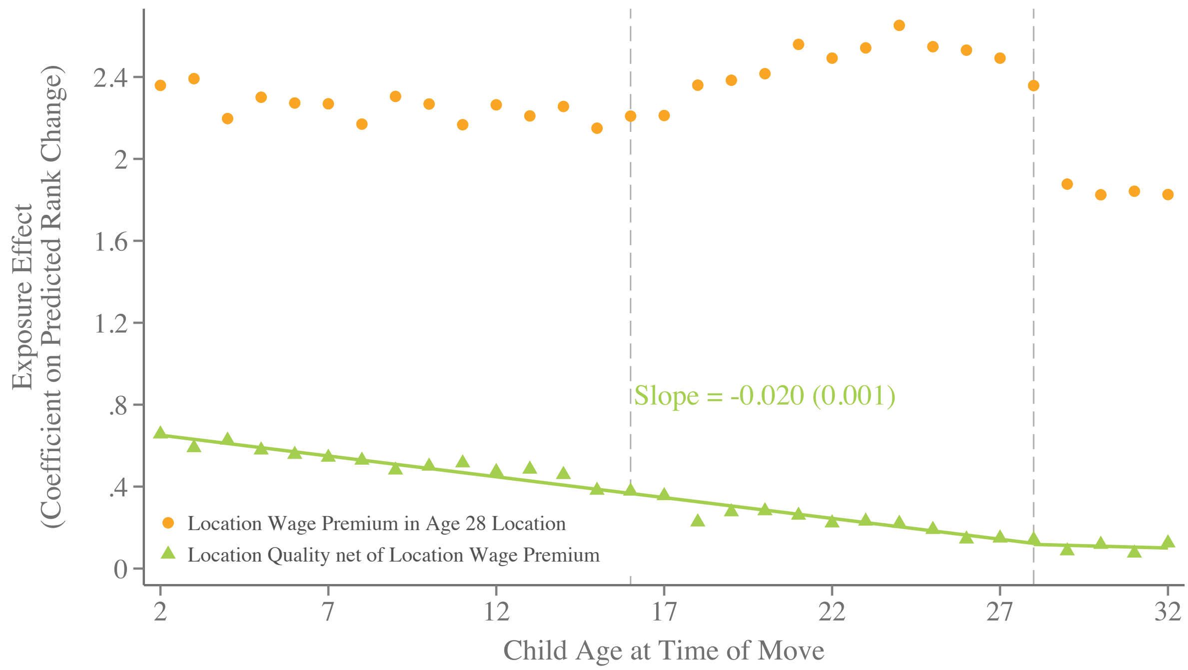


B. Pre-Period Predictions With and Without Demographics Controls



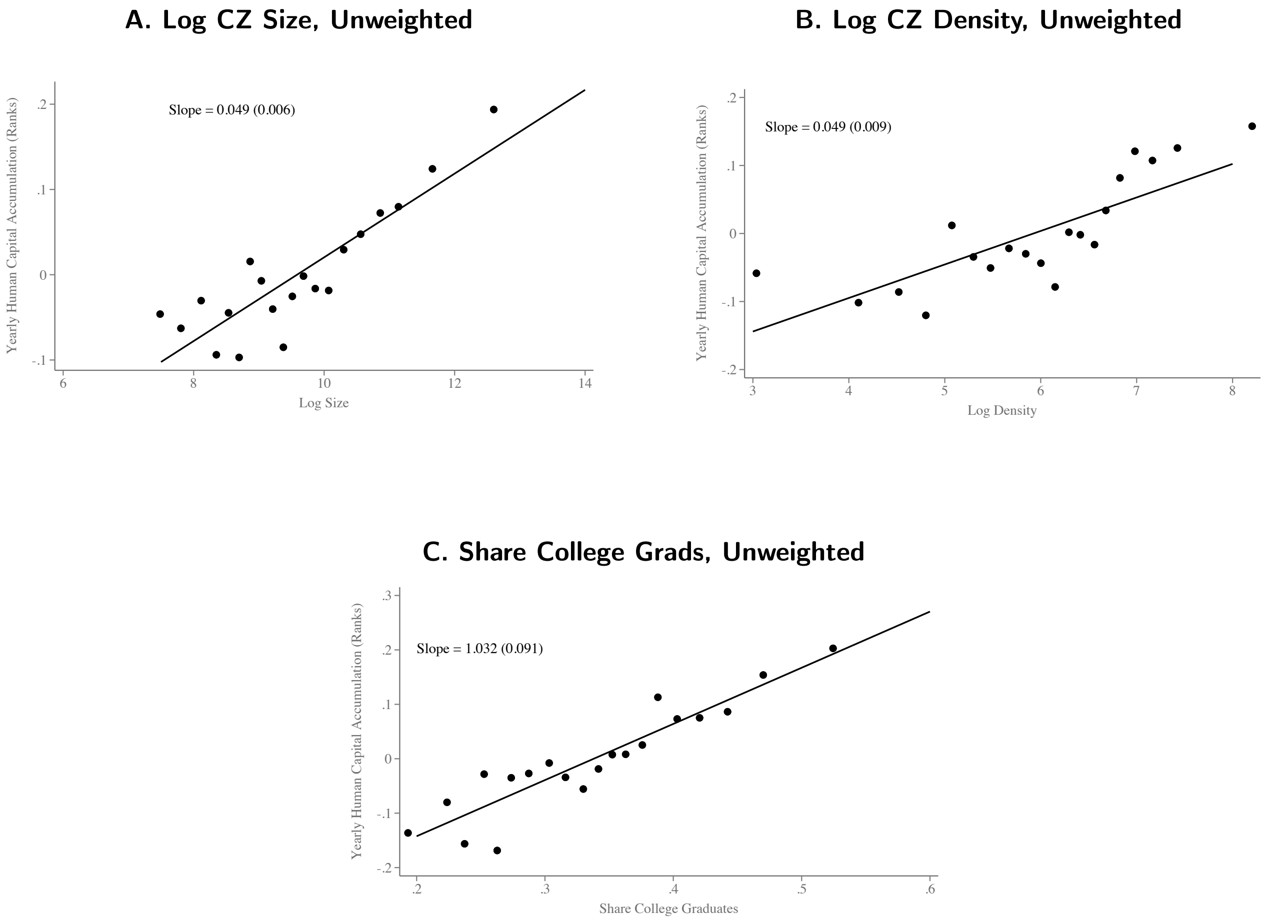
Notes: Just as in Figure 3 Panel C, this figure presents the results of an event study where the year-by-year wages of out-migrants from New Orleans are regressed on the location wage premia estimated among non-New Orleans migrants. In Panel A, the wage trajectories of New Orleans movers are compared to a single location fixed effect estimated among non-New Orleans movers. That fixed effect is estimated in the first full year of arrival in the destination locations. In Panel B repeats the exercise from Figure 3 Panel C without normalizing the effect to zero in the year prior to the move. It shows the results with and without demographic controls added to the regression. These event studies are implemented using split-sample IV (with two-fold cross fitting) to account for potential measurement error in the fixed effects among non-New Orleans movers. The regression is weighted using population count weights corresponding to the number of individuals arriving in the destination who previously left New Orleans. For both Panels the sample is restricted to destinations to which at least 10 individuals in our sample arrive from New Orleans.

APPENDIX FIGURE 8: Childhood Environment Exposure, Realized Location Wage Premia



Notes: Just as in Figure 7, this figure presents evidence on childhood human capital accumulation across place using variation in child age at the time of parental moves. It presents a modified version of the regression presented in Panel C. In this case, rather than regressing observed wages on the difference in location wage premia between a child's parent's origin and a child's parent's destination, observed wages are regressed directly on a measure of the location wage premia in the place where the child is observed at age 28. This measure of location wage premia is plotted alongside a measure of location wage quality, which is measured upward mobility net of location wage quality.

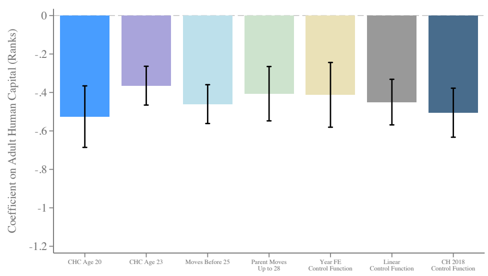
APPENDIX FIGURE 9: Adult Human Capital Accumulation by CZ Characteristics, Unweighted



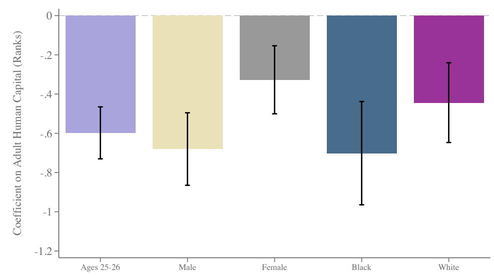
Notes: Just as in Figure 6, this figure plots the relationship between our estimates of adult human capital accumulation across place and characteristics of commuting zones. We measure adult human capital accumulation as the impact of an additional year of exposure to a place on an individual's wage ranks. Panel A shows a binned scatterplot comparing our adult human capital accumulation estimates and log CZ size, with CZ size measured based on the cohort size of children born in 1978-1983 in each CZ. Panel B shows the relationship with adult human capital accumulation and log CZ density, where density is measured using the density of the densest county in the CZ. Panel C shows the relationship with the share of individuals in a CZ who are college graduates. As is the case for all unweighted binscatters, results are shown for the top 641 largest CZs, dropping the bottom 100. All panels report the regression coefficients from the regression in the micro-data.

APPENDIX FIGURE 10: Relationship between Adult and Childhood Human Capital Accumulation, Alternate Specifications

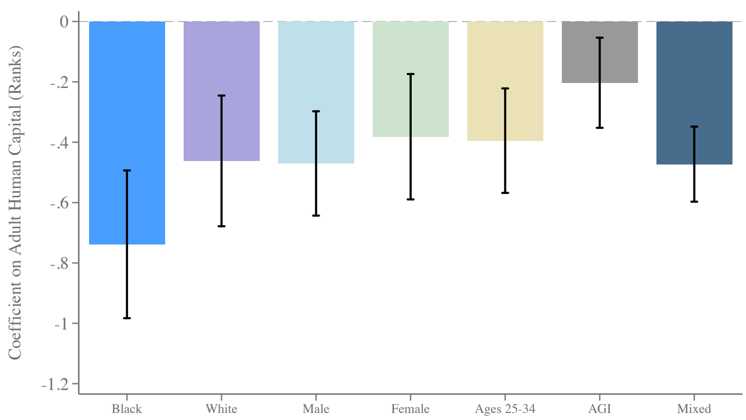
A. Alternate CHC Estimation Strategy



B. Alternate Location Wage Premia



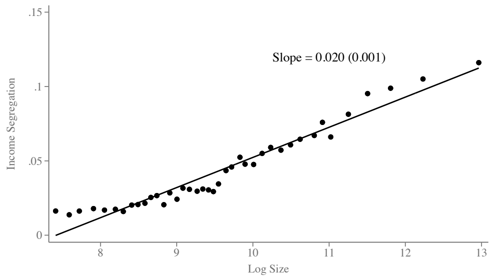
C. Alternate Location Wage Premia and Adult Human Capital Accumulation



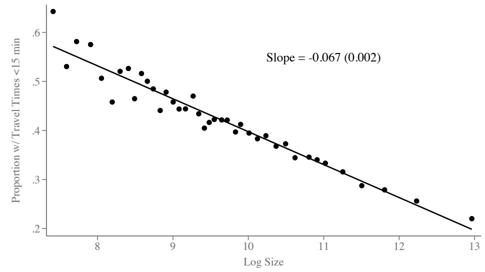
Notes: This figure plots the relationship between our estimates of childhood human capital accumulation and adult human capital accumulation. Panel A shows how our results change when changing our estimation strategy used to construct our estimates of the causal effect of place on childhood human capital. In particular, it shows the effect if we vary the numbers of years of adult human capital exposure that are adjusted for (starting at ages 21 through 24). It shows how the results change when we place alternate sample restrictions, such as calculating one time-movers among parents who only move once before their child turns 28 (rather than 24 in our baseline.) It also shows how the results change under alternate controls functions in Equation 11. This includes adding in a control functions i) solely for cohort, ii) for cohort and parental human capital, iii) a quadratic function of cohort and parental human capital as in Chetty and Hendren 2018. Panel B shows how results change when we use alternate samples to construct our location wage premia. In particular, it shows the results among Black versus White individuals and men versus women. It also shows our results when we vary the age of location wage premia measurement, restricting our analysis to individuals aged 25-26 at the time of their moves. Panel C shows how results change when we use alternate samples to construct our estimates of location wage premia and adult human capital accumulation. It shows variation in our estimates across demographic characteristics as well as variation in the age used to calculate our location wage premia and adult human capital estimates. Finally, it shows our results calculated using family income rather than individual income ranks.

APPENDIX FIGURE 11: Binscatters of CZ Covariates

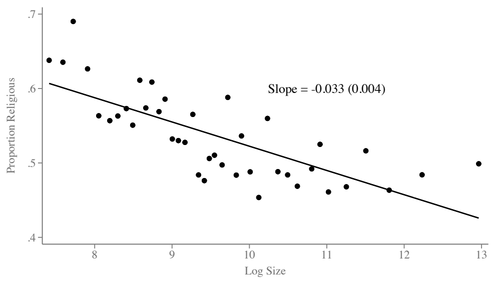
A. Income Segregation by Log CZ Size



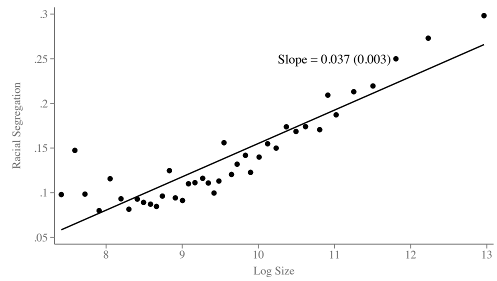
B. Commute Time by Log CZ Size



C. Fraction Religious by Log CZ Size

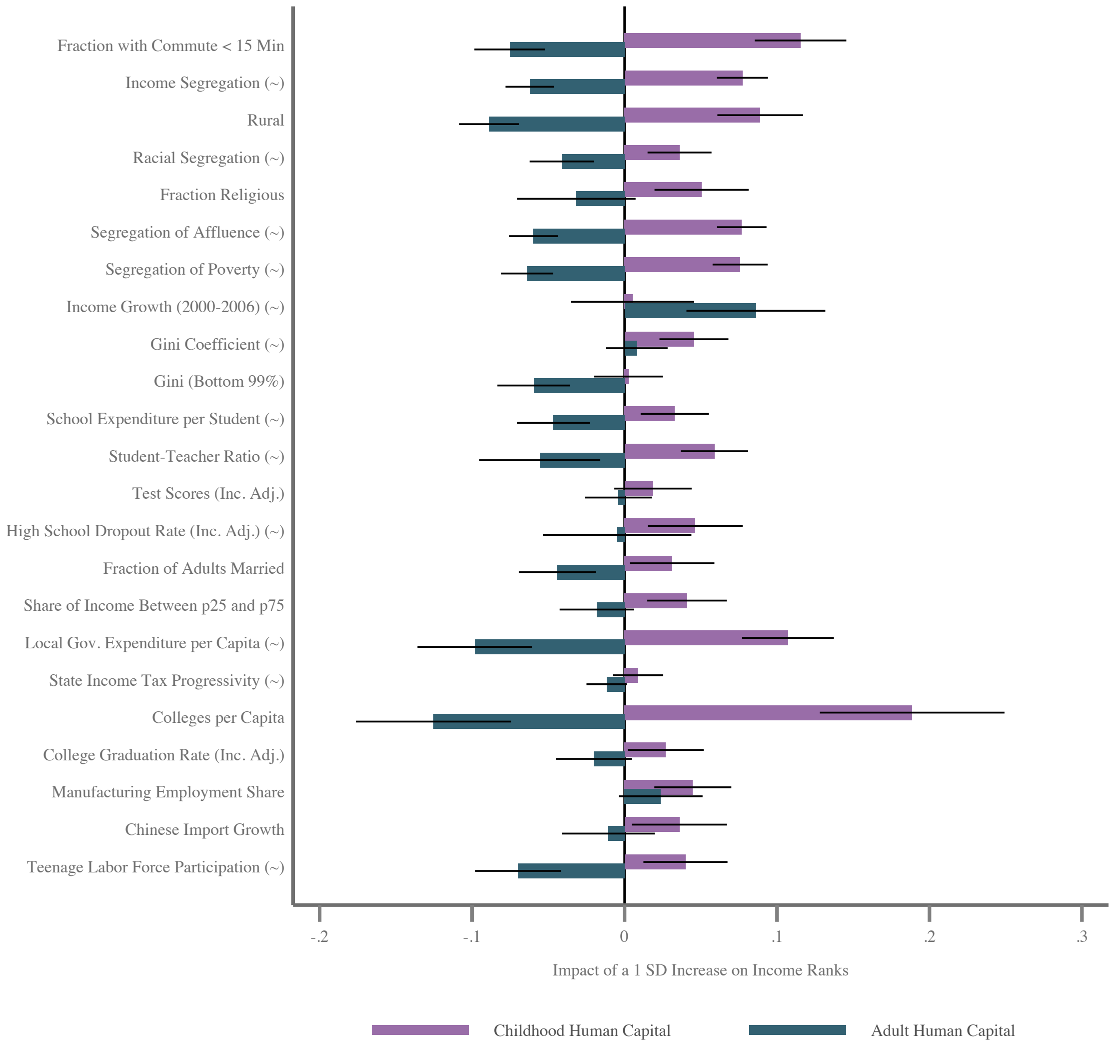


D. Racial Segregation by Log CZ Size



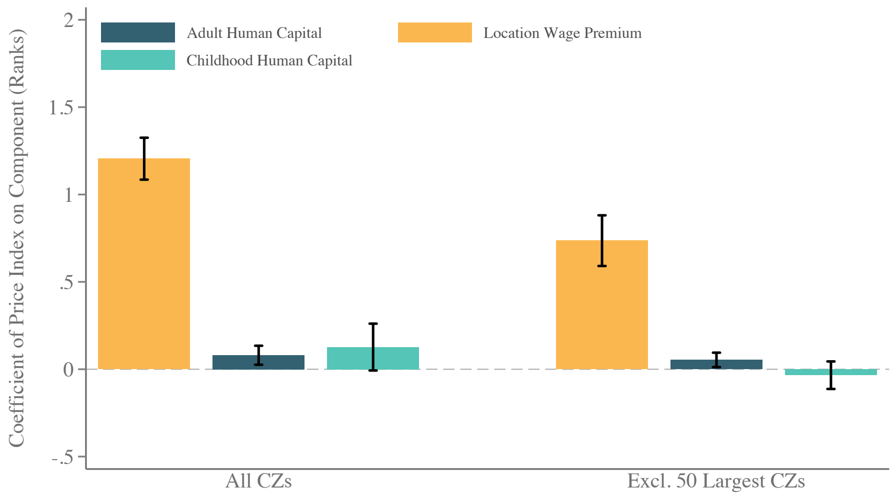
Notes: This figure expands on Figure 10 by exploring the relationship between CZ characteristics we examine and log CZ size. Panel A shows the relationship between tract level income segregation and log CZ size. CZ size is measured based on the cohort size of children born in 1978-1983 in each CZ. Plot B plots the relationship between the fraction of commute times less than 15 minutes and log CZ size. Panel C shows the relationship between the fraction of the population in each CZ that is religious and log CZ size. Panel D shows the relationship between racial segregation in each CZ and log CZ size. (The measures of income segregation, commute time, fraction religious, and racial segregation come from Chetty et al. (2014).)

APPENDIX FIGURE 12: Relationship between CZs Characteristics and Primary Tradeoff



Notes: This figure presents the results of regressions of our place-based determinants of human capital on each of the CZ characteristics from Chetty et al. (2014). The CZ characteristics are normalized by their respective standard deviations. Variable signs are adjusted so all childhood human capital accumulation effects are reported as positive in the graph. (~) is used to indicate variables where the sign of the underlying variable is flipped relative to its label. All human capital effects are normalized to capture the effect of one year of additional exposure to place. Reported regression coefficients are constructed using regressions on the micro-data. Regressions evaluating childhood human capital accumulation are weighted using precision weights, following the random-effects meta-analysis approach outlined in Imai et al. (2021). Regressions evaluating adult human capital accumulation are weighted using count weights corresponding to the number of individuals in our sample originating in the respective CZ. The results are shown for the top 641 largest CZs, omitting the bottom 100 smallest CZs, consistent with Figure 9 above.

APPENDIX FIGURE 13: Prices and Place-Specific Determinants of Wages, Childhood Human Capital with Selection



Notes: Just as in Figure 11, this figure plots the relationship between local prices and place-based determinants of wages. We modify our estimate of childhood human capital accumulation to use our estimates which are inclusive of potential section effects. As in Figure 12, we measure local prices using local rents from the ACS. We make a hedonic adjustment to account for unit characteristics following the approach in Diamond and Moretti (2021). We use a split sample IV (with two-fold cross fitting) to account for potential measurement error in our estimates. In order to capture the total wage gains associated with a year of exposure to childhood or adult environments, we use a simple net present calculation to calculate the value of earning an additional dollar in all subsequent years of labor force participation. This approach, outlined in Appendix C, results in a scaling of our adult human capital effects by a factor of approximately 23 and our childhood human capital effects by approximately 18. We then regress our measure of local prices on each of the three place-based determinants of wages.

Appendix Table 1: Test Scores and Move Rates

	CHC		AHC	
	(1)	(2)	(3)	(4)
Panel A: Reading Test Scores				
	Non-Disadv.	Disadv.	Non-Disadv.	Disadv.
Reading Grade 3	-0.013	0.039	0.035	-0.041
	(0.013)	(0.013)	(0.013)	(0.015)
Reading Grade 4	-0.026	0.031	0.046	-0.033
	(0.014)	(0.014)	(0.013)	(0.015)
Reading Grade 8	-0.045	0.008	0.065	0.010
	(0.013)	(0.015)	(0.017)	(0.014)
Reading Grade 3 (Inc. Adj.)	0.045	0.048	-0.049	-0.047
	(0.019)	(0.018)	(0.024)	(0.021)
Reading Grade 4 (Inc. Adj.)	0.037	0.043	-0.046	-0.045
	(0.021)	(0.020)	(0.025)	(0.021)
Reading Grade 8 (Inc. Adj.)	0.042	0.048	-0.056	-0.034
	(0.027)	(0.025)	(0.028)	(0.024)
Panel B: Math Test Scores				
	Non-Disadv.	Disadv.	Non-Disadv.	Disadv.
Math Grade 3	-0.028	0.014	0.057	-0.020
	(0.013)	(0.014)	(0.014)	(0.016)
Math Grade 4	-0.038	0.002	0.063	-0.013
	(0.013)	(0.014)	(0.014)	(0.015)
Math Grade 8	-0.053	-0.020	0.072	0.018
	(0.014)	(0.015)	(0.022)	(0.018)
Math Grade 3 (Inc. Adj.)	0.023	0.019	-0.011	-0.028
	(0.023)	(0.023)	(0.031)	(0.026)
Math Grade 4 (Inc. Adj.)	0.006	0.001	-0.004	-0.018
	(0.022)	(0.022)	(0.029)	(0.025)
Math Grade 8 (Inc. Adj.)	-0.014	-0.024	0.008	0.020
	(0.019)	(0.019)	(0.022)	(0.022)
Panel C: Move Rates by Age				
	Age 35–44	Age 25–34	Age 35–44	Age 25–34
Total Move Rate in CZ	-2.166	-1.878	0.836	1.763
	(0.386)	(0.276)	(0.347)	(0.311)
Tract Move Rate in CZ	-2.622	-1.911	1.740	1.894
	(0.332)	(0.213)	(0.351)	(0.231)

Notes: This table presents the results of regressions of our place-based determinants of human capital on test scores and move rates. Panel A uses reading test scores among 3rd, 4th and 8th graders from the Education Opportunity Project (Reardon et al., 2024). Panel B uses math test scores at the same ages. Panel C uses move rates within CZ or across tracts within CZs. In both Panels the income adjustment is constructed by regressing mean test scores on mean parental income rank in each CZ and evaluating the relationship between the residual of test scores and the components of human capital. These move rates are calculated on movers in the year 2015 and who are between 25–34 and 35–44 in the years prior to their move. Regressions evaluating childhood human capital accumulation are weighted using precision weights, following the random-effects meta-analysis approach outlined in Imai (2021). Regressions evaluating adult human capital accumulation are weighted using count weights corresponding to the number of individuals in our sample originating in the respective CZ. The results are shown for the top 641 largest CZs, omitting the bottom 100 smallest CZs, consistent with Figure 9 above.

A Empirical Bayes Procedure

In Figure 2 we display estimates of location wage premia across US commuting zones. The estimates displayed in that figure are subject to Empirical Bayes shrinkage. In this appendix we outline the method used to construct those shrunk estimates.

Using the regression outlined in Equation 4 we have an estimate for the location wage premia in each commuting zones, $L\hat{M}_l$ and we have an associated heteroskedasticity-robust standard error for each estimate, $\hat{\sigma}_l$. Ultimately, our approach will shrink CZs toward one of two means. For CZs of above median size we will shrink them toward the mean location wage premia of CZs of above median size. For CZs of below median size we will shrink them toward the mean location wage premia of CZs of below median size.

We assume that our estimates of location wage premia $L\hat{M}_l$ are distributed in the following manner: $L\hat{M}_l \sim \mathcal{N}(LM_l, \hat{\sigma}_l^2)$. Here LM_l is the true value of the location wage premia in location l and $\hat{\sigma}_l^2$ is the square of the standard error. As noted, we allow true values of LM_l to be drawn from one of two different distributions, depending on whether location l is a CZ of above or below median size. In other words, let A be the set of CZs of above median size and B be the set of CZs of below median size. We assume the true distribution of location wage premia is normally distributed such that $LM_l | l \in A \sim \mathcal{N}(LM_A, \sigma_A^2)$ and $LM_l | l \in B \sim \mathcal{N}(LM_B, \sigma_B^2)$.

Next, we need to construct estimates of the means and variances of our hyperdistribution. These are given by $LM_A, LM_b, \sigma_A^2, \sigma_b^2$. We construct our estimates of LM_A using the mean of the location wage premia for CZs within set A. Formally, this is $E[L\hat{M}_l | l \in A]$. (We take this approach because we assume that our estimated location wage premia are unbiased estimates of the true location wage premia.) We can then use the same procedure to estimate LM_B. When it comes to estimating σ_A^2 and σ_B^2 we need to account for the fact that the variance of our estimated location wage premia will also incorporate sampling error. This will produce excess dispersion in the estimates and increase the variance. We estimate a noise corrected variance using the law of total variance. Here we solve for $\hat{\sigma}_A^2$ using the fact that $\hat{\sigma}_A^2 = Var(L\hat{M}_l | l \in A) - Var(\hat{\sigma}_l^2 | l \in A)$. We do the same symmetrically for the hyperdistribution variance of CZs in set B. With our estimates of the means and variance of the hyperdistribution in hand, we can then construct our shrunk estimates.

Given an assumption of normal priors and normal signals we use the standard Bayesian updating procedure. For a CZ in set A, our estimate for the posterior mean is given by $\frac{\hat{\sigma}_A^2}{\hat{\sigma}_A^2+\hat{\sigma}_i^2} LM_i + \frac{\hat{\sigma}_i^2}{\hat{\sigma}_A^2+\hat{\sigma}_i^2} LM_A$. The same is true symmetrically for CZs in set B. Our credible interval for CZs in Set A is given by $\frac{\hat{\sigma}_A^2}{\hat{\sigma}_A^2+\hat{\sigma}_i^2} LM_i + \frac{\hat{\sigma}_i^2}{\hat{\sigma}_A^2+\hat{\sigma}_i^2} LM_A \pm 1.96 \sqrt{\frac{\hat{\sigma}_i^2 \hat{\sigma}_A^2}{\hat{\sigma}_A^2+\hat{\sigma}_i^2}}$. The same is true symmetrically for CZs in set B.

B Hurricane Katrina Estimation Selection Bias Test

In Section 4.2 we seek to validate our estimates of location wage premia using evidence from plausibly exogenous out migration in response to Hurricane Katrina. In particular, we construct a set of location wage premia estimated on a sample of individuals who migrated out of New Orleans in 2005. We also construct a set of location wage premia estimated on a set of individuals who originated in a location out of New Orleans. We argue that the location wage premia estimated among the New Orleans movers are subject to little or no selection. The New Orleans movers made their migration decision under duress. They likely chose their location based on considerations of convenience such of the presence of family, rather than choosing based on the types of considerations that are likely to induce bias into our estimates (a match between location quality and a change in individual-level human capital in the year of a move.) In order to test for selection we regress the New Orleans movers location wage premia on the typical movers location wage premia. We argue that, subject to mild assumptions, the regression coefficient captures the fraction of total variance in our typical movers estimates that are due to treatment rather than selection. Our logic is as follows.

Consider two sets of location wage premia estimates:

$$LM_{typical,l} = T_l + S_l + a_l$$

$$LM_{noselect,l} = T_l + b_l$$

Here our first set of estimates, $LM_{typical,l}$ are estimated on a typical set of movers and $LM_{noselect,l}$ are estimated without selection. Here, T_l is the true treatment effect in location l, the true location wage premia associated with residence in location l. S_l is any potential selection bias in our estimates of the location wage premia in location l. a_l and b_l is place-specific noise in our estimates.

In our test, we regress our estimates without selection on our estimates constructed using typical movers. We estimate: $LM_{noselect,l} = \beta LM_{typical,l} + \pi$. For the moment we make two assumptions. First, $Cov(T_l, S_l) = 0$, our treatment effects T_l are uncorrelated with the degree of selection in our estimates, S_l. Second, our estimates of location wage premia contain no place-specific noise, $a_l = 0$ and $b_l = 0$.

Under these assumptions we can solve for our regression coefficient β in terms of the variance of T_l and S_l. In particular:

$$\beta = \frac{Var(T_l)}{Var(T_l) + Var(S_l)}$$

This means that our coefficient of interest captures the fraction of the total variance in our typical estimates that is the result of treatment effect rather than selection. In the context of our primary results, it means that, on average, our typical location wage premia estimates are almost entirely driven by treatment effects rather than selection.

But, how should we evaluate the validity of the two assumptions we made? As for the covariance, let us consider the case where $Cov(T_l, S_l) \neq 0$. The typical selection story told about location wage premia often suggests that this covariance is positive. For example, it may be suggested that estimates in high-wage cities are biased upward because the typical movers to those locations are positively selected in some manner. Maybe the type of person who moves to New York City just had an increase in their individual human capital that coincides with the decision to move to New York. In that case, if $Cov(T_l, S_l) > 0$ then β actually serves as a lower bound on the fraction of total variance due to selection. This is because the positive covariance term is found in both the numerator and denominator of our expression for β: $\beta = \frac{Var(T_l)+Cov(T_l,S_l)}{Var(T_l)+Var(S_l)+2Cov(T_l,S_l)}$. For a positive values $Cov(T_l, S_l)$ and baseline values of $\frac{Var(T_l)}{Var(T_l)+Var(S_l)}$ above 0.5, this reduces the value of the fraction below the true fraction of variance due to selection. In the context of our results, this bound adjustment is not all that relevant. Our estimated coefficient is so close to 1 that the interpretation of our results don't change if we regard β as a lower bound.

It is also worth acknowledging the flip side of this covariance condition. If it were the case that $Cov(T_l, S_l) < 0$ then our coefficient would be an upper bound on the fraction of variance that comes from selection. The strength of that bound would depend on $Cov(T_l, S_l)$. One possible way for such a negative covariance to occur is if there a substantial degree of negative selection across locations. Card et al. (2025) suggest one potential mechanism when they argue that movers from high location wage premia CZs to low location wage premia CZs may move from firms with lower location wage premia to firms with higher location wage premia. If that were the case, and if the negative covariance is quite substantial, it could drive up our estimated coefficient.

We also established a second condition in our equation for β when we set estimates of place-specific noise equal to zero. While we do not have the ability to estimate our location wage premia without any sampling noise, we are able to use split sample IV to account for any potential sampling noise. That's exactly what we do when we implement our regression in practice, and it accounts for the impact of $Var(a_l)$ on our regression coefficients. If needed, we could also correct for that noise ex-post by using our standard errors from our estimates of $LM_{typical,l}$ to estimate the fraction of the total variance of $LM_{typical,l}$ due to sampling error. In either case, we are able to side-step any bias due to sampling noise and simply consider the relative contributions of selection and treatment.

C Net Present Value Magnitude Calculation

In our primary results, presented in Figure 8, we show the relationship between adult human capital accumulation and childhood human capital accumulation. In particular, we regress our estimates of childhood human capital accumulation on our estimates of adult human capital accumulation. Both estimates measure the impact, in wage ranks, of spending an additional year in a given location. While this rank-rank comparison is useful in quantifying the tradeoff across place, it is also useful to think about the magnitude of these effects in lifecycle terms.

As a result, we conduct a net present value calculation in order to help provide intuition for the magnitude of our estimates. In particular, we consider the change in wages that occur if a parent locates in a place that has strong adult human capital but weak childhood human capital accumulation. We evaluate the tradeoff between them and their children.

Consider a parent who locates in a given location where each additional year of residence increases wages by \$1 due to adult human capital accumulation. Let us assume that they reside in that location starting in the year in which their child is born. Let us assume that they are 30 at the time of the birth of their child. Let us assume that they remain in that location through the time that their child turns 21. After that point, let us assume that they move to a neutral location regarding adult human capital accumulation. Let us assume that they work through age 65. Let us assume that the effect of place is constant in dollar terms throughout the lifecycle of the individual. (This is slightly more conservative than our primary assumption of rank stability, but avoids the need for a lifecycle rank-dollar conversion in this back-of-the-envelope calculation.) In other words, this is an individuals who spent 21 years during their child's upbringing in a place that was better for adult human capital accumulation. If we discount future earnings at 3%, then discounted back to the first year of residence, living in this high adult human capital location increase the individuals wages by approximately \$268.

Now let us consider the impact on the child in this scenario. Our estimates suggest that for each 1 rank increase that a place has an adult human capital accumulation that trades off on average with 0.50 rank decrease in childhood human capital accumulation. Let us therefore assume that each year the child spends in their hometown, it reduces their future wages by an additional \$0.50. Again we've made a rank to dollar adjustment for the sake of simplicity here, understating the magnitude of the future losses as individuals age. We assume that the child spends 21 years in the location with low childhood human capital accumulation before entering the labor force. We assume that their adult labor location is uncorrelated with their childhood location. (If they remained in the location with low childhood human capital accumulation and high adult human capital accumulation they would serve to recoup some of what they lost.) We assume that they remain in the labor force through age 65. When discounted back to their year of birth at a 3% rate, their childhood exposure reduces their future earnings by approximately $136.

When we compare our two sets of estimates we find that $268 in additional earnings due to increased adult human capital accumulation trades off with approximately $136 due to decreased childhood human capital accumulation. Or, when evaluating the ratio of these two, each $1 in increased wages due to adult human capital accumulation trades off with approximately $0.51 in reduced earnings due to childhood human capital accumulation. Somewhat surprisingly, this lines up nearly identically with our rank-rank estimates.

Now it is important to acknowledge that is $0.51 figure is meant to give a sense of magnitude rather than provide a precise figure. There are a number of ways that one could modify this calculation. First, this calculation is done for a single parent and a single child. It could be modified to account for any different sets of family structure. Second, this calculation converts ranks to dollars and then holds them constant throughout the lifecycle. Our estimates suggest that there is relative rank stability in the size of the adult and childhood human capital accumulation estimates. As a result, the dollar magnitude of those effects should increase over the lifecycle. The parent at age 35 should receive a greater benefit in dollar terms than the decrease in wages experienced by the child when they first enter the labor market. But, the magnitude of the child effect should catch up over time. Third, this calculation assumes that individuals reside in neutral locations in all years other than those in which the child is ages 0-21. While this may be the case, it may also be the case that both the parent and the child are likely to stick around in the high adult human capital location after the child enters the labor force. While that would tend to reduce the extent of the tradeoff observed here, the child sticking around could also extend the tradeoff into the next generation. They remain in the high adult human capital location but have a child there within 10 years and the cycle starts over again. Finally, these calculations have assumed that there is no impact of the parental adult human capital accumulation on the wage outcomes of the child. If the gains experienced by the parent were transmitted to the child with an intergenerational earnings elasticity of approximately 0.3, that would serve to offset a meaningful portion of the earnings losses experienced by the child.[101]

In the context of our price results in Figure 11 we conduct a similar net present value calculation. In that case we are seeking the estimate the net present value of an additional year of exposure to a location that increases childhood or adult human capital accumulation. For the purposes of these calculation we assume that year of an individual's change in childhood human capital occurs when they are age 11. We assume that they enter the labor force at age 22 and then

[101] This adjustment also provides another way to think about the implication of our results. Typically an increase in parental earnings would be associated with an improvement in child outcomes as well. But, when it comes to CZ level differences in adult human capital accumulation those effects are more than offset by the weaker levels of childhood human capital accumulation in those places.

continue to work through age 65. For an individual who benefits from additional adult human capital accumulation we align with the age at which prices are measured and assume they gain that benefit at 28. They also continue in the labor force through age 65. In both cases benefits are discounted at 3% back to the time that the human capital is accumulated. For the sake of simplicity (and in order to be conservative) we assume that the effect of place is constant in dollar terms throughout the lifecycle rather than increasing with age. The adjustment factor would be larger if we accounted for lifecycle earnings growth.