# The Geographic Distribution of Human Capital: Measurement of Contributing Mechanisms

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**Abstract**

The skills of residents in a local area matter for tax revenue, and increasing evidence suggests that skills also increase local productivity and growth. The determinants of the geographic distribution of skills at a point in time are the previous generation's distribution of skills, the intergenerational transmission of skill from parents to children, and migration of differently skilled individuals. I estimate how these factors affect the geographic distribution of skill in the United States. For the local skill measure, I take the ratio of high-skilled to low-skilled populations, where skills are defined with an earnings prediction. I find evidence of regression toward the mean of local skills through intergenerational transmission, which is partially offset by selective migration of skills. I also identify characteristics of labor markets that predict their local skill levels. Small and rural labor markets gain the most skills through intergenerational transmission but lose the most skills through migration. Local college enrollments and subsidies are positively correlated with the attraction of skills through migration. Local climate and tax variables also influence skilled migration.

# 1 Introduction

The variance of skill levels across U.S. labor markets is large. Table 1 shows the labor markets with the highest and lowest percent residents with a college degree in the 2000 Census. The gap between the most educated places like the nation's capital, San Francisco, and Boston and the least educated places like rural Appalachia is remarkable.

A recent economics literature investigates whether and how the skill level of a labor market's residents matters. The focus tends to be on the effects of local skill differences rather than how those skill differences arose. For example, Moretti (2004a) finds that an increase in the percent of a city's residents with a college degree increases wages of its residents of all education levels, so education has substantial external benefits.[1] Researching another effect, Glaeser and Saiz (2003) show that the percent of a city's residents with a college degree is positively correlated with city population growth throughout the 20th century.

Consistent with these findings, local governments in the U.S. attempt to retain and attract skilled workers. An example of their efforts is Georgia's HOPE scholarship, which reduces the cost of attending Georgia colleges for academically successful Georgia high school graduates. Several states have subsequently enacted similar scholarship programs with the explicit goal of retaining local talent.

Local skill levels appear to have important consequences for local residents, but economists have limited knowledge about the determinants of the geographic distribution of skill. In particular, we do not know much about the persistence of skill inequality across labor markets over time or about the mechanisms underlying this persistence. In addition, we do not know much about what local characteristics predict that a location will have a high or low level of skill.

This paper contributes empirical evidence about the geographic distribution of skill in the U.S. and a framework for understanding the determinants of this distribution: the

[1]Other papers about the same topic include Rauch (1993), Acemoglu and Angrist (2000), and Ciccone and Peri (2006). Lange and Topel (2006) call into question the identification strategies used in this literature but leave open the possibility that education has external benefits.

locations of previous generations, the intergenerational transmission of skill from parents to children, and migration of differently skilled individuals. I assess how intergenerational transmission and migration affect the persistence over time of labor market skill inequality. I also identify labor market characteristics that predict local skill levels.

I begin with a statistical decomposition of state differences in skills using the U.S. Census. I use a predicted earnings index to categorize workers into skill categories and take as my local skills measure the local ratio of high-skilled to low-skilled populations. I take the state as the location definition, since this is the least aggregated birth location identified in the Census. For each state, I measure the skills of the parent generation, of the next generation by birth state, and of this second generation by adult residence state. I find evidence of mean reversion in state skills through intergeneration transmission; that is, states with the highest- and lowest-skilled parents tend to have children with skills closer to the national mean level of skills. Of course, the Census has weaknesses for this exercise. The most important weakness is that states are poor proxies for labor markets, which are the geographic units of interest for understanding local production and consumption.

To remedy this, I use detailed location data for respondents to the National Education Longitudinal Survey of 1988 (NELS:88), which is a nationally representative sample of U.S. resident students in the eighth grade in 1988. The NELS:88 also provides richer data on individual skills and provides data on linked parent and child skills. In order to use the relatively small sample size of the NELS:88 to study skill distributions of all U.S. labor markets, I add structure to the local skill decomposition framework.

The additional structure is a model that explains the geographic distribution of human capital as the outcome of a dynamic process wherein parents with different skills choose residence locations, they pass skills to their children, and their children choose their own residence locations. The model shows that selective net migration responds to local characteristics that affect the local relative demand and supply for high- and low-skilled residents. Estimating the model for states replicates findings in the Census accounting exercise, which increases confidence in the estimation procedure.

I then estimate the model using groups of counties called commuting zones as the labor market definition. The intergenerational transmission mechanism induces regression toward the mean of labor market skills. Migration of skills toward labor markets with higher parents skills partially offsets the regression toward the mean. Small and rural labor markets gain the most skills through intergenerational transmission but lose the most skills through migration. Local college enrollments and subsidies are positively correlated with the attraction of skills through migration. Labor markets with lower average January temperatures tend to have higher skill levels. Taxation in labor markets with higher skill tends to be tilted toward wage taxes and away from capital taxes.

## 2 Previous literature

The previous literature informing us about determinants of the geographic distribution of human capital can be divided into two segments. The first is the study of differences in migration behavior of people with different skills. Differences by skill in migration frequency, purposes, and destinations affect how migration distributes skills across labor markets. A smaller segment of the literature describes the variation in education levels across locations and identifies location characteristics that are correlated with local education levels.

The main finding of the first literature segment is that more-skilled people are more geographically mobile than less-skilled people. In his survey of the migration literature, Greenwood (1997) notes this as a robust finding.[2] Relatedly, Bound and Holzer (1992) and Wozniak (2006) provide evidence that college graduates are more likely to move in response to local labor demand shocks than those with less schooling. Malamud and Woz-

[2] Many articles show that more education is positively correlated with higher migration frequency. Bowles (1970) shows that the positive relationship between expected income gains from migrating out of the U.S. South and actual outmigration is stronger for people with more years of schooling. Courchene (1970) makes similar findings in Canada. Schultz (1971) shows that local schooling is positively correlated with rural-to-urban migration in Colombia.

niak (2007) argue that the estimated effect of college education on migration frequency is causal.

There also appear to be skill differences along other dimensions of the migration decision. Borjas, Bronars, and Trejo (1992) show that higher-skilled individuals in the National Longitudinal Survey of Youth, 1979 (NLSY79) are more likely than others to move to states with higher wage dispersion; the authors interpret this as evidence to support a Roy (1951) model framework wherein more-skilled individuals sort into labor markets with higher returns to skill. Ham, Li, and Reagan (2006) demonstrate that college graduates who migrate experience wage growth increases, but high school dropouts who migrate experience wage growth decreases. Kodrzycki (2001) uses the NLSY79 to show that recent college graduates tend to move to states with stronger labor markets than their origins. Basker (2003) provides evidence that more-educated migrants are more likely to have a job in hand when migrating than less-educated migrants. These findings suggest that labor market opportunities are more important to higher-skilled migrants than lower-skilled migrants.

A few papers investigate the determinants of local education levels. One determinant is the local education level in a previous year. Berry and Glaeser (2005) and Moretti (2004b) show that MSAs with higher initial proportions of college-educated residents experience more growth in the proportion of college-educated residents between 1970 and 2000. This implies modest divergence of skill levels across MSAs. Bound, Groen, Kezdi, and Turner (2004) study the effect of flows of graduates from state colleges on later stocks of college educated residents and find evidence of a modest positive relationship.

Moretti (2004b) takes a sample of MSAs and regresses the change in percent residents with college degrees between 1990 and 2000 on MSA characteristics. He finds the highest growth in Northeastern MSAs. The increase in the MSA college share is positively correlated with 1990 college share, population, and percent employment in high-tech jobs.

Kodrzycki (2000) is the most similar paper to mine. Kodrzycki studies the differences across Census divisions[3] in percent residents with a college degree. She categorizes regional degrees into those of natives who attend local college and stay, migrants who come for college, migrants who come after college, and natives who leave for college but return. Her focus is on New England, and she shows that New England's top rank in education is due mostly to high rates of native college attendance and graduation, rather than migration of college degree holders.

# 3 A statistical decomposition of state differences in skills

## 3.1 Decomposition of skill supply

In this section, I decompose the relative supply of skills to a state into three factors: the skill distribution of the previous generation in the state, the intergenerational transmission of skills, and the migration of skills. Let the number of high-skilled adults in location $j$ in generation $t$ be $A_{Hjt}$ and the corresponding low-skilled population be $A_{Ljt}$. Let the number of high-skilled children in state $j$ in generation $t$ be $C_{Hjt}$ and the corresponding low-skilled population be $C_{Ljt}$.

The number of adults in a state is the sum of the local children who decided to stay and the people from elsewhere who decided to move to the state. That is,

$$A_{sjt} = \#\text{Stay}_{sjt} + \#\text{InMig}_{sjt}$$

for $s = L, H$. Let $P_{sjkt}$ be the probability that an individual with skill $s$ chooses to migrate from state $j$ to state $k$, so $P_{sjjt}$ is the probability of staying in $j$. Then, the number of stayers in $j$ can be expressed as $\#\text{Stay}_{sjt} = C_{sjt}P_{sjjt}$ for $s = L, H$. Let the ratio of high- to low-skilled adults be $S_{jt} = A_{Hjt}/A_{Ljt}$ and the ratio of high- to low-skilled children be $K_{jt} = C_{Hjt}/C_{Ljt}$.

[3] The nine Census divisions are collections of states. Their names are New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific.

Using these definitions, the relative skill supply to state $j$ is

$$\begin{aligned} S_{jt} = \frac{A_{Hjt}}{A_{Ljt}} &= \frac{\text{\#Stay}_{Hjt} + \text{\#InMig}_{Hjt}}{\text{\#Stay}_{Ljt} + \text{\#InMig}_{Ljt}} \\ &= \frac{\text{\#Stay}_{Hjt}\left(\frac{\text{\#Stay}_{Hjt}+\text{\#InMig}_{Hjt}}{\text{\#Stay}_{Hjt}}\right)}{\text{\#Stay}_{Ljt}\left(\frac{\text{\#Stay}_{Ljt}+\text{\#InMig}_{Ljt}}{\text{\#Stay}_{Ljt}}\right)} \\ &= \frac{C_{Hjt}P_{Hjjt}\left(\frac{\text{\#Stay}_{Hjt}+\text{\#InMig}_{Hjt}}{\text{\#Stay}_{Hjt}}\right)}{C_{Ljt}P_{Ljjt}\left(\frac{\text{\#Stay}_{Ljt}+\text{\#InMig}_{Ljt}}{\text{\#Stay}_{Ljt}}\right)} \\ &= K_{jt}\Lambda_{jt}M_{jt} \\ &= S_{jt-1}\frac{K_{jt}}{S_{jt-1}}\Lambda_{jt}M_{jt}. \end{aligned} \tag{1}$$

In the above equation, $\Lambda_{jt} \equiv P_{Hjjt}/P_{Ljjt}$ is the probability of a high-skilled child staying in $j$ divided by the probability of a low-skilled child staying in the same state. $M_{jt}$ is a factor that describes the rate of skill increase through in-migration.

Taking logarithms of Equation 1 yields

$$\ln(S_{jt}) = \ln(S_{jt-1}) + \ln\left(\frac{K_{jt}}{S_{jt-1}}\right) + \ln(\Lambda_{jt}M_{jt}). \tag{2}$$

Equation 2 decomposes the relative supply of skills to state $j$ into factors due to the skill distribution of the previous generation ($S_{jt-1}$), the intergenerational transmission of skill from that generation to the next ($K_{jt}/S_{jt-1}$), and the migration of skills ($\Lambda_{jt}M_{jt}$).

I calculate each element of Equation 2 using U.S. Census data. The major benefit from using Census data is that the samples are large and allow the calculation of skill distributions for many locations. With these data, the location definition is the state, since that is the most disaggregated level of birthplace identification in the Census. I include Washington, D.C. as a state.

I use a predicted earnings index to measure skills. I take the full-time workers aged 30 to 40 in the 5 percent 2000 Census sample from IPUMS (Ruggles et al. 2004). With this sample, I estimate a regression of the following form:

$$y_{ij} = \beta X_i + \sum_k \delta_k \text{Occ}_{ik} + \alpha_j + \epsilon_{ij}. \tag{3}$$

The dependent variable, $y_{ij}$, is log weekly labor earnings of individual $i$ who lives in state $j$. The vector $X_i$ includes characteristics of individual $i$: sex, race, a quadratic in age, and indicators for completed schooling categories. The other regressors are indicators for three-digit occupation ($\text{Occ}_{ik}$) and indicators for state of residence. The state of residence intercepts capture state differences in wages due to various factors, including cost of living.

Using coefficients from OLS estimation of Equation 3, I predict log weekly labor earnings for all workers, setting the state indicator for New York equal to one and all others to zero. I define a worker as high-skilled if his or her predicted earnings fall in the highest quartile of (national) predicted earnings and low-skilled in the lowest quartile. $S_{jt}$ is the ratio of high-skilled to low-skilled populations living in state $j$ as adults in 2000. $K_{jt}$ is the ratio of high-skilled to low-skilled populations born in state $j$.

I calculate $S_{jt-1}$ using a similar earnings prediction index for an earlier cohort: workers aged 35 to 45 in the 5 percent 1980 Census sample from IPUMS. I use a regression with the same form as Equation 3 to predict log weekly earnings for each member of this older cohort and categorize each member into a quartile of the predicted earnings index. $S_{jt-1}$ is the ratio of high-skilled to low-skilled populations living in state $j$ in 1980.

I calculate $P_{sjjt}$ for $s = L, H$ as the fraction of the skill $s$ population born in $j$ who are also living in $j$ in 2000. I then calculate the relative native retention rate for each state: $\Lambda_{jt} = P_{Hjjt}/P_{Ljjt}$. I also calculate the effect of in-migration on the state skill ratio as $M_{jt} = S_{jt}/(K_{jt} \times \Lambda_{jt})$.

In order for Equation 3 to predict skills accurately, I assume that the error term $\epsilon_{ij}$ does not include interactions between occupation and state of residence. If it did, then the earnings prediction would confuse productivity of a worker's state of residence with the worker's own labor market productivity. I expect productivity differentials between occupation categories to vary across states less the more narrowly occupations are defined. I use the most narrow occupation coding available.

Previous local skill measures used in the economics literature are average years of schooling and percent residents with a college degree.[4] In the present paper, I adopt a different measure: the ratio of local high-skilled to low-skilled populations. The main reason for doing so is that it is the measure most closely related to most economic models of a geographic distribution of people with heterogeneous skills (eg, Berry and Glaeser (2005), Glaeser and Saiz (2003), Moretti (2004a)), including the model in this paper. In addition, this measure uses wages to infer labor market productivity of individual characteristics and captures more variation in skill than schooling alone.[5]

### 3.2 Results from U.S. state skill accounting exercise

I find evidence of regression toward the mean of state skills from one generation to the next. This works through intergenerational transmission of skills: states with the highest- and lowest-skilled parents tend to have children with skills closer to the national mean level of skills. Across states, migration does not send skills disproportionately to states with higher or lower skills in the previous generation.

Table B.6 in Appendix B lists the parameter estimates for all states. Table 2 displays descriptive statistics of them. Differences in the distributions of $K_{jt}$ and $K_{jt}\Lambda_{jt}$ capture the effects on state skills of native skill retention. Differences in the distributions of $K_{jt}\Lambda_{jt}$ and $S_{jt}$ capture the effects on state skills of in-migration. The fact that $\Lambda_{jt}$ is less than one for

[4]Acemoglu and Angrist (2000) and Rauch (1993) study the impact of local average years of schooling on residents' individual wages. Moretti (2004a) investigates the impact of an MSA's percent college on its residents' own wages. Moretti (2004b) and Berry and Glaeser (2005) investigate trends in percent college residents of MSAs.

[5]The ratio of high-skilled to low-skilled populations is clearly related to other measures. For example, define the high-skilled to be college graduates and the low-skilled to be all others. Let $C$ be the number of college graduates and $HS$ be the number of other residents. The percent college is 100 times $\frac{C}{HS+C} = \frac{C}{HS} \times \frac{1}{1+C/HS}$. Percent college graduates is strictly increasing in the ratio of high-skilled to low-skilled residents. That is, $\frac{d(C/(HS+C))}{d(C/HS)} = (1 + C/HS)^{-2} > 0$. So, if the ratio measure is higher in a location, then the percent college graduates much also be higher.

all states is a dramatic effect of the relationship between individual skill and migration behavior. More-skilled people are more mobile, so out-migrants are more skilled than natives for all states. The fact that $M_{jt}$ is greater than one for all states shows the same relationship from the opposite perspective. Table 3 lists correlations between parameters to show the average relationships between skill measures of states.

The slope coefficient from a regression of $\ln(S_{jt})$ on $\ln(S_{jt-1})$ is a measure of generation-to-generation persistence in local skills. The impact of intergenerational transmission on generation-to-generation local skill persistence is the relationship between a generation's skills and the skills of the next generation if there were no migration. The predicted next generation skill measure due to intergenerational transmission is $\ln(S_{jt-1}) + \ln\left(\frac{K_{jt}}{S_{jt-1}}\right)$. Similarly, the impact of migration on generation-to-generation local skill persistence is the relationship between a generation's skills and the skills of the next generation if there were no intergenerational transmission. The predicted next generation skill measure due to migration is $\ln(S_{jt-1}) + \ln(\Lambda_{jt} M_{jt})$.

Table 4 illustrates the roles that intergenerational transmission and migration play in determining the persistence of skills across states. Each column represents a separate regression where observations are states and the variables are skill ratios or predicted skill ratios. Column 1 includes results from regressing a state's skill ratio on the skill ratio of the previous generation in the state. State skill ratios are persistent across generations, although there is some regression toward the mean in skill. The slope coefficient of the regression of log skill ratio on previous generation log skill ratio at the state level is 0.65 with a standard error of 0.14. The $R^2$ is 0.32, implying that factors other than the previous generation's skills have a large role in determining a state's skill level.

Figure 1 illustrates this relationship with a scatter plot where I plot for each state the skill ratio of adults measured in 2000 against the skill ratio of their parents' generation measured in 1980. Southeastern states Mississippi, South Carolina, and Arkansas are near the bottom of both skill distributions. North Carolina started low but gained skills during this time. Massachusetts gained skills to top the second generation's skill distribution.

Columns 2 and 3 of Table 4 decompose the persistence of local skills into parts due to intergenerational transmission and migration. The dependent variable in Column 2 is the state skill ratio if intergenerational transmission were the only mechanism affecting the geographic skill distribution. This is equivalent to the skill distribution of natives in the state. I regress this variable on the natural logarithm of the previous generation's state skill ratio. The slope coefficient of 0.66 (close to the overall slope of 0.65) implies that overall mean reversion from generation to generation comes through intergenerational transmission of skills. Figure 2 plots for each state the second generation's skills assigned to their birth states against their parents' skills. The plot is similar to the one describing adult locations of these two generations.

This relationship at the location level is comparable to the literature on intergenerational transmission of skills within the family. Solon (1999) surveys the literature on the intergenerational transmission of earnings. The consensus estimate of the elasticity of child earnings with respect to parent earnings lies between 0.3 and 0.5 in the U.S. (page 1780). Local skill ratio persistence appears to be higher than family-level intergenerational earnings persistence.

The literature studying the relationship between parents' schooling and children's schooling are also consistent with family-level persistence and some mean reversion. In cross sections, children's schooling tends to increase less than one-for-one with parents' schooling. This is the case in Behrman and Rosenzweig (2002) with U.S. data and in Black, Devereux, and Salvanes (2005) with Norwegian data. Much of the recent literature on this topic attempts to decompose the cross-sectional correlation into parts due to genetic and environmental factors.

The regression in Column 3 of Table 4 has as its dependent variable the state skill ratio if migration were the only mechanism determining the geographic skill distribution. The slope coefficient is very close to one, indicating that skill gains through migration are allocated evenly across states with high and low skills in the previous generation. Figure 3 shows this relationship in a scatter plot. Virginia, Arizona, and Colorado lie above the regression line, so they gain more than average through migration. Iowa, Montana, Wyoming, and the Dakotas tend to lose skills through migration.

The regression in Column 4 of Table 4 describes the relationship between skills of a state's natives and skills of that state's adults from the same generation after migration. There is significant persistence in skills from birth to adult locations. Still, adult location skills increase less than one-for-one with native skills. In the regression of $\ln(S_{jt})$ on $\ln(K_{jt})$, the slope coefficient estimate is 0.79 with a standard error of 0.1, so the slope is less than one with 95 percent confidence.

Figure 4 plots for each state the skill ratio of adults in 2000 against the skill ratio of natives from the same cohort. Massachusetts has the highest ratio of high- to low-skilled workers at birth and adult residence in this cohort. New York, New Jersey, Connecticut, Washington D.C., and Minnesota are also high-skilled states overall. Southern states South Carolina, Mississippi, and Arkansas are at the opposite end of the spectrum with low skill ratios among births and adult residences. Colorado has a medium level of native skill but gains dramatically through migration. North and South Dakota, Iowa, and Montana have reasonably high native skills but lose many of them through migration.

# 4 A model of the geographic distribution of human capital over time

## 4.1 Introduction of the framework

The primary purpose of the model is to provide a link from individual skill acquisition and migration behavior to the geographic distribution of human capital. This will highlight the mechanisms underlying human capital distributions and provide a framework for estimating the distributions with individual-level data. A secondary purpose of the model is to indicate what kinds of labor market characteristics affect local skill levels.

The framework is an over-lapping generations model. There are two decisions that each member of each generation makes. The first is which skill level to acquire as a child. Skill is indexed by $s$ and takes on values $H$ and $L$ for high- and low-skilled individuals, respectively. The second decision is where to live as an adult. Individuals can choose to stay in their origin location or to move to any of the other locations in the economy.

Figure 5 illustrates the timing of events in the model. People are born and grow up in a labor market. In their birthplace, they decide whether to become high- or low-skilled workers. They make a migration decision as adults, choosing to stay in their origin or move to any other labor market. After the migration decision, they work and have children in their chosen location and die. Members of the new generation then make the skill investment and migration decisions and have children and work in their chosen location. Each labor market clears in each period (generation) so that the relative supply of high- to low-skilled workers in each labor market equals the relative demand for high- to low-skilled workers there.

## 4.2 Decomposition of local relative supply of skills

The local supply of skills is the aggregation of skill acquisition and migration decisions. I describe skill acquisition and then migration decisions. I then aggregate them to represent local relative skill supply.

Let $U_{sij}$ be the net benefit to individual $i$ growing up in location $j$ of having skill level $s$. This is a function of expected benefits and costs to investing in skills. Individual $i$ chooses to invest in high skills if $U_{Hij} - U_{Lij} > 0$ and chooses low skills otherwise. Let $\text{Par}_{Hi}$ be an indicator for child $i$ having high-skilled parents and $z_j$ be a vector of characteristics of $i$'s origin location $j$. The following equation represents net benefits of high relative to low skill acquisition for individual $i$:

$$U_{Hij} - U_{Lij} = \alpha_1 + \alpha_2 \text{Par}_{Hi} + \alpha_3 z_j + \alpha_4 \text{Par}_{Hi} z_j - \epsilon_{ij}.$$

Parents' skills affect the costs of acquiring skill, as do location characteristics in $z_j$, such as proximity to college. Assume $\epsilon_{ij} \sim N(0,1)$. Then, the following formulas measure skill acquisition rates:

$$\begin{aligned} P_{HLj} &= \Phi(\alpha_1 + \alpha_3 z_j) \\ P_{HHj} &= \Phi(\alpha_1 + \alpha_2 + (\alpha_3 + \alpha_4) z_j). \end{aligned}$$

$\Phi(\cdot)$ is the standard normal cumulative distribution function. $P_{HLj}$ is an estimate of the probability a child growing up with low-skilled parents in a location with characteristics $z_j$ will be high-skilled. $P_{HHj}$ is the probability a child growing up with high-skilled parents in a location with characteristics $z_j$ will be high-skilled.

The next decision individuals make is where to live when adults.[6] Let $s(i)$ be a function that gives the skill level of individual $i$ and $b(i)$ be a function that gives the birthplace of individual $i$. The utility that individual $i$ attains from residing in location $k$ in generation $t$ is

$$V_{ikt} = \gamma \ln \bar{W}_{s(i)kt} + \beta_{s(i)t} z_{b(i)kt} + \epsilon_{ikt},$$

where $\bar{W}_{s(i)kt}$ is the location $k$ average wage among residents with skill level $s$ and $z_{b(i)kt}$ is a vector of location characteristics. This vector includes interactions between origin and destination characteristics, so individuals from different origins attach different values to destination characteristics. For example, distance between origin and a potential destination is allowed to enter $V_{ikt}$.

Note also the treatment of wages. Average wages enter the utility function, which could be justified by assuming individuals have imperfect information about wages they will be able to earn in any given location. This is unrealistic but perhaps not extreme in this context, where my focus is on estimating average preferences and behavior. Moreover, I constrain the marginal utility of labor earnings ($\gamma$) to be the same for both skill

[6]The model at present does not allow the skill acquisition and migration decisions to interact. The primary reason is simplicity, both in model exposition and estimation. If children acquire skills because they are anticipating their use of those skills in some labor market other than their origin, then this method will mistakenly identify location characteristics as inducing migration instead of the acquisition of skills.

levels.

The residual $\epsilon_{ikt}$ is distributed extreme value independently and identically across $i$, $k$, and $t$. This distribution of the residuals implies that the probability of utility-maximizing individual $i$ locating in $k$ is (letting $i$'s origin be $j$ and $i$'s generation be $t$)

$$P_{ijkt} = \frac{\exp(\gamma \ln \bar{W}_{s(i)kt} + \beta_{s(i)t} z_{jkt})}{\sum_l \exp(\gamma \ln \bar{W}_{s(i)lt} + \beta_{s(i)t} z_{jlt})}. \tag{4}$$

See McFadden (1974).

I now aggregate the skill acquisition and migration decisions in order to characterize the relative supply of skills to a labor market. I take notation from the accounting exercise above, so $S_{jt} = A_{Hjt}/A_{Ljt}$ is the relative supply of high- to low-skilled adults of generation $t$ to location $j$, and $P_{sjkt}$ is the probability that an individual with skill $s$ chooses to migrate from location $j$ to location $k$. I add here that an expression for the number of in-migrants to $j$ with skill level $s$ is #InMig$_{sjt} = \sum_{k \neq j} C_{skt} P_{skjt}$. Then, following Equation 1, the location $j$ relative supply of skills can be expressed as

$$S_{jt} = \frac{C_{Hjt} P_{Hjjt} \left( \frac{\sum_k C_{Hkt} P_{Hkjt}}{C_{Hjt} P_{Hjjt}} \right)}{C_{Ljt} P_{Ljjt} \left( \frac{\sum_k C_{Lkt} P_{Lkjt}}{C_{Ljt} P_{Ljjt}} \right)}. \tag{5}$$

I can decompose this supply into the intergenerational transfer mechanism and migration. The former is the mechanism that maps local parents' skills into local children's skills. Define the skill transmission function to be

$$\begin{aligned} K_j \left( \frac{A_{Hjt-1}}{A_{Ljt-1}} \right) &= \frac{(A_{Hjt-1}/A_{Ljt-1}) P_{HHj} + P_{HLj}}{(1 - P_{HLj}) + (A_{Hjt-1}/A_{Ljt-1})(1 - P_{HHj})} \\ &= \frac{A_{Hjt-1} P_{HHj} + A_{Ljt-1} P_{HLj}}{A_{Ljt-1}(1 - P_{HLj}) + A_{Hjt-1}(1 - P_{HHj})} = \frac{C_{Hjt}}{C_{Ljt}}. \end{aligned} \tag{6}$$

Defining $K_j$ as a function rather than a multiplier, as in the accounting exercise, allows a more explicit treatment of intergenerational transmission, which is possible with the NELS:88. Further define $\Lambda_{jt} = P_{Hjjt}/P_{Ljjt}$ to describe the effect of retention of natives on the local skill distribution. Finally, define

$$M_{jt} = \left( \frac{\sum_k C_{Hkt} P_{Hkjt}}{C_{Hjt} P_{Hjjt}} \right) \Bigg/ \left( \frac{\sum_k C_{Lkt} P_{Lkjt}}{C_{Ljt} P_{Ljjt}} \right)$$

to describe the effect of in-migration on the local skill distribution. $M_{jt}$ is the growth of high skills relative to the growth of low skills through in-migration.

Plugging these definitions into Equation 5, the evolution of relative skills in location $j$ follows

$$S_{jt} = K_j(S_{jt-1}) \times \Lambda_{jt} \times M_{jt}. \tag{7}$$

I will estimate each element of this equation in order to assess how the intergenerational transmission of skills and migration contribute to the geographic distribution of skill.

## 4.3 Equilibrium in local labor markets

Each labor market of the model clears in every period (generation). Equilibrium is reached when the relative supply of skills in each labor market equals the relative demand for skills. The relative supply of skills to labor market $j$ is, plugging the location choice probabilities of Equation 4 into the supply Equation 1,

$$\begin{aligned}
S_{jt} = \frac{A_{Hjt}}{A_{Ljt}} &= \frac{\text{\#Stay}_{Hjt} + \text{\#InMig}_{Hjt}}{\text{\#Stay}_{Ljt} + \text{\#InMig}_{Ljt}} \\
&= \frac{\sum_k C_{Hkt} P_{Hkjt}}{\sum_k C_{Lkt} P_{Lkjt}} \\
&= \frac{\sum_k C_{Hkt} \left( \frac{\exp(\gamma \ln \bar{W}_{Hjt} + \beta_{Ht} z_{kjt})}{\sum_l \exp(\gamma \ln \bar{W}_{Hlt} + \beta_{Ht} z_{klt})} \right)}{\sum_k C_{Lkt} \left( \frac{\exp(\gamma \ln \bar{W}_{Ljt} + \beta_{Lt} z_{kjt})}{\sum_l \exp(\gamma \ln \bar{W}_{Llt} + \beta_{Lt} z_{klt})} \right)} \\
&= \frac{\exp(\gamma \ln \bar{W}_{Hjt}) \sum_k C_{Hkt} \left( \frac{\exp(\beta_{Ht} z_{kjt})}{\sum_l \exp(\gamma \ln \bar{W}_{Hlt} + \beta_{Ht} z_{klt})} \right)}{\exp(\gamma \ln \bar{W}_{Ljt}) \sum_k C_{Lkt} \left( \frac{\exp(\beta_{Lt} z_{kjt})}{\sum_l \exp(\gamma \ln \bar{W}_{Llt} + \beta_{Lt} z_{klt})} \right)}
\end{aligned}$$

Let $s_{jt} \equiv \ln(S_{jt})$ and $w_{jt} \equiv \ln(\bar{W}_{Hjt}/\bar{W}_{Ljt})$. Then, the relative supply of skills to location $j$ is

$$s_{jt} = \gamma w_{jt} + \Psi_{jt}, \tag{8}$$

where $\Psi_{jt}$ is a function of attributes of location $j$ at time $t$ relative to other locations.

Let $D_{jt}$ be the local relative demand for high- and low-skilled individuals, and $d_{jt} \equiv \ln(D_{jt})$. The following equation describes the local relative demand for skills:

$$d_{jt} = -\sigma w_{jt} + e_{jt}. \tag{9}$$

$\gamma$ and $\sigma$ are positive parameters that represent elasticities with respect to the local relative wage.[7]

In equilibrium, each local labor market must clear so that $s_{jt} = d_{jt}$. This implies the following:

$$d_{jt} = s_{jt} = \frac{\gamma}{\gamma + \sigma} e_{jt} + \frac{\sigma}{\gamma + \sigma} \Psi_{jt}. \tag{10}$$

The local skill premium is

$$w_{jt} = \frac{e_{jt} - \Psi_{jt}}{\gamma + \sigma}.$$

Relative wages tend to be higher in labor markets with strong relative demand for skills ($e_{jt}$) and lower in labor markets with amenities valued more by higher- than lower-skilled workers ($\Psi_{jt}$).

The rate of growth in local relative skills that comes through migration is given by the

[7] This representation of local relative labor supply and demand draws upon Bound, Groen, Kezdi, and Turner (2004).

term $\Lambda_{jt} \times M_{jt}$ in Equation 7. [8] In equilibrium, the following holds:

$$\begin{aligned} \ln(\Lambda_{jt} \times M_{jt}) &= s_{jt} - \ln[K_j(S_{jt-1})] \\ &= \frac{\gamma}{\gamma+\sigma} e_{jt} + \frac{\sigma}{\gamma+\sigma} \Psi_{jt} - \ln[K_j(S_{jt-1})]. \end{aligned} \tag{11}$$

This equation makes clear that relative skill flows from migration depend upon current location characteristics (relative to other locations) that affect relative demand and supply, previous generations' location decisions, and the local intergenerational transmission of human capital. This is a reduced form equation I will estimate in order to identify characteristics of labor markets that draw skills through migration.

An important feature of the model to keep in mind is that quantities are always ratios. As a result, local characteristics that affect high- and low-skilled individuals in the same way do not affect the equilibrium relative skill level. For example, cost of living that deflates all nominal wages in a city by the same proportion should not have an effect on the local relative supply of skills. Amenities that are valued the same between high- and low-skilled individuals should not affect the relative supply of skills. Amenities that are normal goods, however, will tend to draw the higher skilled (with higher incomes) at higher rates.[9]

[8] To see this, note that

$$\begin{aligned} \Lambda_{jt} \times M_{jt} &= \frac{P_{Hjjt}\left(\frac{\sum_k C_{Hkt} P_{Hkjt}}{C_{Hjt} P_{Hjjt}}\right)}{P_{Ljjt}\left(\frac{\sum_k C_{Lkt} P_{Lkjt}}{C_{Ljt} P_{Ljjt}}\right)} \\ &= \frac{\frac{\sum_k C_{Hkt} P_{Hkjt}}{C_{Hjt}}}{\frac{\sum_k C_{Lkt} P_{Lkjt}}{C_{Ljt}}} \\ &= \frac{\sum_k C_{Hkt} P_{Hkjt} / \sum_k C_{Lkt} P_{Lkjt}}{C_{Hjt}/C_{Ljt}} \end{aligned}$$

[9] Cost of living and amenities in this model do affect total population flows into and out of locations, but my focus will be on relative flows of high- and low-skilled populations.

# 5 Data description

The location definition in this study approximates a labor market, which I consider to be the smallest geographic space where most residents work and most workers reside. I use the commuting zone (CZ) as the location definition. Tolbert and Sizer (1996) describe the identification of CZs using journey-to-work data from the 1990 Census. Each CZ is a collection of counties (or single county) that share particularly strong commuting links. The CZ definition has the added feature of encompassing both rural and urban areas.[10]

There are 741 CZs in the U.S. 604 of them are entirely contained by a single state, 129 of them by two states, and 8 of them by three states (eg, Washington, D.C.). CZ populations in 2000 range from 1,193 (Murdo, SD) to 16,393,360 (Los Angeles, CA). 258 CZs contain a metropolitan statistical area.

I calculate some average characteristics of CZs with the U.S. Census. I use the 1990 and 2000 5 percent samples available through IPUMS. These characteristics include average wages, percent with college degrees, and percent employment in manufacturing. The smallest identifiable area in the Census is the public use microdata area (PUMA), which is a Census-defined place with population no less than 100,000. This definition does not allow perfect matching of boundaries for all CZs. The method used to convert PUMA averages to CZ averages involves assigning PUMA characteristics to a CZ based on the population weight of the PUMA in the CZ. The data appendix includes a more detailed description of the method.

Additional CZ characteristics come from various sources. I aggregate CZ population from county population files available through IPUMS. Region and urban status come directly from Tolbert and Sizer (1996). I calculate average climate characteristics (such as average temperatures and snowfall) using data from the National Climatic Data Center. I characterize CZs as being coastal if at least one of the counties making up the CZ has an ocean coastal property. The distance between two CZs is the great circle distance between

[10]This is the same location definition used in Autor and Dorn (2007) to study the interactions of different types of workers within labor markets.

their latitude and longitude coordinates, in kilometers.

I use state higher education appropriations and public college tuition data from Fortin (2007). From the data Fortin make available, I calculate higher education appropriations per full-time equivalent student and public tuition per public college student for each state. The higher education subsidy variable I use in some specifications is the appropriations variable divided by the tuition variable.

I also calculate college enrollment for each CZ. I acquire college enrollment in each county from the Integrated Postsecondary Education Data System (IPEDS) at the National Center for Education Statistics (NCES) and sum over counties to get CZ enrollments. The enrollment measure is the full-time equivalent number of undergraduate students at two-year and four-year colleges.

I use state wage and capital tax data from Daniel Feenberg at the National Bureau of Economic Research (NBER). The variables I use are the highest marginal tax rates that people face in each state. These rates combine Federal and state taxes. Information about the program used to calculate tax rates (TAXSIM) is available in Feenberg and Coutts (1993).

CZs sometimes consist of counties in more than one state. For state-level variables (higher education appropriations, tuition, and tax rates), I assign to each CZ the characteristics of the state with the larger share of CZ population.

Table 5 displays descriptive statistics for the 741 CZs. The range of percent residents with college degrees from Table 1 is repeated. People choosing residential location have a set of choices that is very diverse along many dimensions, which helps identify characteristics that contribute to the skill distribution. The range of average wages, temperatures, industry structures, populations, tax policies, and subsidy rates for public higher education are all quite large.

To investigate both the intergenerational transmission of skill and early migration decisions, I use the National Education Longitudinal Study of 1988 (NELS:88). Several features of the NELS:88 address the weaknesses of using the Census for the present purposes. First, the restricted-use version of the NELS:88 has zip code data that identify the CZ of residence for each respondent, both in 8th grade and at age 26. Second, the NELS:88 includes more informative data on individual skills and family background, most notably test scores and parent's education. Third, the NELS:88 has information about the parents of each respondent, allowing investigation of the intergenerational transmission of skill at the family level. Fourth, the NELS:88 identifies location of respondents at 8th grade, which is more likely to approximate the location of skill acquisition than the birth state in the Census data.

NELS:88 data collection began with a representative sample of students in the eighth grade of U.S. schools in 1988. Follow-up surveys were completed in 1990, 1992, 1994, and 2000. In the final follow-up, students were around 26 years old and mostly out of school. They were making early family formation and labor market decisions, including geographic location choices. Labor market information includes annual earnings and whether full-time, in addition to occupation and industry.

Figure 6 implies that a weakness of the NELS:88 data for my purposes is the relatively young age at final follow-up. Figure 6 plots different types of average migration rates from the 2000 Census by age. The series refer to migration defined as changing houses, changing PUMAs, and changing states between 1995 and 2000. Five-year migration rates peak around the age of the final location information from NELS:88 respondents. The model above includes a single location decision for each agent, which may not be approximated well by the relatively early location decisions in these data.

Table 6 provides summary statistics for the NELS:88 sample I use. There are 11,079 respondents with non-missing location information in 8th grade and the 2000 follow-up survey. For this table and all estimation with the NELS:88, I apply sample weights that make the NELS:88 sample representative of 8th grade students in U.S. schools in 1988. Table 6 also shows that migration out of one's origin CZ is common. About 35 percent of respondents lived at age 26 in a CZ other than their 8th grade CZ.

Migration behavior varies substantially across skill levels and family backgrounds.

Table 6 shows that college graduation, the test score index, parent's education, parent's income, and early labor market earnings are all higher for those who had migrated away from their 8th grade labor market. The test score index is defined such that a 0.1 increase in the index represents a change in math and verbal scores on an 8th grade test that predict a 0.1 increase in log earnings.[11]

# 6 Estimation of the model and results

## 6.1 Estimation of model parameters

In estimation, I depart from the model in one significant way. When defining skill categories of parents and children, I allow there to be four skill levels instead of two. I use four skill levels in order to have more of a distinction between high- and low-skilled individuals than splitting the sample in half would yield, while using all of the data available.

The first step in estimating the model is measuring, for each U.S. labor market, the skill distribution of the generation of NELS:88 parents. I take this cohort to be workers in the 5 percent 1990 Census who were ages 34 through 56. With full-time workers from this sample, I estimate Equation 3 by OLS. I use coefficients from this regression to predict log weekly labor earnings for all workers, setting the state indicator for New York equal to one and all others to zero. High-skilled people make up the highest quartile of the national predicted earnings distribution, and low-skilled people make up the lowest quartile. The estimate of $S_{jt-1}$, the skill ratio in labor market $j$ among the parent generation, is the ratio of high-skilled to low-skilled populations in CZ $j$.

The next steps in estimating the model are estimating the intergenerational transmission of skill and location choice models with the NELS:88. I categorize NELS:88 respondents into skill categories that correspond with quartiles of a predicted earnings distribution. The form of the regressions is similar to the one used with the Census, although

[11]The index ranges from 9.950 to 10.145. The index at mean eighth grade test scores is 10.030. The index at one standard deviation higher on verbal and math scores is 10.052, representing a gain in predicted annual earnings of about 2 percent.

earnings predictions with the NELS:88 use data on test scores and parents' education but not occupation. The other difference is that I measure annual earnings in the NELS:88 rather than weekly earnings.

I also categorize NELS:88 parents into skill groups. Characteristics of parents are somewhat limited, and the earnings data seem less reliable than for their children (respondents). So, I define parent skills by a ranking of completed schooling and family income. I rank the parents by years of schooling of the parent with the higher value. This is a categorical variable and does not induce equal quartiles. So, within years of schooling, I rank parents by their family income. I then define the parents in the highest quartile of this education and income ranking to be high-skilled and parents in the lowest quartile to be low-skilled.

I then estimate separate probit models for students attaining each skill level, as functions of parents' skill categories and characteristics of the origin CZ. The results from these probit models are in Table B.1 of Appendix B. As expected, the skill level of parents is a clear predictor of child skill. Some location characteristics are correlated with the skill acquisition of local youth. These specifications include many location characteristics, making interpretation of marginal effects difficult. For example, the coefficient on log college subsidy needs to be interpreted as the partial effect of subsidies controlling for variables including college enrollment per capita, wage taxes, local wages, and percent residents with college degrees. The purpose of including so many variables is to capture much of the variation across labor markets in the intergenerational transmission of skills.

One of these probit models estimates the probability a high-skilled parent in a CZ with the characteristics of $j$ will have a high-skilled child. In model language, this is an estimate of $P_{HHj}$. The probit models also estimate the probabilities of intergenerational skill transfer between all pairs of parent and child skill types in all CZs. Using these, I calculate the model parameter $K_j(S_{jt-1})$ for each labor market $j$, using the estimated $S_{jt-1}$ from the Census and a four-skill analogue of Equation 6.[12]

[12]More specifically, let $MH$ and $ML$ denote medium-high and medium-low skills, respectively. These refer to the second-highest and third-highest quartiles in the predicted earnings index. From the 1990

Next, I estimate migration probabilities using a separate logit model for each skill category, where the choice is among CZs of residence. The form of the logits that I estimate uses the following specification for the utility to individual $i$ living in CZ $k$:

$$V_{ik} = \gamma_{s(i)} \ln \bar{W}_{s(i)k} + \beta_{s(i)1}\text{Home}_{ik} + \beta_{s(i)2}\text{Distance}_{ik} + \beta_{s(i)3}\text{Distance}^2_{ik} + \beta_{s(i)4} z_k + \beta_{s(i)5}\text{Home}_{ik} z_k + \beta_{s(i)6}\text{Rural}_{b(i)} z_k + \beta_{s(i)7} z_k z_{b(i)} + \epsilon_{ik},$$

where $\text{Home}_{ik}$ is an indicator for $k$ being $i$'s origin CZ, $\text{Distance}_{ik}$ is the distance in kilometers between $k$ and $i$'s origin CZ, $\text{Rural}_{b(i)}$ is an indicator for $i$'s origin CZ being rural, $z_k$ is a vector of destination characteristics, and $z_{b(i)}$ is a vector of origin characteristics. I estimate $\bar{W}_{s(i)k}$ for each destination as the average wage of local workers in skill category $s$. I do not constrain $\gamma_{s(i)}$ to be the same across skill levels as the model assumes.

Tables B.2 through B.5 display parameters from four logit models that estimate location choices of NELS:88 respondents. The coefficient on local average wages is negative for three of the skill groups. In reality, destination choices depend on both supply and demand factors, so the coefficient on average wages can be positive or negative. One would not expect this estimate necessarily to be consistent for the slope of the relative supply curve. In addition, the average wage measure I use is surely different from the offer wages that workers receive. Other local characteristics appear to affect utility more than this average wage measure.

The coefficients on $\text{Home}_{ik}$ show that people of all skill levels are much more likely to stay in their labor market of origin than move to another. There is also a significant utility reduction associated with distance from origin, and this is quite consistent across skill levels.

Census, I estimate local adult populations $A_{Hjt-1}$, $A_{MHjt-1}$, $A_{MLjt-1}$, and $A_{Ljt-1}$. Then, estimates of the next generation's child skill populations are

$$\begin{aligned} C_{Hjt} &= A_{Hjt-1}P_{HHj} + A_{MHjt-1}P_{HMHj} + A_{MLjt-1}P_{HMLj} + A_{Ljt-1}P_{HLj} \\ C_{Ljt} &= A_{Hjt-1}P_{LHj} + A_{MHjt-1}P_{LMHj} + A_{MLjt-1}P_{LMLj} + A_{Ljt-1}P_{LLj} \end{aligned}$$

and $K_j(S_{jt-1}) = C_{Hjt}/C_{Ljt}$.

Conditional on other location characteristics, the Northeast is the least attractive destination for all skill levels, and the West is the most attractive destination for all except low-skilled individuals. The percent college at origin tends to encourage people to leave, although the percent college of non-home destinations tends to be a positive amenity (or it is correlated with some other positive amenity in the residual). This is most clearly the case with higher-skilled individuals.

In model language, the logit models yield estimates of $P_{Hjkt}$ and $P_{Ljkt}$ for all combinations of labor markets $j$ and $k$, including $j = k$. With these, I calculate $\Lambda_{jt} = P_{Hjjt}/P_{Ljjt}$ and $M_{jt} = \left(\frac{\sum_k C_{Hkt} P_{Hkjt}}{C_{Hjt} P_{Hjjt}}\right) \Big/ \left(\frac{\sum_k C_{Lkt} P_{Lkjt}}{C_{Ljt} P_{Ljjt}}\right)$ for each $j$, where $C_{Hjt}$ and $C_{Ljt}$ come from the procedure used to calculate $K_j(S_{jt-1})$ (see Footnote 12). The final parameter to estimate is $S_{jt} = K_j(S_{jt-1})\Lambda_{jt} M_{jt}$ for each $j$.

As a robustness check, I estimate the model with the NELS:88 using states instead of CZs as locations. If the model estimation procedure is reliable, then this exercise will replicate findings from the accounting exercise that uses Census data alone. For the most part, this is the case. I describe the results in Appendix C. Overall, model estimation with the NELS:88 has enough precision to replicate findings in the Census, and this adds credibility to the procedure for understanding the geographic distribution of human capital.

## 6.2 Model estimation results about the geographic distribution of human capital

Figures 7 through 10 illustrate the persistence of skills in CZs from generation to generation. Tables 7 through 13 describe how migration and intergenerational transmission interact with skills of labor markets. The results indicate that intergenerational transmission causes some regression to the mean of skills across CZs, as it does across states. Migration works against this tendency across CZs, unlike across states. That is, migration transfers more skills to CZs that had higher parent skills. Intergenerational transmission transfers skills toward smaller and more rural labor markets, while migration transfers skills toward larger and more urban labor markets. Overall, CZs that gain more skills tend to be larger and to have lower temperatures in January, higher supplies of higher education services, and more taxation of wages relative to than capital.

Table 7 displays descriptive statistics of model estimates for CZs with the NELS:88. The variation in skills across CZs is dramatic. Take, for example, the parent generation skill ratios estimated with the 1990 Census. They range from 0.28 to 1.87. Also, the skewness of the distribution of skills across CZs at adult residence (3.8) is higher than the skewness of the child skill distribution (1.12). Migration contributes to skewness in the skill ratio distribution, as a few CZs accumulate high rates of skill.

The mean of adult skill ratios across labor markets ($\overline{S_{jt}} = 0.92$) is smaller than the mean of skill ratios for children ($\overline{K_j(S_{jt-1})} = 1.11$). The national sample has an equal number of high- and low-skilled individuals, by definition. The mean of skill ratios across labor markets need not equal one, however, because CZs get equal weight in these averages, although their populations differ dramatically. When larger CZs tend to have higher skill ratios, the average of skill ratios is below one. So, migration tends to move skills toward larger CZs. Also, the mean of parent skill ratios ($\overline{S_{jt-1}} = 0.77$) is smaller than the mean of child skill ratios ($\overline{K_j(S_{jt-1})} = 1.11$). This implies that intergenerational transmission tends to move skills toward smaller CZs.

Table 8 lists correlations between parameters from the model. The correlation between intergenerational transmission's effect on the skill ratio ($K_j(S_{jt-1})/S_{jt-1}$) and pre-existing skill ($S_{jt-1}$) is -0.448. This reflects mean reversion in skills through intergenerational transmission. The correlation between the total migration effect on the skill ratio ($\Lambda_{jt}M_{jt}$) and the parent generation skills ($S_{jt-1}$), on the other hand, is positive (0.241). So, migration across CZs tends to work against the mean reversion due to intergenerational transmission.

In addition, skills of the previous generation's adults predict skills of the next generation's adults: the correlation between skill ratios $S_{jt-1}$ and $S_{jt}$ is 0.453. The intergenerational transmission effect on skills is negatively correlated with the total migration effect on skills. That is, the correlation between $K_j(S_{jt-1})/S_{jt-1}$ and $\Lambda_{jt}M_{jt}$ is -0.273. This is consistent with intergenerational transmission moving skills to smaller labor markets and migration moving skills to larger labor markets. Native retention of skills ($\Lambda_{jt}$) is negatively correlated with in-migration of skills ($M_{jt}$); this correlation is -0.35.

It is likely that model estimation with the NELS:88 adds extra sampling variation that is not present in estimates relying only on Census data. Comparisons between the standard deviation and skewness of $S_{jt-1}$ and other parameters such as $K_j(S_{jt-1})$ and $S_{jt}$ may be misleading, since $S_{jt-1}$ is estimated with 1990 Census data only. In particular, the standard deviation of $S_{jt-1}$ being lower than the standard deviations of $K_j(S_{jt-1})$ and $S_{jt}$ may be the result of sampling variation rather than an increase in the inequality of skills across CZs over time. In addition, extra variation of a variable that is bounded below by zero, like these ratios, likely induces right skewness. So, I do not make much out of the increase in skewness from $S_{jt-1}$ to $K_j(S_{jt-1})$. However, comparisons between $K_j(S_{jt-1})$ and $S_{jt}$, which both use the NELS:88 to estimate distributions of CZs, seem more reliable.

I turn next to quantifying the effects of intergenerational transmission and migration on the generation-to-generation persistence of CZ skills.[13] Column 1 of Table 9 displays results from a regression of the log skill ratio for adults in a CZ on the log skill ratio in that CZ of the previous generation. The slope coefficient is clearly less than one, so there appears to be some mean reversion. The $R^2$ of 0.22 indicates that factors other than the previous generation's skills play a significant role in determining the current generation's local skills. Figure 7 illustrates this relationship with a scatter plot.

Column 2 of Table 9 has results from a regression where the dependent variable is a prediction of what the CZ's adult log skill ratio would be if there were no migration. This is the same as the log skill ratio among children in the CZ. The independent variable in the regression is the previous generation's log skill ratio. The coefficient estimate is lower than the coefficient from Column 1, indicating that intergenerational transmission

[13]At present, the results on persistence assume the model parameters are estimated without error. To the extent that they have sampling error, the persistence results are biased, with the effects of the bias increasing with the variability of the estimates. I am working on estimating the extent of sampling error to correct for this potential bias.

is driving the overall mean reversion. Figure 8 illustrates this relationship with a scatter plot.

Migration works against mean reversion by moving more skills to CZs with higher parents' skills. The regression in Column 3 of Table 9 has as its dependent variable the predicted CZ log skill ratio if there were no intergenerational transmission effect on skills. This equals the sum of the log parent skill ratio and the log migration effect: $\ln(S_{jt-1}) + \ln(\Lambda_{jt}M_{jt})$. The coefficient estimate is greater than one, indicating that CZs with higher parent skill ratios gain more skills through migration than others. Figure 9 illustrates this relationship. The points are distributed more tightly around the regression line than the plots involving intergenerational transmission. Selective migration is relatively tightly linked with the previous generation's skills.

The regression in Column 4 of Table 9 describes the relationship between skills of children in a CZ and the skills of adults from the same cohort in the CZ after migration choices are made. The coefficient estimate is 0.858 with a standard error of 0.034. There is substantial persistence between child and adult local skills, but the slope is less than one. So, adult skills increase less than one-for-one in child skills. Figure 10 illustrates this relationship.

Comparison between Columns 3 and 4 of Table 9 reveals that the previous generation's adult skills in the CZ has a stronger effect on skilled migration to the CZ than the skills of the same generation as children. The slope coefficient and $R^2$ are both higher in the regression on parent skills. This implies that different location characteristics predict the skills of local children and adults. In particular, it is consistent with previous findings that high-skilled adults tend to move to larger CZs, while intergenerational transmission tends to move high-skilled children toward smaller CZs.

Tables 10 through 15 display results from regressions of model parameters on location characteristics. Overall, the results show that small labor markets lose skilled workers at high rates through migration. Other local characteristics, such as higher education policy, weather, and taxes, also affect the local skill mix. The intergenerational transmission of skills contributes to mean reversion of local skills, as small CZs gain more than larger CZs through migration. Skilled migration, on the other hand, contributes to persistence of inter-location inequality in skills, as large and urban CZs with the highest skill levels among the previous generation gain the most skills through migration.

Table 10 displays a series of regressions that describe characteristics of CZs that affect the degree to which migration behavior shifts the local skill distribution ($\ln(\Lambda_{jt} \times M_{jt})$). This specification follows Equation 11 from the model. Column 1 reiterates the negative correlation between native skill and the skill content of migration. This is not a particularly large offsetting force to a change in local native skills, however. For example, if $K_j(S_{jt-1})$ increases by 10 percent, then on average the off-setting decrease in $\Lambda_{jt}M_{jt}$ means that $S_{jt} = K_j(S_{jt-1})\Lambda_{jt}M_{jt}$ still increases by about 8.5 percent.

Western labor markets gain the most skill through migration. Small and rural labor markets acquire significantly less skill through migration than large cities. The specification in Column 2 implies that an average major metropolitan area in the West gains 5 high-skilled migrants for every 4 low-skilled migrants, whereas an average small town in the West gains only 3 high-skilled migrants for every 4 low-skilled migrants.[14] The differences in skilled migration across population categories remain large after controlling for a battery of other CZ characteristics.

CZs with colder winters (measured with average January temperature) gain more skill through migration than warmer labor markets. College enrollment per capita and state college subsidies are both positively correlated with skill gains through migration. The college subsidy variable is state higher education appropriations per public college student divided by average public college tuition. The tax structures of places gaining skills through migration tend to be tilted toward wage taxes and away from capital taxes. Column 7 demonstrates that the previous findings hold when not controlling for initial skill mix of native children.

[14]This statement uses figures for non-coastal CZs in the West. Due to the log specification, which estimates a proportional effect, these level differences are smaller for other regions, where the average level of skilled migration is smaller.

Table 11 shows local characteristics that are correlated with the local intergenerational transmission of skill, here defined as $\ln(K_j(S_{jt-1})) - \ln(S_{jt-1})$. The first row repeats the negative correlation between parents' skill ratio and gains from intergenerational transmission. This negative correlation remains after controlling for a battery of local characteristics. Smaller CZs gain more skill through intergenerational transmission than larger CZs, and small towns gain the most. This confirms results above that imply intergenerational transmission tends to move skills toward smaller CZs, in contrast to migration, which moves skills toward larger CZs (see Table 10).

Local college enrollment and state college subsidies are positively correlated with skill gains through intergenerational transmission. The college subsidy effect becomes larger after controlling for state taxes. College subsidies conditional on state tax levels proxy for the emphasis placed on higher education in the state budget. Conditional on state taxes and other controls, an increase in this subsidy of 10 percent is correlated with an increase in the rate of skill gain through intergenerational transmission of about 1 percent. CZs with colder Januaries tend to gain more skill through intergenerational transmission, as do CZs in states with lower capital taxes. Manufacturing is positively correlated with the intergenerational transmission of skill.

The next two tables identify correlates with the effects on local skills of natives leaving and of others migrating into the area. The dependent variable in Table 12 is the relative native retention rate $\ln(\Lambda_{jt})$. Locations with higher skills among their children tend to keep a higher rate as some natives decide to leave. Major metropolitan areas retain skills at the highest rates, and larger rural labor markets lose the most skills through out-migration. College supply factors are negatively correlated with the retention of skills. It is possible that local college supply is a reaction to the loss of skilled natives or that local colleges are correlated with factors that increase the mobility of skilled native children.

Table 13 shows that a higher skill mix of native stayers is correlated with a lower skill mix of in-migrants. Small rural CZs experience much less skilled in-migration than major metropolitan areas. Specifications that do not control for the skill ratio of native stayers imply a relatively high rate of skill gain through migration for larger rural CZs. This is the category of CZs that experiences the greatest loss of skills through out-migration, so controlling for stayers' skills makes a large difference.

Skilled migrants appear to be drawn to colder CZs. More-skilled migrants appear to value college supply factors more than less-skilled migrants. The taxes of places gaining skill through migration are tilted toward wage taxes and away from capital taxes. CZs with a higher manufacturing share of industry tend to gain less skill through migration.

The next two tables display correlates with skill ratios, rather than mechanisms that change skill ratios. The dependent variable of specifications in Table 14 is the natural logarithm of the skill ratio of native children, $\ln(K_j(S_{jt-1}))$. The first row shows that parents transferring skills to their children contribute to the persistence of inequality across locations, although there is substantial regression to the mean, repeating the specification in Column 1 of Table 9. This persistence in skills remains after controlling for labor market size, region, weather, college supply, tax rates, and local manufacturing. These parameters indicate that initial skill inequality across CZs would become quite small after a few generations, absent any migration.

Warmer Januaries are negatively correlated with native skills. An increase in average January temperature of 10 degrees (F.) is correlated with a decrease of the native children skill ratio of about 12 percent. The native children skill ratio is increasing in college enrollment and the subsidy rate for college.

Conditional on the local parent generation's skill ratio, smaller CZs tend to have higher levels of native skill. The specification in column 8 that does not condition on parent generation skills reveals a much less clear relationship between CZ size and native skill ratio, where small towns and major metropolitan areas have the most-skilled children. The highest proportions of skilled children are in the Northeast and Midwest.

Table 15 displays results from regressing the natural logarithm of adult (post-migration) skill ratios ($\ln(S_{jt})$) on local characteristics. The first row shows the persistence of local skills across generations, which is significant but not complete, repeating the Column 1 specification of Table 9. Column 2 of Table 15 shows a specification that does not control for the previous generation's skill ratio. Skill ratios increase in CZ size. Controlling for the previous generation's skill ratio flattens this gradient somewhat, but doing so shows that even small towns at similar starting points end up after a generation with significantly lower skills than larger CZs. Subsequent specifications show that colder CZs and those with more higher education supply tend to have higher skill ratios. Taxes tend to tilt toward wage taxes and away from capital taxes in CZs with high skills. Higher manufacturing shares predict higher skills but only when conditioning on previous skills.

# 7 Conclusion

This paper examines the determinants of labor market skill distributions. The framework decomposes labor market supplies of skills into the previous generation's skills, the intergenerational transfer of skill from local parents to their children, and the migration of people with different skill levels. I estimate parameters that describe these factors with a combination of Census and NELS:88 data sets. The model estimates replicate the main findings from an accounting exercise for state skills that uses the Census and fewer model assumptions.

I find that intergenerational transmission of skills contributes to mean reversion of local skills. This is true across states and labor markets defined as commuting zones (CZs). More specifically, smaller CZs tend to gain the most skill through intergenerational transmission. Migration across CZs works against this mechanism. CZs with higher skills in the previous generation gain more skill through migration. This manifests in high rates of skilled migration toward larger and more urban CZs at the expense of smaller and more rural CZs. In this way, migration adds to persistence over time in skill inequality across CZs.

I also estimate correlations between other labor market characteristics and skilled migration. Skilled migrants are drawn to the West and to colder climates. Skill growth is higher in states with tax structures tilted toward wage taxes and away from capital taxes.

I find that the relationship between local college supply factors and skilled migration is positive and substantial. The estimates here assume that college supply factors are exogenous. It is likely, however, that other factors influencing skilled migration are correlated with local college supply. An example is a local industry that both supports local university research and also hires many college graduates from outside the area. It would be useful from a policy perspective to estimate the effect of local college supply on skilled migration. The challenge would be to find some variation in local college supply that is orthogonal to other causes of skilled migration. Since colleges typically open and close infrequently and expand slowly, it is difficult to find such variation at the institutional level. Tuition policies may display more useful variation.

The results presented here, in particular about the persistence of skill inequality, are potentially sensitive to bias due to sampling error of model estimates. This is an errors-in-variables issue similar to that raised in Deaton (1985) and studied recently in Devereux (2007). So far, I assume that model parameters are estimated without error. This is clearly not true. I am working on estimating the sampling error in the model estimates in order to correct for potential bias in regressions of model parameter estimates on other model parameter estimates. Regressions of model parameters exclusively on CZ characteristics, such as Column 2 of Table 10, should not be susceptible to this bias.

A weakness of this analysis is that the NELS:88 only follows individuals to age 26. As Figure 6 makes clear, many migration decisions occur after this age, so it is not clear that NELS:88 respondents have settled down in the labor market where I last observe them to reside. I plan to estimate the parameters of the model using data from the National Longitudinal Survey of Youth, 1979 (NLSY79). This panel data set has many of the attractive features of the NELS:88, and the NLSY79 respondents are interviewed much later in their life cycles.

# References


[1] Acemoglu, Daron and Joshua Angrist (2000) "How Large are the Social Returns to Education? Evidence from Compulsory Schooling Laws" *NBER Macroannual* 9-59.

[2] Autor, David and David Dorn (2007) "Inequality and Specialization: The Growth of Low-Skill Service Jobs in the United States" working paper.

[3] Basker, Emek (2003) "Education, Job Search and Migration" working paper.

[4] Behrman, Jere R. and Mark R. Rosenzweig (2002) "Does Increasing Women's Schooling Raise the Schooling of the Next Generation?" *American Economic Review* 92(1) 323-334.

[5] Berry, Christopher R. and Edward L. Glaeser (2005) "The Divergence of Human Capital Levels across Cities" *Papers in Regional Science* 84(3) 407-444.

[6] Black, Sandra E., Paul J. Devereux, and Kjell G. Salvanes (2005) "Why the Apple Doesnt Fall Far: Understanding Intergenerational Transmission of Human Capital" *American Economic Review* 95(1) 437-449.

[7] Borjas, George J., Stephen G. Bronars, and Stephen J. Trejo (1992) "Self-Selection and Internal Migration in the United States" *Journal of Urban Economics* 32, 159-185.

[8] Bound, John, J. Groen, G. Kezdi, and Sarah E. Turner (2004) "Trade in University Training: Cross-State Variation in the Production and Stock of College-Educated Labor" *Journal of Econometrics* 121 (1-2): 143-173.

[9] Bound, John and Harry J. Holzer (2000) "Demand Shifts, Population Adjustments, and Labor Market Outcomes during the 1980s" *Journal of Labor Economics* 18(1) 20-54.

[10] Bowles, Samuel (1970) "Migration as Investment: Empirical Tests of the Human Investment Approach to Geographical Mobility" *The Review of Economics and Statistics* 52(4) 356-362.

[11] Ciccone, Antonio and Giovanni Peri (2006) “Identifying Human-Capital Externalities: Theory with Applications” *Review of Economic Studies* 73(2) 381-412.

[12] Courchene, Thomas J. (1970) “Interprovincial Migration and Economic Adjustment” *The Canadian Journal of Economics* 3(4) 550-576.

[13] Deaton, Angus (1985) “Panel Data from a Time Series of Cross-Sections” *Journal of Econometrics* 30, 109-126.

[14] Devereux, Paul J. (2007) “Improved Errors-in-Variables Estimators for Grouped Data” *Journal of Business and Economic Statistics* 25(3) 278-287.

[15] Feenberg, Daniel. “Maximum State Income Tax Rates, 1977-2005.” Data accessed at URL: <http://www.nber.org/ taxsim/state-rates/ >.

[16] Feenberg, Daniel Richard, and Elizabeth Coutts (1993) “An Introduction to the TAXSIM Model” *Journal of Policy Analysis and Management* 12(1) 189-194.

[17] Fortin, Nicole M. (2006) “Higher-Education Policies and the College Wage Premium: Cross-State Evidence from the 1990s” *The American Economic Review* 96(4) 959-987. Data accessed at URL: <http://www.e-aer.org/ >.

[18] Glaeser, Edward L. and Albert Saiz (2003) “The Rise of the Skilled City” NBER Working Paper 10191.

[19] Greenwood, Michael J. (1997) “Internal Migration in Developed Countries” Chapter 12 in M.R. Rosenzweig and O. Stark, eds. *Handbook of Population and Family Economics* (Elsevier Science) 648-720.

[20] Ham, John C., Xianghong Li, and Patricia B. Reagan (2006) “Propensity Score Matching, a Distance-Based Measure of Migration, and the Wages of Young Men” working paper.

[21] Kodrzycki, Yolanda K. (2000) "New Englands Educational Advantage: Past Successes and Future Prospects" *New England Economic Review* , January/February, 25-40.

[22] Kodrzycki, Yolanda K. (2001) "Migration of Recent College Graduates: Evidence from the National Longitudinal Survey of Youth" *New England Economic Review* , January/February, 13-34.

[23] Lange, Fabian and Robert Topel (2006) "The Social Value of Education and Human Capital" in Eric Hanushek and Finis Welch, eds. *Handbook of Education Economics* Volume 1.

[24] Malamud, Ofer and Abigail Wozniak (2008) "The Impact of College Graduation on Geographic Mobility: Identifying Education Using Multiple Components of Vietnam Draft Risk" working paper.

[25] McFadden, Daniel (1974) "Conditional Logit Analysis of Qualitative Choice Behavior" in P. Zarembka, ed. *Frontiers in Econometrics* New York: Academic Press, 105-142.

[26] Moretti, Enrico (2004a) "Estimating the Social Return to Higher Education: Evidence from Longitudinal and Repeated Cross-sectional Data" *Journal of Econometrics* 121 175-212.

[27] Moretti, Enrico (2004b) "Human Capital Externalities in Cities" Chapter 51 in J. Vernon Henderson and Jacques-Franqois Thissel, Eds. *Handbook of Regional and Urban Economics* Volume 4. North Holland-Elsevier, 2243-2291.

[28] Rauch, James (1993) "Productivity Gains from Geographic Concentration in Cities" *Journal of Urban Economics* 34 380-400.

[29] Roy, A.D. (1951) "Some Thoughts on the Distribution of Earnings" *Oxford Economic Papers* 3(2) 135-146.

[30] Ruggles, Steven, Matthew Sobek, Trent Alexander, Catherine A. Fitch, Ronald Goeken, Patricia Kelly Hall, Miriam King, and Chad Ronnander (2004) *Integrated Public Use Microdata Series: Version 3.0* [Machine-readable database]. Minneapolis, MN: Minnesota Population Center [producer and distributor].

[31] Schultz, T. Paul (1971) "Rural-Urban Migration in Colombia" *The Review of Economics and Statistics* 53(2) 157-163.

[32] Solon, Gary (1999) "Intergenerational Mobility in the Labor Market" Chapter 29 in O. Ashenfelter and D. Card, eds. *Handbook of Labor Economics* Volume 3. (Elsevier Science) 1761-1800.

[33] Tolbert, Charles M. and Molly Sizer (1996) "U.S. Commuting Zones and Labor Market Areas. A 1990 Update." Economic Research Service Staff Paper No. 9614.

[34] U.S. Census Bureau. "ZCTAs (ZIP Code Tabulation Areas)". Data file accessed at URL: <http://www.census.gov/geo/www/gazetteer/places2k.html >.

[35] U.S. Census Bureau (2005) Table No. 212. "Educational Attainment by Race and Hispanic Origin: 1960 to 2003" *Statistical Abstract of the United States: 2004-2005.* Available at: <http://www.census.gov/prod/www/statistical-abstract-2001_2005.html >.

[36] U.S. Department of Commerce. National Climatic Data Center. Data accessed at URL: <http://cdo.ncdc.noaa.gov/pls/plclimprod/somdmain.somdwrapper?datasetabbv=DS3220&countryabbv=&georegionabbv= .>.

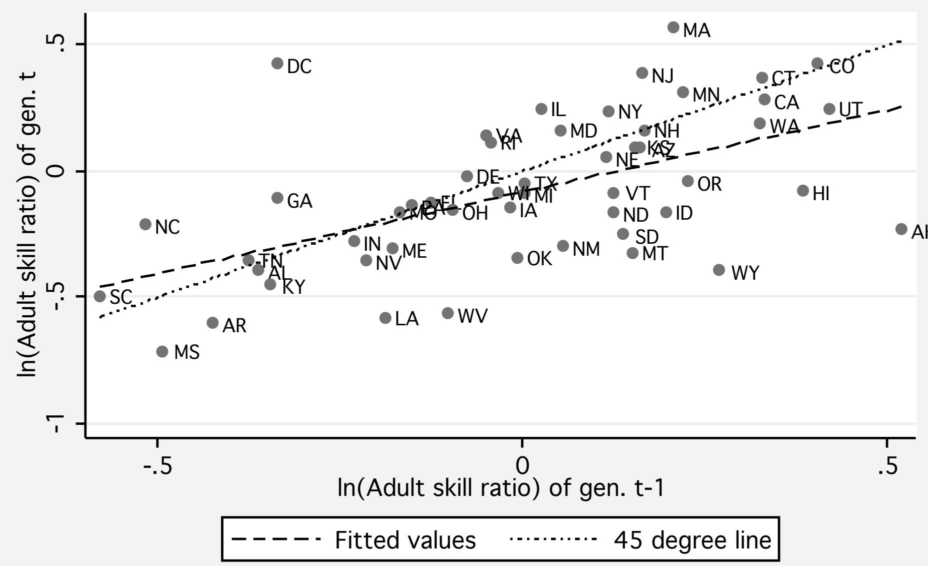
[37] U.S. Department of Education. National Center for Education Statistics. Integrated Postsecondary Education Data System. Data accessed at URL: <http://www.nces.ed.gov/ipedspas/dct/index.asp >.

[38] Wozniak, Abigail (2006) "Why Are College Graduates More Responsive to Distant Labor Market Opportunities?" working paper.

[39] ZipInfo.com. <http://www.zipinfo.com/products/products.htm >.

# 8 Figures and Tables

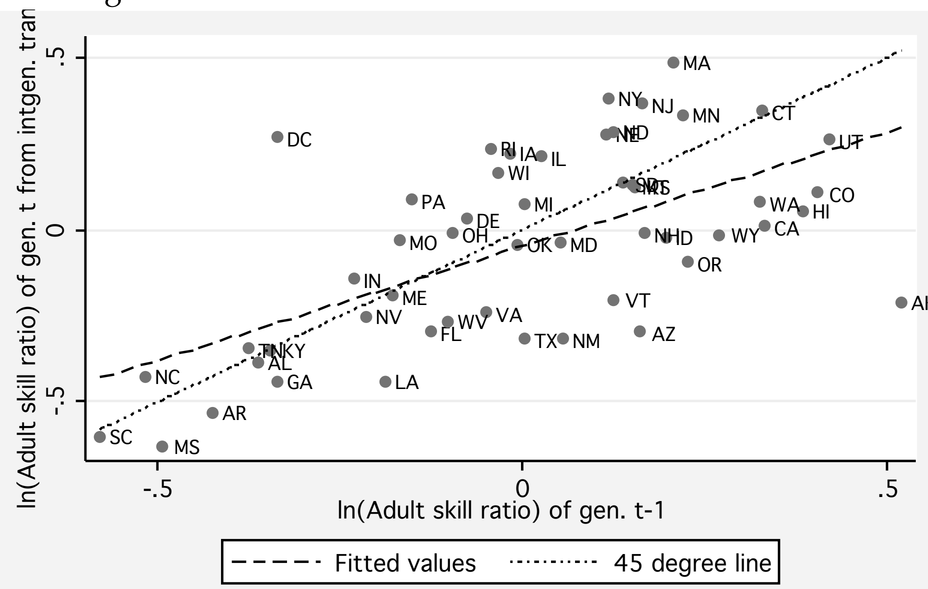
Figure 1: Generation-to-Generation Persistence in Adult Skills of States




Regression line: ln(S_{jt})=-.08 + .65 * ln(S_{jt-1}) , R^2=.32
(.03) (.13)

Notes: Each data point represents a pair of statistics describing a state.
Estimates use the 1980 and 2000 Census as described in the text.

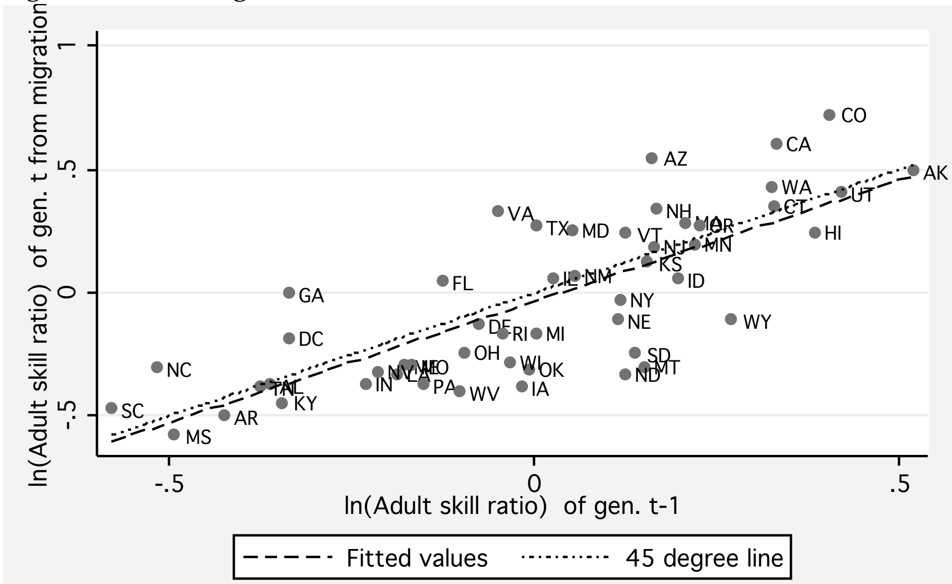
Figure 2: The Intergenerational Transmission Effect on Persistence in Adult Skills of States




Regression line: Predicted ln(S_{jt})=-.05 + .66 * ln(S_{jt-1}) , R^2=.39
(.03) (.12)

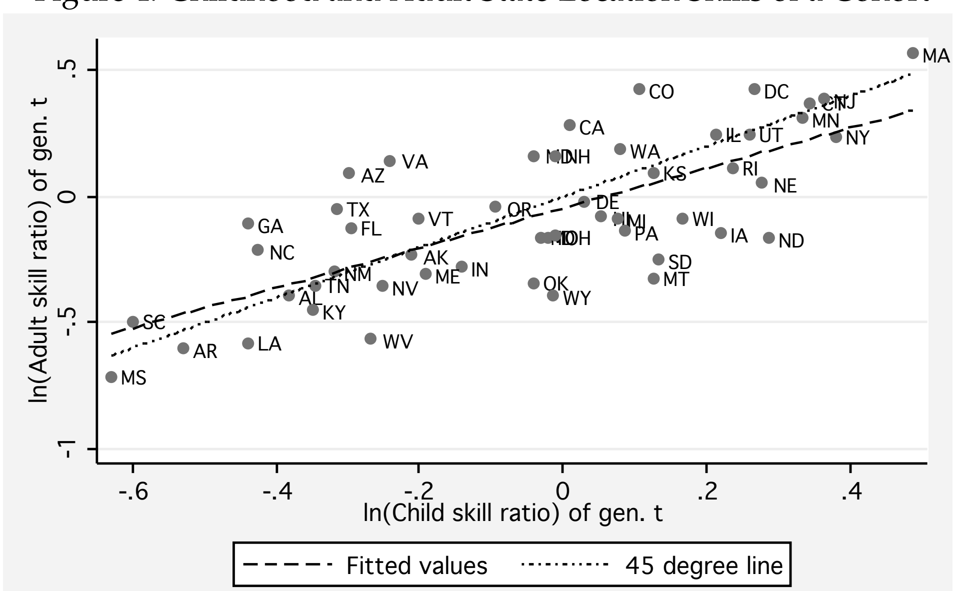
Notes: Each data point represents a pair of statistics describing a state.
Estimates use the 1980 and 2000 Census as described in the text.

Figure 3: The Migration Effect on Persistence in Adult Skills of States




Regression line: Predicted ln(S_{jt})=-.03 + .98 * ln(S_{jt-1}) , R^2=.6
(.03) (.11)
Notes: Each data point represents a pair of statistics describing a state.
Estimates use the 1980 and 2000 Census as described in the text.

Figure 4: Childhood and Adult State Location Skills of a Cohort




Regression line: ln(S_{jt})=-.04 + .79 * ln(K_{jt}) , R^2=.54
(.03) (.1)
Notes: Each data point represents a pair of statistics describing a state.
Estimates use the 2000 Census as described in the text.

Figure 5: Timing of the OLG Model

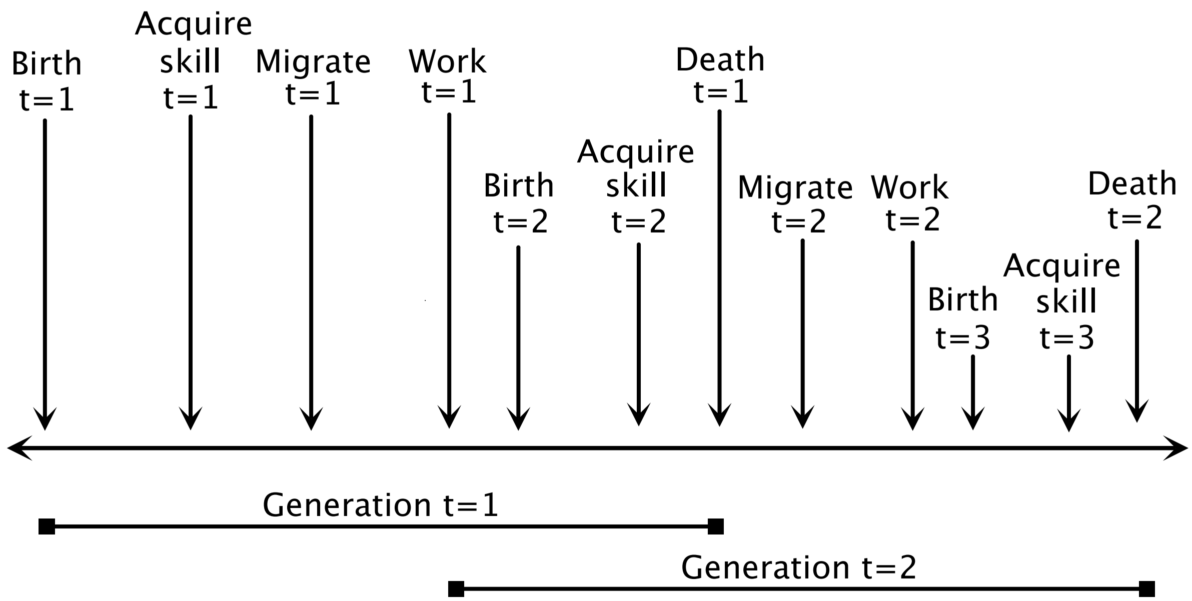



Figure 6: Migration by Age, 2000 Census

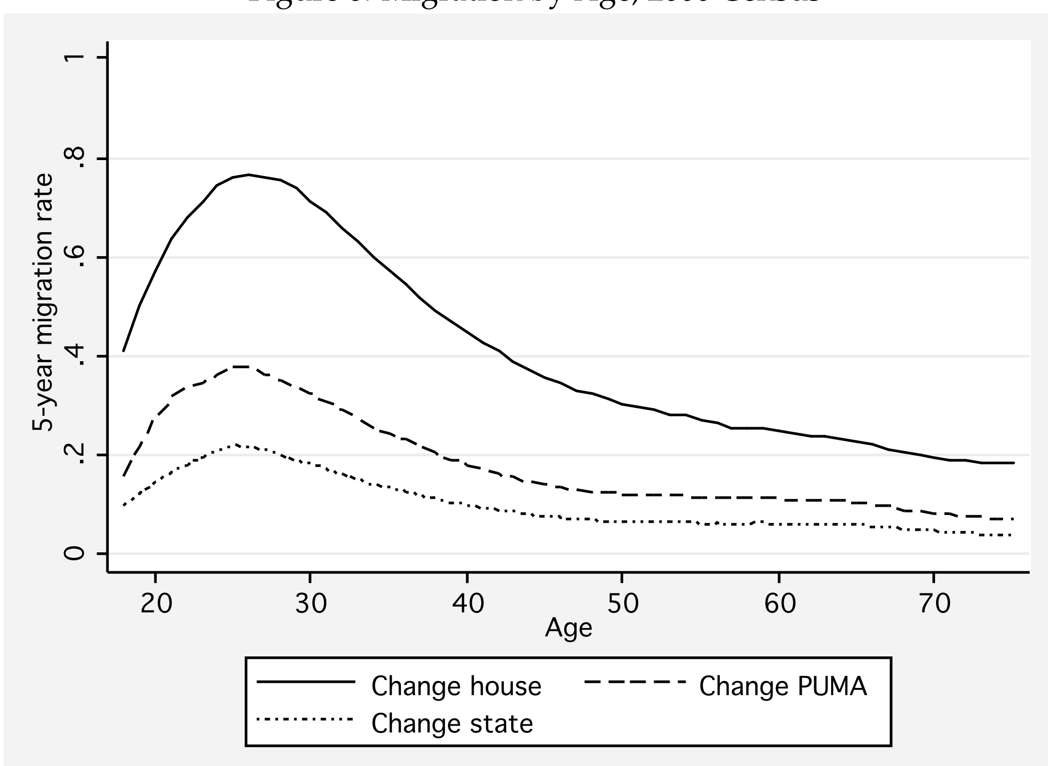


Figure 7: Generation-to-Generation Persistence in Adult Skills of CZs

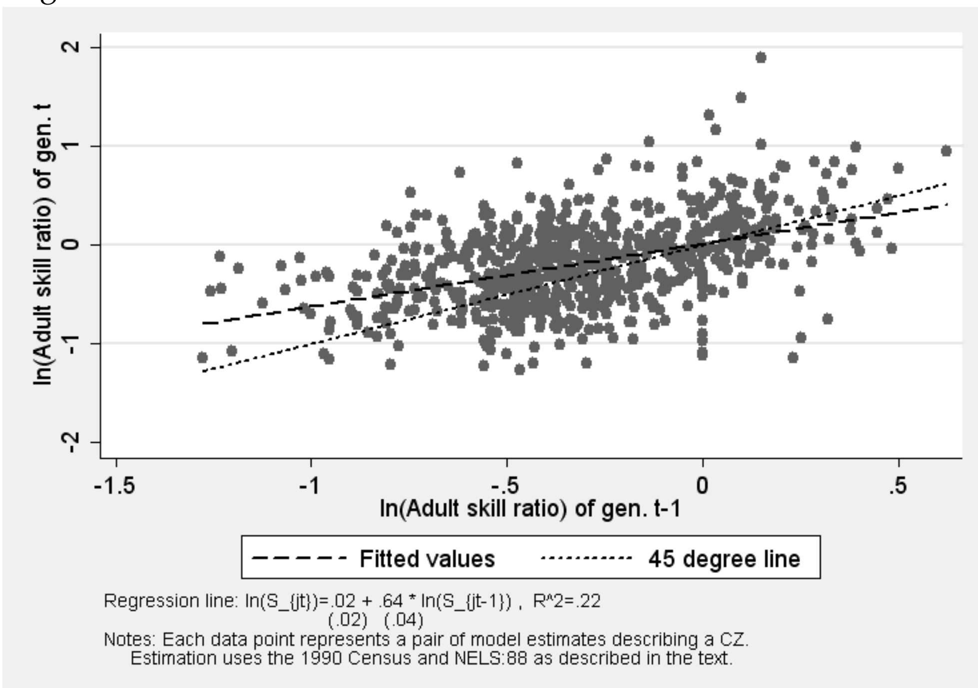



Figure 8: The Intergenerational Transmission Effect on Persistence in Adult Skills of CZs

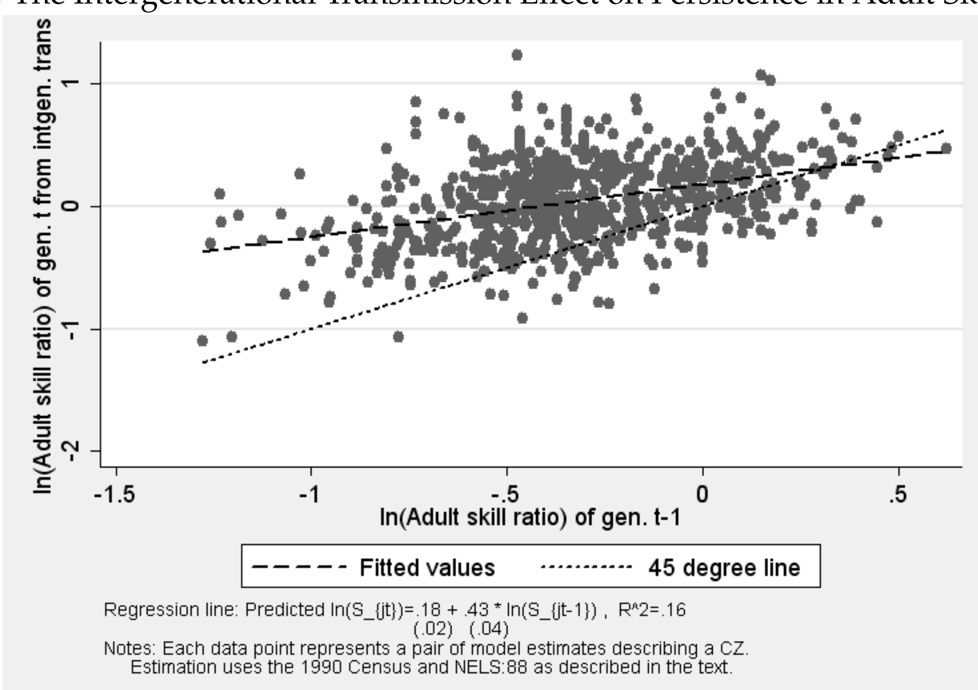


Figure 9: The Migration Effect on Persistence in Adult Skills of CZs

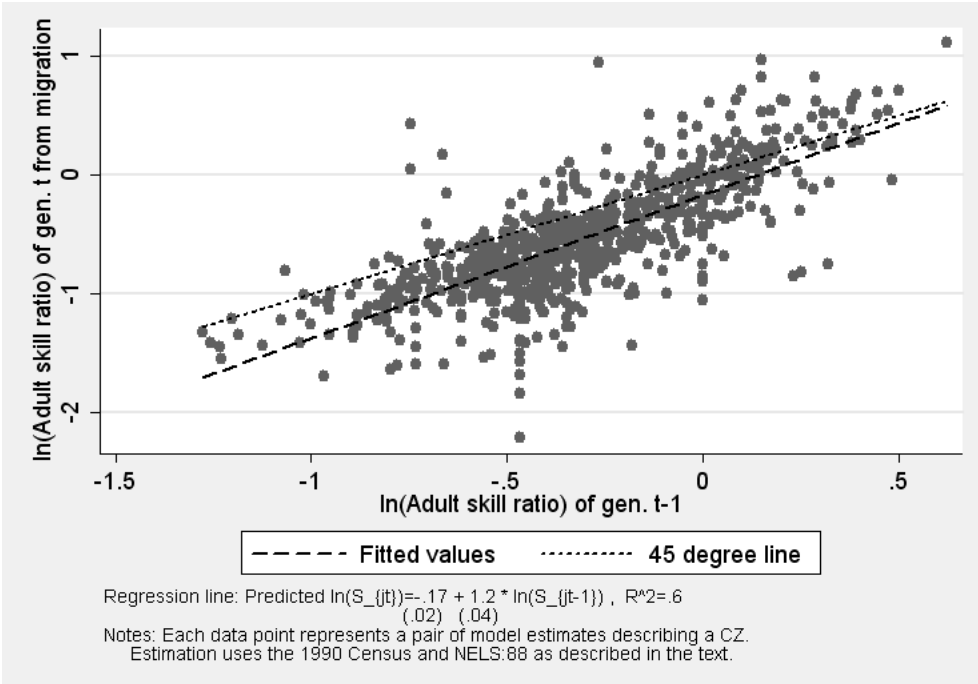



Figure 10: Childhood and Adult CZ Location Skills of a Cohort

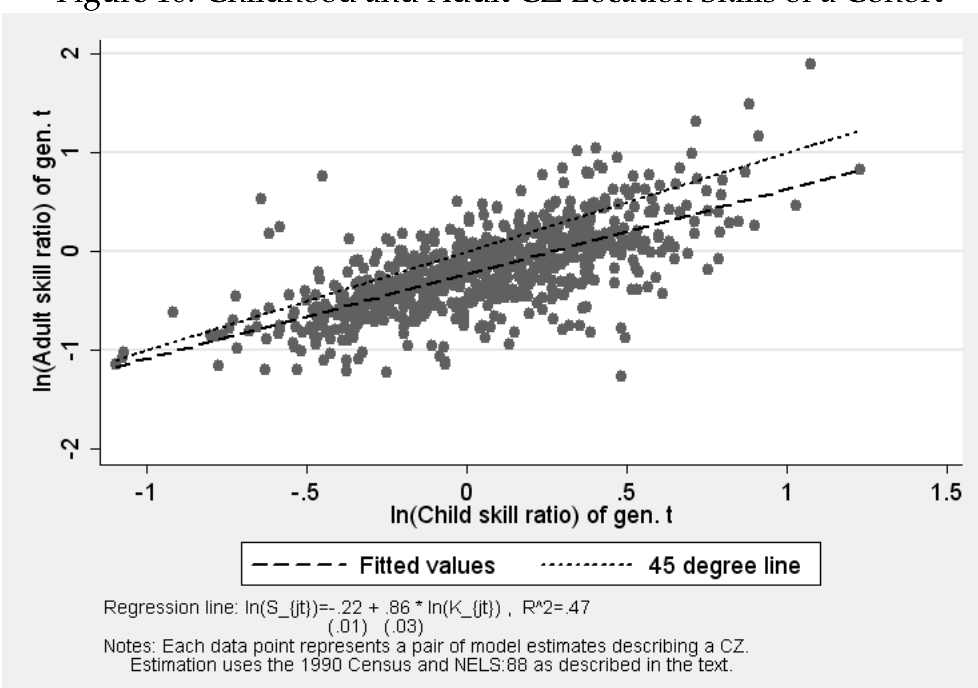


Table 1: Commuting Zones with Highest and Lowest Percent College, 2000

| (1) Rank | (2) Name | (3) Percent | (4) Rank | (5) Name | (6) Percent |
|---|---|---|---|---|---|
| 1 | Washington, D.C. | 44.3 | 732 | Corbin, KY | 10.4 |
| 2 | Kremmling, CO | 42.7 | 733 | Henderson, KY | 10.4 |
| 3 | Gunnison, CO | 42.7 | 734 | Pikeville, KY | 10.4 |
| 4 | Boston, MA | 40.1 | 735 | Jonesville, LA | 10.4 |
| 5 | San Francisco, CA | 39.3 | 736 | Waycross, GA | 10.2 |
| 6 | Glenwood Springs, CO | 38.5 | 737 | Campbellsville, KY | 10 |
| 7 | San Jose, CA | 37.6 | 738 | Somerset, KY | 9.7 |
| 8 | Vineyard Haven CDP, MA | 37.6 | 739 | Hazard, KY | 9.6 |
| 9 | Nantucket CDP, MA | 37.6 | 740 | Middlesborough, KY | 9.1 |
| 10 | Denver, CO | 37.4 | 741 | Glasgow, KY | 8.8 |
| Among CZs containing an MSA | | | | | |
| 1 | Washington, D.C. | 44.3 | 249 | Bakersfield, CA | 14.2 |
| 2 | Boston, MA | 40.1 | 250 | Morganton, NC | 14.1 |
| 3 | San Francisco, CA | 39.3 | 251 | Goldsboro, NC | 14.1 |
| 4 | San Jose, CA | 37.6 | 252 | Parkersburg, WV | 13.9 |
| 5 | Denver, CO | 37.4 | 253 | Brownsville, TX | 13.3 |
| 6 | Austin, TX | 37 | 254 | Mansfield, OH | 12.7 |
| 7 | Raleigh, NC | 36.9 | 255 | Gadsden, AL | 12.4 |
| 8 | Madison, WI | 36.8 | 256 | Yuma, AZ | 12 |
| 9 | Newark, NJ | 36.3 | 257 | Houma, LA | 11.6 |
| 10 | Minneapolis, MN | 35.9 | 258 | Henderson, KY | 10.4 |

Notes: Commuting zones are county groups with strong commuting ties. They approximate labor markets and are defined in Tolbert and Sizer (1996). Percent college variable comes from the 2000 Census. See Appendix A for the variable definition.

Table 2: Accounting for Skills across States, Census

| Description | Variable | (1) Mean | (2) StDev | (3) Skew | (4) Min | (5) Max |
|---|---|---|---|---|---|---|
| Parent gen. skill ratio | $S_{jt-1}$ | 1.03 | .26 | .25 | .56 | 1.68 |
| Child skill ratio | $K_{jt}$ | .99 | .27 | .27 | .53 | 1.63 |
| Stayers skill ratio | $K_{jt}\Lambda_{jt}$ | .71 | .24 | .71 | .38 | 1.37 |
| Adult skill ratio | $S_{jt}$ | .96 | .29 | .67 | .49 | 1.76 |
| | | | | | | |
| Intergenerational factor | $K_{jt}/S_{jt-1}$ | .98 | .23 | .82 | .48 | 1.83 |
| Native retention factor | $\Lambda_{jt}$ | .71 | .11 | -.89 | .3 | .98 |
| In-migration factor | $M_{jt}$ | 1.42 | .45 | 3.75 | 1.05 | 3.95 |
| Total migration factor | $\Lambda_{jt}M_{jt}$ | .99 | .21 | .52 | .64 | 1.47 |

Notes: Estimates from accounting exercise described in Section 3. Data come from the 1980 and 2000 Census.

Table 3: Correlations between Accounting Exercise Characteristics of States, Census

| | (1) $S_{jt-1}$ | (2) $K_{jt}$ | (3) $K_{jt}\Lambda_{jt}$ | (4) $S_{jt}$ | (5) $K_{jt}/S_{jt-1}$ | (6) $\Lambda_{jt}$ | (7) $M_{jt}$ | (8) $\Lambda_{jt}M_{jt}$ |
|---|---|---|---|---|---|---|---|---|
| $S_{jt-1}$ | 1 | | | | | | | |
| $K_{jt}$ | .53 | 1 | | | | | | |
| $K_{jt}\Lambda_{jt}$ | .545 | .851 | 1 | | | | | |
| $S_{jt}$ | .516 | .738 | .746 | 1 | | | | |
| | | | | | | | | |
| $K_{jt}/S_{jt-1}$ | -.376 | .557 | .313 | .316 | 1 | | | |
| $\Lambda_{jt}$ | .143 | .03 | .539 | .263 | -.227 | 1 | | |
| $M_{jt}$ | -.115 | -.109 | -.383 | .303 | .154 | -.509 | 1 | |
| $\Lambda_{jt}M_{jt}$ | .032 | -.26 | -.059 | .443 | -.281 | .336 | .566 | 1 |

Notes: Estimates from accounting exercise described in Section 3. Data come from the 1980 and 2000 Census.

Table 4: Generation-to-Generation Persistence of Skills across States, Census

| | (1) Adult skill ratio | (2) Intergenerational transmission effect | (3) Migration effect | (4) Adult skill ratio |
|---|---|---|---|---|
| VARIABLES | $\ln(S_{jt})$ | $\ln(S_{jt-1}) + \ln\left(\frac{K_{jt}}{S_{jt-1}}\right)$ | $\ln(S_{jt-1}) + \ln(\Lambda_{jt} M_{jt})$ | $\ln(S_{jt})$ |
| $\ln(S_{jt-1})$ | .647*** | .663*** | .985*** | |
| | (.135) | (.119) | (.115) | |
| $\ln(K_{jt})$ | | | | .793*** |
| | | | | (.104) |
| Constant | -.0823** | -.0475 | -.0349 | -.0449 |
| | (.035) | (.0309) | (.0298) | (.0291) |
| Observations | 51 | 51 | 51 | 51 |
| R-squared | 0.321 | 0.388 | 0.601 | 0.545 |

Notes: ***p<0.01 **p<0.05 *p<0.1. Dependent variable is the column heading. Each column has results from a separate regression. Variables are estimates from accounting exercise described in Section 3. Data come from the 1980 and 2000 Census.

Table 5: Characteristics of the 741 Commuting Zones, 2000

| Variable | (1) Mean | (2) StDev | (3) Min | (4) Max |
|---|---|---|---|---|
| South | .394 | .489 | 0 | 1 |
| Midwest | .34 | .474 | 0 | 1 |
| West | .209 | .407 | 0 | 1 |
| Northeast | .057 | .231 | 0 | 1 |
| Coastal | .124 | .33 | 0 | 1 |
| Annual snow (in.) | 22.3 | 24.7 | 0 | 157.3 |
| Avg January temp (degF) | 31.8 | 12.3 | -23 | 70.4 |
| Avg July temp (degF) | 74.5 | 6.4 | 42.3 | 91.6 |
| Percent college degree | 20 | 6 | 8.8 | 44.3 |
| Percent unemployed | 5.6 | 2.1 | 2.5 | 16 |
| Avg weekly wage | 661 | 94 | 504 | 1160 |
| Percent manufacturing | 15.9 | 8.2 | 2.4 | 44.4 |
| Wage tax | 43.6 | 1.8 | 40.8 | 46.7 |
| Capital tax | 23.9 | 1.8 | 21.2 | 27.1 |
| Higher ed subsidy | 2.7 | 1.1 | .4 | 5.8 |
| College enrollment | 14648 | 38924 | 0 | 657298 |
| Population | 379787 | 1047226 | 1193 | 16393360 |

Notes: Commuting zones are county groups with strong commuting ties. They approximate labor markets and are defined in Tolbert and Sizer (1996). See Section 5 for a description of data sources. Appendix A has additional information.

Table 6: Characteristics of Respondents, by Move Status, NELS:88

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | All | | Movers | | Stayers | |
| | [$N = 11079$] | | [$N = 3833$] | | [$N = 7246$] | |
| | | | [$Rate = .346$] | | [$Rate = .654$] | |
| Variable | Mean | SE | Mean | SE | Mean | SE |
| HS Dropout | .068 | .007 | .057 | .013 | .074 | .008 |
| College Grad | .293 | .008 | .444 | .014 | .217 | .009 |
| Test Index | 10.026 | .001 | 10.039 | .001 | 10.019 | .001 |
| Parents Ed | 13.847 | .04 | 14.504 | .06 | 13.514 | .052 |
| Parents Income | 41627 | 596 | 49358 | 1034 | 37715 | 701 |
| Predict Log Earnings | 10.187 | .006 | 10.269 | .008 | 10.146 | .007 |
| Female | .504 | .011 | .491 | .015 | .51 | .014 |
| Asian | .035 | .003 | .034 | .005 | .035 | .004 |
| Hispanic | .105 | .006 | .068 | .008 | .123 | .009 |
| Black | .132 | .011 | .075 | .009 | .16 | .016 |
| White | .714 | .011 | .814 | .012 | .664 | .015 |
| Married | .47 | .011 | .48 | .015 | .466 | .014 |
| Any Kids | .407 | .011 | .278 | .014 | .472 | .014 |

Notes: The test index is a log earnings prediction using respondent 8th grade math and verbal test scores as predictors. This is described in Section 5. Parents Ed is the higher of parents' years of schooling. Predict Log Earnings is a prediction of log annual earnings for a person with the respondent's characteristics from a regression with full-time workers in the NELS:88. Moving is defined as living in a CZ at age 26 other than the CZ of a respondent's 8th grade school.

Table 7: Summary Statistics of Model Parameters, CZs

| Description | Variable | (1) Mean | (2) StDev | (3) Skew | (4) Min | (5) Max |
|---|---|---|---|---|---|---|
| Parent gen. skill ratio | $S_{jt-1}$ | .77 | .25 | .92 | .28 | 1.87 |
| Child skill ratio | $K_{jt}$ | 1.11 | .39 | 1.12 | .33 | 3.41 |
| Stayers skill ratio | $K_{jt}\Lambda_{jt}$ | .84 | .68 | 3.13 | .06 | 6.28 |
| Adult skill ratio | $S_{jt}$ | .92 | .49 | 3.8 | .28 | 6.64 |
| Intergenerational factor | $K_{jt}/S_{jt-1}$ | 1.54 | .6 | 1.6 | .56 | 5.47 |
| Native retention factor | $\Lambda_{jt}$ | .74 | .49 | 3.45 | .12 | 5.41 |
| In-migration factor | $M_{jt}$ | 1.43 | 1.34 | 12.82 | .07 | 27.34 |
| Total migration factor | $\Lambda_{jt}M_{jt}$ | .84 | .29 | 2.59 | .17 | 3.36 |

Notes: Variables from model estimation described in Section 6.1. Data used are 1990 Census and NELS:88.

Table 8: Correlations between Model Parameters, CZs

| | (1) $S_{jt-1}$ | (2) $K_{jt}$ | (3) $K_{jt}\Lambda_{jt}$ | (4) $S_{jt}$ | (5) $K_{jt}/S_{jt-1}$ | (6) $\Lambda_{jt}$ | (7) $M_{jt}$ | (8) $\Lambda_{jt}M_{jt}$ |
|---|---|---|---|---|---|---|---|---|
| $S_{jt-1}$ | 1 | | | | | | | |
| $K_{jt}$ | .342 | 1 | | | | | | |
| $K_{jt}\Lambda_{jt}$ | .051 | .507 | 1 | | | | | |
| $S_{jt}$ | .453 | .649 | .365 | 1 | | | | |
| $K_{jt}/S_{jt-1}$ | -.448 | .635 | .416 | .208 | 1 | | | |
| $\Lambda_{jt}$ | -.109 | .077 | .864 | .073 | .155 | 1 | | |
| $M_{jt}$ | .06 | -.13 | -.314 | .18 | -.178 | -.35 | 1 | |
| $\Lambda_{jt}M_{jt}$ | .241 | -.083 | -.01 | .624 | -.273 | -.006 | .564 | 1 |

Notes: Variables from model estimation described in Section 6.1. Data used are 1990 Census and NELS:88.

Table 9: Generation-to-Generation Persistence of Skills across CZs, NELS:88

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Adult skill ratio | Intergenerational transmission effect | Migration effect | Adult skill ratio |
| VARIABLES | $\ln(S_{jt})$ | $\ln(S_{jt-1}) + \ln\left(\frac{K_{jt}}{S_{jt-1}}\right)$ | $\ln(S_{jt-1}) + \ln(\Lambda_{jt} M_{jt})$ | $\ln(S_{jt})$ |
| $\ln(S_{jt-1})$ | .635*** | .432*** | 1.2*** | |
| | (.0445) | (.0369) | (.0363) | |
| $\ln(K_{jt})$ | | | | .858*** |
| | | | | (.0335) |
| Constant | .016 | .184*** | -.168*** | -.225*** |
| | (.0198) | (.0164) | (.0161) | (.0116) |
| Observations | 741 | 741 | 741 | 741 |
| R-squared | 0.216 | 0.156 | 0.598 | 0.470 |

Notes: ***p<0.01 **p<0.05 *p<0.1. Dependent variable is the column heading. Each column has results from a separate regression. Variables are from model estimation described in Section 6.1. Data used are 1990 Census and NELS:88.

Table 10: Correlates with the Skill Content of Migration, $\ln(\Lambda_{jt} M_{jt})$

| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| ln(K_jt) | -.142*** | | .00127 | .0753* | -.00216 | .0219 | .0204 | |
| | (.0335) | | (.0351) | (.0389) | (.0363) | (.0375) | (.0375) | |
| South | | -.167*** | -.167*** | -.293*** | -.303*** | -.286*** | -.302*** | -.302*** |
| | | (.0273) | (.0282) | (.038) | (.0334) | (.0334) | (.0368) | (.0368) |
| Midwest | | -.288*** | -.288*** | -.373*** | -.359*** | -.354*** | -.368*** | -.365*** |
| | | (.0282) | (.0291) | (.0371) | (.0326) | (.0328) | (.0358) | (.0353) |
| Northeast | | -.274*** | -.275*** | -.285*** | -.155*** | -.152*** | -.167*** | -.164*** |
| | | (.0475) | (.0483) | (.0512) | (.0459) | (.0467) | (.0488) | (.0485) |
| Coastal | | -.042 | -.0418 | -.000512 | .00611 | .0182 | .0252 | .0245 |
| | | (.0324) | (.0328) | (.0361) | (.0317) | (.0316) | (.0324) | (.0323) |
| Small town | | -.551*** | -.551*** | -.51*** | -.48*** | -.471*** | -.463*** | -.463*** |
| | | (.0466) | (.0467) | (.047) | (.0418) | (.0416) | (.0424) | (.0423) |
| Small urban | | -.305*** | -.305*** | -.262*** | -.297*** | -.289*** | -.289*** | -.291*** |
| | | (.0441) | (.0442) | (.0441) | (.0388) | (.0385) | (.0385) | (.0382) |
| Larger urban | | -.201*** | -.201*** | -.168*** | -.237*** | -.23*** | -.231*** | -.234*** |
| | | (.0481) | (.0482) | (.0475) | (.0421) | (.0418) | (.0419) | (.0417) |
| Small metro | | -.271*** | -.271*** | -.241*** | -.276*** | -.271*** | -.273*** | -.274*** |
| | | (.0467) | (.0467) | (.046) | (.0405) | (.0402) | (.0403) | (.0402) |
| Medium metro | | -.121** | -.121** | -.103** | -.141*** | -.135*** | -.135*** | -.136*** |
| | | (.0485) | (.0485) | (.0476) | (.0419) | (.0416) | (.0416) | (.0415) |
| Jan Temp (degF) | | | | -.00197 | -.0072*** | -.00649*** | -.00661*** | -.0069*** |
| | | | | (.00182) | (.00164) | (.00164) | (.00164) | (.00155) |
| July Temp (degF) | | | | .00905** | .00932*** | .0103*** | .011*** | .011*** |
| | | | | (.00367) | (.00323) | (.00322) | (.0033) | (.00329) |
| Ann. Snow (in) | | | | -.00207*** | -.00108* | -.000807 | -.0007 | -.00068 |
| | | | | (.000645) | (.000571) | (.000572) | (.000582) | (.00058) |
| College enroll/Pop | | | | | 1.12*** | 1.1*** | 1.13*** | 1.18*** |
| | | | | | (.242) | (.241) | (.243) | (.228) |
| Ln(College subsidy) | | | | | .35*** | .35*** | .351*** | .352*** |
| | | | | | (.025) | (.0271) | (.0272) | (.0269) |
| Wage tax | | | | | | .0336*** | .0331*** | .0333*** |
| | | | | | | (.0126) | (.0126) | (.0126) |
| Capital tax | | | | | | -.0181 | -.0187 | -.0197 |
| | | | | | | (.0127) | (.0127) | (.0126) |
| % Manufacturing | | | | | | | .00134 | .00137 |
| | | | | | | | (.00132) | (.00132) |
| Constant | -.225*** | .239*** | .239*** | -.29 | -.499** | -1.65*** | -1.68*** | -1.65*** |
| | (.0116) | (.0463) | (.0464) | (.248) | (.218) | (.393) | (.394) | (.392) |
| Observations | 741 | 741 | 741 | 741 | 741 | 741 | 741 | 741 |
| R-squared | 0.024 | 0.305 | 0.305 | 0.338 | 0.491 | 0.501 | 0.502 | 0.501 |

Notes: ***p<0.01 **p<0.05 *p<0.1. Each column has results from a separate OLS model with CZs as observations. Dependent variable is the model estimate of a CZ's skill migration parameter ($\ln(\Lambda_{jt} M_{jt})$). Major metro area is the omitted CZ size category. West is the omitted CZ region. $\ln(K_{jt})$ is a model estimate of the CZ's log child skill ratio. See text for definitions of other variables.

Table 11: Correlates with the Intergenerational Transmission Effect on Local Skill, $\ln(K_j(S_{jt-1})) - \ln(S_{jt-1})$

| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| $\ln(S_{jt-1})$ | -.568*** | | -.423*** | -.552*** | -.606*** | -.607*** | -.56*** | |
| | (.0369) | | (.0394) | (.0382) | (.0372) | (.0358) | (.0368) | |
| South | | .162*** | .0108 | .137*** | .119*** | .0941*** | .0396 | .108*** |
| | | (.0273) | (.029) | (.0342) | (.0329) | (.0318) | (.0337) | (.0383) |
| Midwest | | .394*** | .315*** | .247*** | .229*** | .247*** | .195*** | .251*** |
| | | (.0281) | (.0271) | (.0328) | (.0315) | (.0305) | (.0322) | (.0368) |
| Northeast | | .347*** | .301*** | .186*** | .181*** | .239*** | .186*** | .233*** |
| | | (.0474) | (.0443) | (.0451) | (.044) | (.0431) | (.0441) | (.0505) |
| Coastal | | -.233*** | -.191*** | -.109*** | -.0837*** | -.0931*** | -.0697** | -.114*** |
| | | (.0323) | (.0303) | (.0319) | (.0307) | (.0294) | (.0295) | (.0337) |
| Small town | | .523*** | .337*** | .172*** | .201*** | .191*** | .249*** | .553*** |
| | | (.0465) | (.0466) | (.0455) | (.0437) | (.042) | (.0433) | (.0441) |
| Small urban | | .469*** | .249*** | .119*** | .0984** | .0996** | .127*** | .445*** |
| | | (.044) | (.0458) | (.044) | (.0422) | (.0406) | (.0405) | (.0398) |
| Larger urban | | .4*** | .226*** | .126*** | .0694 | .0792* | .0942** | .352*** |
| | | (.048) | (.0475) | (.0448) | (.0435) | (.0418) | (.0414) | (.0434) |
| Small metro | | .338*** | .213*** | .121*** | .0829** | .0799** | .0896** | .278*** |
| | | (.0465) | (.0448) | (.0422) | (.0407) | (.0389) | (.0385) | (.0418) |
| Medium metro | | .142*** | .0792* | .053 | .024 | .0238 | .0324 | .131*** |
| | | (.0484) | (.0454) | (.042) | (.0404) | (.0387) | (.0382) | (.0433) |
| Jan Temp (degF) | | | | -.0108*** | -.0116*** | -.012*** | -.0121*** | -.0095*** |
| | | | | (.00154) | (.0015) | (.00144) | (.00142) | (.00162) |
| July Temp (degF) | | | | -.00165 | -.000255 | -.00141 | .00181 | .0062* |
| | | | | (.00321) | (.00308) | (.00295) | (.003) | (.00343) |
| Ann. Snow (in) | | | | .000772 | .000935* | .000319 | .000696 | .000315 |
| | | | | (.000565) | (.000544) | (.000527) | (.000527) | (.000604) |
| College enroll/Pop | | | | | 1.8*** | 1.78*** | 1.85*** | 1.4*** |
| | | | | | (.221) | (.211) | (.209) | (.238) |
| Ln(College subsidy) | | | | | .0245 | .0937*** | .0969*** | .103*** |
| | | | | | (.0238) | (.0247) | (.0244) | (.028) |
| Wage tax | | | | | | .0223* | .0216* | .0391*** |
| | | | | | | (.0116) | (.0115) | (.0131) |
| Capital tax | | | | | | -.0574*** | -.0611*** | -.0794*** |
| | | | | | | (.0116) | (.0115) | (.0131) |
| % Manufacturing | | | | | | | .00562*** | .011*** |
| | | | | | | | (.00124) | (.00137) |
| Constant | .184*** | -.204*** | -.0945** | .387* | .233 | .683* | .491 | -.417 |
| | (.0164) | (.0462) | (.0442) | (.217) | (.209) | (.362) | (.36) | (.408) |
| Observations | 741 | 741 | 741 | 741 | 741 | 741 | 741 | 741 |
| R-squared | 0.243 | 0.473 | 0.545 | 0.615 | 0.648 | 0.679 | 0.688 | 0.588 |

Notes: ***p<0.01 **p<0.05 *p<0.1. Each column has results from a separate OLS model with CZs as observations. Dependent variable is the model estimate of a CZ's skill gains through intergenerational transmission ($\ln(K_j(S_{jt-1})) - \ln(S_{jt-1})$). Major metro area is the omitted CZ size category. West is the omitted CZ region. $\ln(S_{jt-1})$ is a model estimate of the CZ's log skill ratio in the previous generation. See text for definitions of other variables.

Table 12: Correlates with the Skill Content of Native Leaving and Staying, $\ln(\Lambda_{jt})$

| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| $\ln(K_{jt})$ | .132** | | .0819 | .222*** | .332*** | .335*** | .32*** | |
| | (.0514) | | (.0589) | (.0657) | (.0687) | (.0716) | (.0704) | |
| South | | -.0884* | -.0724 | -.278*** | -.275*** | -.282*** | -.433*** | -.438*** |
| | | (.0459) | (.0473) | (.0641) | (.0632) | (.0639) | (.069) | (.07) |
| Midwest | | -.0661 | -.0831* | -.171*** | -.178*** | -.19*** | -.33*** | -.282*** |
| | | (.0473) | (.0488) | (.0626) | (.0618) | (.0627) | (.0671) | (.0672) |
| Northeast | | -.126 | -.146* | -.182** | -.193** | -.212** | -.352*** | -.305*** |
| | | (.0799) | (.081) | (.0864) | (.0869) | (.0893) | (.0916) | (.0922) |
| Coastal | | -.427*** | -.416*** | -.393*** | -.41*** | -.416*** | -.348*** | -.359*** |
| | | (.0544) | (.055) | (.0609) | (.0601) | (.0605) | (.0607) | (.0615) |
| Small town | | -.145* | -.152* | -.0546 | -.117 | -.121 | -.0421 | -.0393 |
| | | (.0783) | (.0784) | (.0793) | (.0793) | (.0794) | (.0795) | (.0805) |
| Small urban | | -.0733 | -.0691 | .00235 | .00348 | -.00106 | -.0018 | -.0412 |
| | | (.0742) | (.0742) | (.0743) | (.0734) | (.0736) | (.0723) | (.0727) |
| Larger urban | | -.473*** | -.472*** | -.422*** | -.377*** | -.383*** | -.401*** | -.436*** |
| | | (.0809) | (.0808) | (.0801) | (.0798) | (.0799) | (.0786) | (.0792) |
| Small metro | | -.244*** | -.248*** | -.201** | -.175** | -.176** | -.193** | -.211*** |
| | | (.0784) | (.0784) | (.0776) | (.0768) | (.0768) | (.0755) | (.0764) |
| Medium metro | | -.176** | -.175** | -.161** | -.135* | -.139* | -.139* | -.153* |
| | | (.0815) | (.0814) | (.0802) | (.0794) | (.0794) | (.078) | (.079) |
| Jan Temp (degF) | | | | .00473 | .00659** | .00646** | .00533* | .000784 |
| | | | | (.00306) | (.0031) | (.00313) | (.00308) | (.00295) |
| July Temp (degF) | | | | .0181*** | .0165*** | .0161*** | .0232*** | .0227*** |
| | | | | (.0062) | (.00612) | (.00614) | (.00618) | (.00626) |
| Ann. Snow (in) | | | | .000979 | .000767 | .000698 | .00174 | .00206* |
| | | | | (.00109) | (.00108) | (.00109) | (.00109) | (.0011) |
| College enroll/Pop | | | | | -2.19*** | -2.21*** | -1.9*** | -1.19*** |
| | | | | | (.458) | (.46) | (.456) | (.434) |
| Ln(College subsidy) | | | | | -.0121 | -.0311 | -.0231 | .00649 |
| | | | | | (.0474) | (.0518) | (.0509) | (.0512) |
| Wage tax | | | | | | -.0319 | -.0371 | -.0346 |
| | | | | | | (.024) | (.0236) | (.0239) |
| Capital tax | | | | | | .0297 | .0236 | .00865 |
| | | | | | | (.0242) | (.0238) | (.0239) |
| % Manufacturing | | | | | | | .013*** | .0134*** |
| | | | | | | | (.00247) | (.0025) |
| Constant | -.435*** | -.132* | -.136* | -1.61*** | -1.46*** | -.714 | -.985 | -.6 |
| | (.0179) | (.0778) | (.0778) | (.418) | (.414) | (.751) | (.74) | (.745) |
| Observations | 741 | 741 | 741 | 741 | 741 | 741 | 741 | 741 |
| R-squared | 0.009 | 0.154 | 0.156 | 0.188 | 0.212 | 0.214 | 0.243 | 0.222 |

Notes: ***p<0.01 **p<0.05 *p<0.1. Each column has results from a separate OLS model with CZs as observations. Dependent variable is the model estimate of a CZ's native skill retention parameter ($\ln(\Lambda_{jt})$). Major metro area is the omitted CZ size category. West is the omitted CZ region. $\ln(K_{jt})$ is a model estimate of the CZ's log child skill ratio. See text for definitions of other variables.

Table 13: Correlates with the Skill Content of In-Migration, $\ln(M_{jt})$

| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| $\ln(K_j(S_{jt-1}) \times \Lambda_{jt})$ | -.669*** | | -.655*** | -.674*** | -.69*** | -.694*** | -.69*** | |
| | (.0225) | | (.0233) | (.0229) | (.0196) | (.0197) | (.0201) | |
| South | | -.0787 | -.265*** | -.176*** | -.2*** | -.199*** | -.176*** | .135* |
| | | (.0504) | (.0355) | (.0484) | (.0414) | (.0416) | (.0463) | (.0736) |
| Midwest | | -.222*** | -.129*** | -.207*** | -.214*** | -.193*** | -.173*** | -.0837 |
| | | (.0519) | (.0361) | (.0463) | (.0396) | (.0398) | (.0436) | (.0707) |
| Northeast | | -.148* | -.0753 | -.152** | -.0286 | .0134 | .0335 | .141 |
| | | (.0876) | (.0607) | (.0646) | (.0563) | (.0571) | (.0599) | (.0971) |
| Coastal | | .385*** | .0176 | .0919** | .116*** | .12*** | .112*** | .384*** |
| | | (.0597) | (.0433) | (.0468) | (.0401) | (.0401) | (.0407) | (.0648) |
| Small town | | -.405*** | -.446*** | -.531*** | -.437*** | -.434*** | -.445*** | -.424*** |
| | | (.0858) | (.0595) | (.0596) | (.0516) | (.0514) | (.0522) | (.0848) |
| Small urban | | -.231*** | -.313*** | -.354*** | -.37*** | -.364*** | -.363*** | -.25*** |
| | | (.0813) | (.0564) | (.0555) | (.0476) | (.0473) | (.0473) | (.0766) |
| Larger urban | | .272*** | -.0457 | -.081 | -.187*** | -.178*** | -.173*** | .202** |
| | | (.0887) | (.0624) | (.0612) | (.0527) | (.0524) | (.0526) | (.0834) |
| Small metro | | -.0261 | -.158*** | -.196*** | -.253*** | -.252*** | -.249*** | -.0628 |
| | | (.0859) | (.0597) | (.0585) | (.0502) | (.0498) | (.0499) | (.0805) |
| Medium metro | | .0545 | -.0647 | -.0633 | -.124** | -.12** | -.119** | .0174 |
| | | (.0893) | (.062) | (.0604) | (.0517) | (.0514) | (.0514) | (.0832) |
| Jan Temp (degF) | | | | -.0123*** | -.0172*** | -.0171*** | -.0169*** | -.00768** |
| | | | | (.00222) | (.00194) | (.00193) | (.00193) | (.00311) |
| July Temp (degF) | | | | .00119 | .0036 | .00384 | .00278 | -.0118* |
| | | | | (.00466) | (.00399) | (.00397) | (.00409) | (.0066) |
| Ann. Snow (in) | | | | -.0014* | -.000403 | -.000479 | -.000632 | -.00274** |
| | | | | (.000817) | (.000702) | (.000705) | (.000718) | (.00116) |
| College enroll/Pop | | | | | 3.09*** | 3.12*** | 3.07*** | 2.37*** |
| | | | | | (.282) | (.28) | (.283) | (.457) |
| Ln(College subsidy) | | | | | .371*** | .415*** | .414*** | .346*** |
| | | | | | (.0308) | (.0333) | (.0333) | (.0539) |
| Wage tax | | | | | | .0486*** | .0494*** | .0678*** |
| | | | | | | (.0155) | (.0155) | (.0252) |
| Capital tax | | | | | | -.0555*** | -.0546*** | -.0283 |
| | | | | | | (.0155) | (.0155) | (.0252) |
| % Manufacturing | | | | | | | -.00183 | -.0121*** |
| | | | | | | | (.00165) | (.00263) |
| Constant | -.0572*** | .371*** | .321*** | .673** | .2 | -.672 | -.635 | -1.05 |
| | (.0164) | (.0853) | (.0591) | (.313) | (.269) | (.482) | (.483) | (.784) |
| Observations | 741 | 741 | 741 | 741 | 741 | 741 | 741 | 741 |
| R-squared | 0.544 | 0.247 | 0.639 | 0.661 | 0.753 | 0.757 | 0.758 | 0.362 |

Notes: ***p<0.01 **p<0.05 *p<0.1. Each column has results from a separate OLS model with CZs as observations. Dependent variable is the model estimate of a CZ's parameter measuring skill gains through in-migration ($\ln(M_{jt})$). Major metro area is the omitted CZ size category. West is the omitted CZ region. $\ln(K_j(S_{jt-1}) \times \Lambda_{jt})$ is a model estimate of the CZ's log skill ratio of native children who stayed. See text for definitions of other variables.

Table 14: Correlates with the Local Native Children Skill Ratio, $\ln(K_j(S_{jt-1}))$

| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| $\ln(S_{jt-1})$ | .432*** | | .577*** | .448*** | .394*** | .393*** | .44*** | |
| | (.0369) | | (.0394) | (.0382) | (.0372) | (.0358) | (.0368) | |
| South | | -.195*** | .0108 | .137*** | .119*** | .0941*** | .0396 | -.0141 |
| | | (.0288) | (.029) | (.0342) | (.0329) | (.0318) | (.0337) | (.0365) |
| Midwest | | .208*** | .315*** | .247*** | .229*** | .247*** | .195*** | .152*** |
| | | (.0297) | (.0271) | (.0328) | (.0315) | (.0305) | (.0322) | (.035) |
| Northeast | | .237*** | .301*** | .186*** | .181*** | .239*** | .186*** | .149*** |
| | | (.0501) | (.0443) | (.0451) | (.044) | (.0431) | (.0441) | (.0481) |
| Coastal | | -.134*** | -.191*** | -.109*** | -.0837*** | -.0931*** | -.0697** | -.0349 |
| | | (.0341) | (.0303) | (.0319) | (.0307) | (.0294) | (.0295) | (.0321) |
| Small town | | .0838* | .337*** | .172*** | .201*** | .191*** | .249*** | .0089 |
| | | (.0491) | (.0466) | (.0455) | (.0437) | (.042) | (.0433) | (.042) |
| Small urban | | -.0517 | .249*** | .119*** | .0984** | .0996** | .127*** | -.123*** |
| | | (.0465) | (.0458) | (.044) | (.0422) | (.0406) | (.0405) | (.0379) |
| Larger urban | | -.0119 | .226*** | .126*** | .0694 | .0792* | .0942** | -.108*** |
| | | (.0507) | (.0475) | (.0448) | (.0435) | (.0418) | (.0414) | (.0413) |
| Small metro | | .0433 | .213*** | .121*** | .0829** | .0799** | .0896** | -.0587 |
| | | (.0492) | (.0448) | (.0422) | (.0407) | (.0389) | (.0385) | (.0399) |
| Medium metro | | -.00638 | .0792* | .053 | .024 | .0238 | .0324 | -.0448 |
| | | (.0511) | (.0454) | (.042) | (.0404) | (.0387) | (.0382) | (.0412) |
| Jan Temp (degF) | | | | -.0108*** | -.0116*** | -.012*** | -.0121*** | -.0142*** |
| | | | | (.00154) | (.0015) | (.00144) | (.00142) | (.00154) |
| July Temp (degF) | | | | -.00165 | -.000255 | -.00141 | .00181 | -.00163 |
| | | | | (.00321) | (.00308) | (.00295) | (.003) | (.00327) |
| Ann. Snow (in) | | | | .000772 | .000935* | .000319 | .000696 | .000995* |
| | | | | (.000565) | (.000544) | (.000527) | (.000527) | (.000575) |
| College enroll/Pop | | | | | 1.8*** | 1.78*** | 1.85*** | 2.21*** |
| | | | | | (.221) | (.211) | (.209) | (.227) |
| Ln(College subsidy) | | | | | .0245 | .0937*** | .0969*** | .0923*** |
| | | | | | (.0238) | (.0247) | (.0244) | (.0267) |
| Wage tax | | | | | | .0223* | .0216* | .00792 |
| | | | | | | (.0116) | (.0115) | (.0125) |
| Capital tax | | | | | | -.0574*** | -.0611*** | -.0467*** |
| | | | | | | (.0116) | (.0115) | (.0125) |
| % Manufacturing | | | | | | | .00562*** | .0014 |
| | | | | | | | (.00124) | (.0013) |
| Constant | .184*** | .0553 | -.0945** | .387* | .233 | .683* | .491 | 1.21*** |
| | (.0164) | (.0488) | (.0442) | (.217) | (.209) | (.362) | (.36) | (.388) |
| Observations | 741 | 741 | 741 | 741 | 741 | 741 | 741 | 741 |
| R-squared | 0.156 | 0.344 | 0.493 | 0.571 | 0.607 | 0.642 | 0.652 | 0.583 |

Notes: ***p<0.01 **p<0.05 *p<0.1. Each column has results from a separate OLS model with CZs as observations. Dependent variable is the model estimate of a CZ's native children skill ratio parameter ($\ln(K_j(S_{jt-1}))$). Major metro area is the omitted CZ size category. West is the omitted CZ region. $\ln(S_{jt-1})$ is a model estimate of the CZ's log skill ratio of the previous generation. See text for definitions of other variables.

Table 15: Correlates with the Local Adult Skill Ratio, $\ln(S_{jt})$

| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| $\ln(S_{jt-1})$ | .635*** | | .615*** | .552*** | .457*** | .471*** | .538*** | |
| | (.0445) | | (.0575) | (.0592) | (.0531) | (.0526) | (.0542) | |
| South | | -.363*** | -.143*** | -.13** | -.171*** | -.174*** | -.251*** | -.316*** |
| | | (.0398) | (.0423) | (.053) | (.047) | (.0468) | (.0496) | (.0523) |
| Midwest | | -.0803* | .0343 | -.0937* | -.118*** | -.0869* | -.16*** | -.214*** |
| | | (.0409) | (.0396) | (.0507) | (.045) | (.0449) | (.0475) | (.0502) |
| Northeast | | -.037 | .0303 | -.0722 | .0372 | .105* | .0303 | -.0148 |
| | | (.0691) | (.0646) | (.0698) | (.0629) | (.0634) | (.0649) | (.069) |
| Coastal | | -.176*** | -.237*** | -.127** | -.0863** | -.086** | -.053 | -.0104 |
| | | (.0471) | (.0442) | (.0493) | (.0438) | (.0432) | (.0434) | (.046) |
| Small town | | -.467*** | -.197*** | -.289*** | -.249*** | -.242*** | -.161** | -.454*** |
| | | (.0677) | (.0679) | (.0704) | (.0624) | (.0617) | (.0638) | (.0602) |
| Small urban | | -.356*** | -.0361 | -.0936 | -.163*** | -.147** | -.109* | -.414*** |
| | | (.0642) | (.0668) | (.0681) | (.0603) | (.0597) | (.0596) | (.0544) |
| Larger urban | | -.213*** | .0405 | -.000996 | -.138** | -.116* | -.0945 | -.342*** |
| | | (.07) | (.0693) | (.0694) | (.0622) | (.0615) | (.061) | (.0593) |
| Small metro | | -.227*** | -.0463 | -.0881 | -.171*** | -.165*** | -.152*** | -.333*** |
| | | (.0678) | (.0653) | (.0653) | (.0581) | (.0573) | (.0567) | (.0572) |
| Medium metro | | -.127* | -.0362 | -.0353 | -.106* | -.0984* | -.0862 | -.181*** |
| | | (.0705) | (.0662) | (.065) | (.0577) | (.0569) | (.0563) | (.0591) |
| Jan Temp (degF) | | | | -.0132*** | -.0184*** | -.0184*** | -.0186*** | -.0211*** |
| | | | | (.00238) | (.00214) | (.00211) | (.00209) | (.00221) |
| July Temp (degF) | | | | .00749 | .00919** | .00899** | .0135*** | .00932** |
| | | | | (.00497) | (.0044) | (.00434) | (.00442) | (.00469) |
| Ann. Snow (in) | | | | -.00135 | -.000246 | -.000582 | -.0000502 | .000316 |
| | | | | (.000875) | (.000778) | (.000775) | (.000776) | (.000825) |
| College enroll/Pop | | | | | 2.85*** | 2.85*** | 2.95*** | 3.39*** |
| | | | | | (.316) | (.311) | (.308) | (.325) |
| Ln(College subsidy) | | | | | .374*** | .446*** | .45*** | .445*** |
| | | | | | (.0341) | (.0364) | (.036) | (.0383) |
| Wage tax | | | | | | .0589*** | .0579*** | .0412** |
| | | | | | | (.0171) | (.0169) | (.0179) |
| Capital tax | | | | | | -.0788*** | -.084*** | -.0664*** |
| | | | | | | (.0171) | (.0169) | (.0179) |
| % Manufacturing | | | | | | | .00793*** | .00277 |
| | | | | | | | (.00183) | (.00187) |
| Constant | .016 | .295*** | .135** | .0853 | -.298 | -1.05** | -1.32** | -.447 |
| | (.0198) | (.0673) | (.0644) | (.336) | (.298) | (.533) | (.53) | (.557) |
| Observations | 741 | 741 | 741 | 741 | 741 | 741 | 741 | 741 |
| R-squared | 0.216 | 0.203 | 0.311 | 0.343 | 0.488 | 0.506 | 0.518 | 0.452 |

Notes: ***p<0.01 **p<0.05 *p<0.1. Each column has results from a separate OLS model with CZs as observations. Dependent variable is the model estimate of a CZ's skill ratio parameter ($\ln(S_{jt})$). Major metro area is the omitted CZ size category. West is the omitted CZ region. $\ln(S_{jt-1})$ is a model estimate of the CZ's log skill ratio in the previous generation. See text for definitions of other variables.

# A Data Appendix

## A.1 Commuting zones and their characteristics

Tolbert and Sizer (1996) describe the procedure they used to create the CZ classification. CZs were defined using confidential 1990 Census journey-to-work data. They are clusters of counties or county equivalents (boroughs, parishes, Census areas, and independent cities) with particularly strong commuting ties. There are 741 of them. CZs cross state lines and cover the entire United States (unlike alternative geographic units like MSAs).

Tolbert and Sizer (1996) provide some useful characterizations of CZs. They categorize CZs into four regions of the U.S.: Northeast, South, Midwest, and West. They also classify CZs as falling into one of six categories: small town, small urban, large urban, small metro, medium metro, and major metro. These are descriptions of the largest population center in each CZ. Small towns have fewer than 5,000 residents, small urban centers have between 5,000 and 20,000, and larger urban centers have at least 20,000 but no MSAs in the CZ. The remaining three categories are CZs with at least one MSA in their territory. They are classified according to the size of the largest MSA, where small metro centers have fewer than 250,000 residents, medium metro centers have between 250,000 and 1 million, and major metro centers have more than 1 million. These population figures refer to 1990.

I obtain additional characteristics of CZs from the 5 percent samples of the 1990 and 2000 Census (Ruggles et al. 2004). I follow Autor and Dorn (2007) in matching Census data to CZs. The least aggregated geographic unit identifiable in the 1990 and 2000 5 percent samples from IPUMS is the public use microdata area (PUMA). These are county clusters and are on average smaller than CZs. However, there exist PUMAs that overlap CZ boundaries. In order to match the two classifications, I weight average characteristics of PUMAs according to 2000 county populations when attributing those characteristics to a CZ. More specifically, I break down CZs into their individual counties. I assign to each county the average characteristic in the county's PUMA. I then create the CZ average characteristic by taking the weighted average of county characteristics, where the weights are the proportion of CZ residents residing in each county.

The CZ characteristics derived from the 2000 Census are the following:

- Percent with at least a bachelor's degree. The population here is restricted to those at least 24 years old and no older than 64.

- Average weekly wage. The population here is restricted to those currently employed and at least 16 years old and no older than 64. I weight by a labor supply variable, which is weeks worked in the previous year times usual weekly hours. For those with missing values of these variables, I impute labor supply as the average in their education-occupation cell, or just their education cell if the previous includes only themselves. I take wage and salary income from the previous year as the baseline earnings measure. I multiply top-coded ($175,000 in 2000) values by 1.5. The weekly wage is the resulting number divided by weeks worked.

- Percent employed in the manufacturing industry. These are workers with 2000 Census industry codes between 107 and 399, inclusive. The population includes only those working positive hours in the previous year.

All samples are restricted to include only non-institutionalized residents. I also create a similar data set from the 1990 Census, using the same methods and definitions as much as possible.

I assign a latitude and longitude to each CZ. I acquire latitude and longitude of ZIP code tabulation areas (ZCTAs) from the U.S. Census Bureau. These correspond roughly with zip codes. I then assign zip codes to CZs, using a zip code file purchased from ZipInfo.com and counties as the merging variable. I assign to each CZ the latitude that is the midpoint between the minimum and maximum latitudes of zip codes in that CZ. I assign CZ longitudes similarly.

I use these latitudes and longitudes to calculate distances between CZs. The distance measure I use is the great circle distance between coordinates, in kilometers.

## A.2 NELS:88

The procedure used to match NELS:88 respondents to CZ of residence uses zip code variables in the restricted-use version of the data. I match zip codes to U.S. counties using a commercial crosswalk (ZipInfo.com). Since CZs are collections of counties, it is then straightforward to identify the respondent's CZ. I assign the zip code of the 8th grade school as the origin of the student and the zip code of residence at the final follow-up (2000) as the final destination. For some respondents, I am not able to identify the CZ due to missing data. Tables A.1 and A.2 compare characteristics of respondents for which I do and do not have CZ identified. I drop respondents with missing CZ from the analysis.

Table A.3 indicates that post-secondary schooling still affects the choices of a significant number of NELS:88 respondents in the final follow-up (2000). Twenty-two percent of respondents were attending classes at either an academic or vocational school at the final follow-up. Five percent were attending school and not working at all. The cohort had not all moved on from the school attendance phase of life, and this is a weakness for the purpose of estimating geographic skill distributions from the model. I plan to estimate the model with NLSY79 data, where final observed location is later in each respondent's life.

Table A.1: Characteristics of Respondents, by Base Year Location Data Status

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | CZ identified [$N = 11145$] | | CZ not identified [$N = 239$] | |
| Variable | Mean | SE | Mean | SE |
| HS Dropout | .068 | .007 | .08 | .043 |
| College Grad | .294 | .008 | .254 | .042 |
| Test Index | 10.026 | .001 | 10.03 | .004 |
| Parents Ed | 13.851 | .04 | 13.489 | .412 |
| Parents Income | 41685 | 595 | 41466 | 4113 |
| Predict Log Earnings | 10.188 | .006 | 10.194 | .025 |
| Female | .503 | .011 | .493 | .065 |
| Asian | .035 | .003 | .033 | .01 |
| Hispanic | .104 | .006 | .152 | .044 |
| Black | .131 | .011 | .025 | .009 |
| White | .715 | .011 | .782 | .047 |
| Full-time Work 2000 | .594 | .01 | .606 | .061 |
| Married | .471 | .01 | .42 | .063 |
| Any Kids | .407 | .011 | .357 | .062 |

Table A.2: Characteristics of Respondents, by Final Follow-up (2000) Location Data Status

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | CZ identified [$N = 11314$] | | CZ not identified [$N = 70$] | |
| Variable | Mean | SE | Mean | SE |
| HS Dropout | .068 | .007 | .021 | .016 |
| College Grad | .293 | .008 | .467 | .106 |
| Test Index | 10.026 | .001 | 10.037 | .01 |
| Parents Ed | 13.839 | .04 | 14.549 | .293 |
| Parents Income | 41606 | 590 | 53121 | 8789 |
| Predict Log Earnings | 10.187 | .006 | 10.327 | .051 |
| Female | .504 | .011 | .336 | .087 |
| Asian | .035 | .003 | .028 | .013 |
| Hispanic | .106 | .006 | .029 | .014 |
| Black | .129 | .011 | .078 | .037 |
| White | .716 | .011 | .859 | .046 |
| Full-time Work 2000 | .594 | .01 | .66 | .087 |
| Married | .469 | .01 | .615 | .099 |
| Any Kids | .406 | .011 | .426 | .117 |

Table A.3: School Attendance at Final Follow-Up, NELS:88

| | (1) N | (2) Proportion |
|---|---|---|
| Total respondents | 11079 | 1 |
| In school (final follow-up) | 2407 | .22 |
| In school and PT work | 1346 | .12 |
| In school and FT work | 689 | .06 |
| In school and no work | 527 | .05 |

# B Results appendix

Table B.1: Probits for Skill Level of Child

| | (1) Low | (2) Medium-Low | (3) Medium-High | (4) High |
|---|---|---|---|---|
| Parent low skill | .163*** | .0507** | -.0721*** | -.167*** |
| | (.0286) | (.0231) | (.0188) | (.0141) |
| Parent medium-low skill | .0473* | .0308 | -.018 | -.0854*** |
| | (.025) | (.0246) | (.0225) | (.017) |
| Parent high skill | -.178*** | -.0576*** | .0202 | .166*** |
| | (.0174) | (.0202) | (.0194) | (.0194) |
| Jan Temp (degF) | .00186 | .0014 | -.00416** | .000668 |
| | (.00235) | (.00262) | (.00194) | (.00186) |
| July Temp (degF) | -.00453 | .00341 | .000384 | .000763 |
| | (.00773) | (.00481) | (.00476) | (.00422) |
| Ann. Snow (in) | -.00018 | -.000268 | -.000656 | .000809 |
| | (.00124) | (.00102) | (.000934) | (.000784) |
| Wage tax | -.00697 | .0137** | -.00203 | -.00375 |
| | (.0102) | (.00674) | (.00747) | (.00605) |
| Ln(college subsidy) | -.00556 | -.0514 | .0881*** | -.0312 |
| | (.0427) | (.0376) | (.034) | (.0314) |
| College enroll/Pop | .189 | -.95 | .159 | .511 |
| | (.734) | (.675) | (.578) | (.539) |
| No local college | -.0309 | -.0899 | .102 | .00742 |
| | (.122) | (.0698) | (.138) | (.0908) |
| Ln(avg wkly wage) | .283 | -.205 | -.0115 | -.109 |
| | (.303) | (.199) | (.21) | (.172) |
| % College Grad | -.00953 | .00707 | -.00103 | .00414 |
| | (.00765) | (.00539) | (.00558) | (.00413) |

Continued on next page

Table B.1 – continued from previous page

| | Low | Medium-Low | Medium-High | High |
|---|---|---|---|---|
| % Unemployed | -.00489 | -.00815 | .000401 | .0135* |
| | (.0128) | (.0104) | (.00988) | (.00816) |
| % Manufacturing | -.00151 | -.0015 | -.00126 | .00469** |
| | (.00371) | (.00227) | (.0024) | (.0019) |
| Ln(population) | .00386 | .0063 | .000214 | -.00683 |
| | (.0245) | (.0158) | (.0177) | (.0154) |
| ParLow × Jan Temp | .000657 | -.0067* | .00464 | .0024 |
| | (.00333) | (.00377) | (.003) | (.00289) |
| ParLow × July Temp | .0126 | -.000469 | -.00528 | -.0142** |
| | (.00979) | (.00755) | (.00704) | (.00694) |
| ParLow × Snow | .000717 | -.000154 | .000786 | -.00137 |
| | (.00191) | (.0017) | (.00151) | (.00119) |
| ParLow × Tax | .0202 | -.00914 | -.0154 | -.00697 |
| | (.0126) | (.00934) | (.0104) | (.00945) |
| ParLow × Ln(col subsidy) | .0531 | .0455 | -.104** | -.0329 |
| | (.0649) | (.0555) | (.0515) | (.0482) |
| ParLow × Col enroll/Pop. | -.501 | -.478 | .836 | 1.03 |
| | (1.04) | (.993) | (.843) | (.76) |
| ParLow × No college | -.0727 | .0313 | .13 | -.0321 |
| | (.172) | (.133) | (.156) | (.13) |
| ParLow × Log(wkly wage) | .00925 | -.214 | .0298 | .276 |
| | (.436) | (.339) | (.317) | (.301) |
| ParLow × College grad | .00831 | .00421 | -.00637 | -.0116* |
| | (.00951) | (.00766) | (.00747) | (.00659) |
| ParLow × Unemployed | .0123 | .0141 | -.0121 | -.0253** |
| | (.0159) | (.0143) | (.0135) | (.0113) |
| ParLow × Manufacture | .0024 | -.00171 | .00299 | -.00315 |
| | (.0044) | (.00336) | (.00327) | (.00314) |
| ParLow × Log(pop) | -.0264 | .00443 | .0222 | .00124 |
| | (.0363) | (.0264) | (.0271) | (.0261) |
| ParMedLow × Jan Temp | .00159 | -.00281 | .00396 | -.00301 |
| | (.00337) | (.00342) | (.00288) | (.00274) |
| ParMedLow × July Temp | .00157 | .0137* | -.00994 | -.00795 |
| | (.00926) | (.00798) | (.00768) | (.00647) |
| ParMedLow × Snow | -.00071 | .00196 | -.00143 | .000529 |
| | (.00159) | (.00144) | (.00134) | (.00137) |
| ParMedLow × Tax | .0167 | -.0347*** | .0132 | .00366 |
| | (.0136) | (.013) | (.0138) | (.0109) |
| ParMedLow × Ln(col subsidy) | -.115* | .0959 | -.086 | .12** |
| | (.0604) | (.0599) | (.0561) | (.049) |
| ParMedLow × Col enroll/Pop. | -.678 | 2.07** | -1.27 | .069 |
| | (1.03) | (.952) | (.91) | (.881) |

Continued on next page

Table B.1 – continued from previous page

| | Low | Medium-Low | Medium-High | High |
|---|---|---|---|---|
| ParMedLow × No college | -.0227 | .0138 | -.0638 | .0064 |
| | (.23) | (.133) | (.172) | (.129) |
| ParMedLow × Log(wkly wage) | .0644 | .328 | -.191 | -.225 |
| | (.402) | (.328) | (.316) | (.263) |
| ParMedLow × College grad | .00661 | -.0038 | .00429 | -.0107 |
| | (.00982) | (.00762) | (.00837) | (.00689) |
| ParMedLow × Unemployed | .0345** | -.00101 | .003 | -.0518*** |
| | (.0171) | (.0155) | (.0135) | (.0116) |
| ParMedLow × Manufacture | .00323 | -.00195 | .00263 | -.00402 |
| | (.00458) | (.00312) | (.00372) | (.00298) |
| ParMedLow × Log(pop) | -.00901 | .0065 | -.0314 | .0441* |
| | (.0347) | (.0256) | (.0278) | (.0244) |
| ParHigh × Jan Temp | .00258 | -.00545* | .0057** | -.000976 |
| | (.0032) | (.00326) | (.00266) | (.0024) |
| ParHigh × July Temp | -.00239 | -.00327 | -.00843 | .00858 |
| | (.00945) | (.00681) | (.00652) | (.00563) |
| ParHigh × Snow | .0000839 | -.000671 | .000797 | -.000195 |
| | (.00166) | (.00141) | (.00122) | (.00109) |
| ParHigh × Tax | .0184 | -.0161 | .00108 | .00172 |
| | (.0125) | (.0107) | (.01) | (.00848) |
| ParHigh × Ln(col subsidy) | .00445 | .0598 | -.0841* | .0206 |
| | (.0568) | (.0585) | (.0483) | (.0443) |
| ParHigh × Col enroll/Pop. | .239 | 1.05 | .205 | -.984 |
| | (.896) | (.918) | (.773) | (.731) |
| ParHigh × No college | -.0037 | .0454 | .0586 | -.0856 |
| | (.199) | (.157) | (.161) | (.132) |
| ParHigh × Log(wkly wage) | -.466 | .205 | -.209 | .349 |
| | (.376) | (.317) | (.297) | (.242) |
| ParHigh × College grad | .00765 | -.00958 | -.00636 | .0038 |
| | (.00916) | (.009) | (.00725) | (.00611) |
| ParHigh × Unemployed | .0000114 | .00248 | .00265 | -.0107 |
| | (.0161) | (.0151) | (.0138) | (.0117) |
| ParHigh × Manufacture | .00323 | -.000951 | -.00261 | -.000435 |
| | (.00445) | (.00392) | (.00322) | (.00284) |
| ParHigh × Log(pop) | .00218 | -.00222 | .0485* | -.0367* |
| | (.0307) | (.0254) | (.0256) | (.0216) |
| Observations | 11079 | 11079 | 11079 | 11079 |
| Pseudo $R^2$ | 0.0953 | 0.0330 | 0.0237 | 0.103 |

***p<0.01 **p<0.05 *p<0.1. Dependent variable equals one if respondent's skill is column heading skill level. Marginal effects reported. Sample weights used.

Table B.2: Destination CZ Choice Logit, Low Skilled

| VARIABLES | (1)<br>No interaction | (2)<br>Home × | (3)<br>Rural Origin × |
|---|---|---|---|
| $\ln(\bar{W})$ | .667 | | |
| | (.959) | | |
| Home | 13.9*** | | |
| | (4.85) | | |
| South | .816*** | -.733 | .191 |
| | (.296) | (.533) | (.468) |
| Midwest | 1.29*** | -1.87*** | -.0362 |
| | (.327) | (.554) | (.401) |
| West | 1.14* | -2.58*** | .613 |
| | (.619) | (.533) | (.734) |
| Ocean coast | -.52* | -.147 | .0799 |
| | (.276) | (.398) | (.488) |
| Small town | -.408 | .671 | -.592 |
| | (.894) | (1.25) | (1.49) |
| Small urban | .0524 | -.469 | -.478 |
| | (.69) | (.828) | (1.1) |
| Large urban | -.307 | .67 | -.329 |
| | (.544) | (.755) | (.941) |
| Small metro | -.0498 | -.0383 | -.461 |
| | (.572) | (.64) | (.873) |
| Medium metro | .33 | -.31 | .0602 |
| | (.325) | (.408) | (.673) |
| Jan temp | .06*** | -.0656*** | -.0578** |
| | (.0169) | (.0241) | (.028) |
| July temp | -.0297 | -.0646 | .134*** |
| | (.0269) | (.0415) | (.0471) |
| Ann. Snow | -.00152 | -.0275*** | .0182* |
| | (.00779) | (.00887) | (.0101) |
| Wage tax | -.0399 | .124 | .0457 |
| | (.0487) | (.0783) | (.0718) |
| Ln(college subsidy) | -.81*** | .395 | .636* |
| | (.305) | (.43) | (.362) |
| College enroll/Pop | 2.17* | -1.22 | -7.47* |
| | (1.13) | (4.53) | (4.22) |
| No college | 1.42 | -.792 | -2.78** |
| | (1.08) | (.875) | (1.22) |
| % BA | .01 | -.0635** | .00154 |
| | (.0143) | (.0277) | (.0248) |
| % Manufacturing | .0134 | -.016 | -.0167 |
| | (.0139) | (.0206) | (.0253) |
| Ln(population) | .816*** | -.278 | -.315 |
| | (.174) | (.201) | (.219) |
| Distance | -.0025*** | | |
| | (.000311) | | |
| Distance$^2$ | 2.77e-07*** | | |
| | (4.40e-08) | | |
| BY CZ Col enroll/Pop × Dest. Ln(pop) | .35 | | |
| | (1.32) | | |
| BY CZ Col enroll/Pop × Dest. Ln(col enroll) | -4.97 | | |
| | (37.9) | | |
| Observations | 2515 | | |

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Results are from a single logit estimation of destination CZ choice. Columns represent interactions between column heading and row variable. Robust standard errors in parentheses.

Table B.3: Destination CZ Choice Logit, Medium-Low Skilled

| VARIABLES | (1)<br>No interaction | (2)<br>Home × | (3)<br>Rural Origin × |
|---|---|---|---|
| $\ln(\bar{W})$ | -.94 | | |
| | (.858) | | |
| Home | 7.69** | | |
| | (3.69) | | |
| South | .198 | -.213 | .763 |
| | (.303) | (.433) | (.477) |
| Midwest | .0297 | -.403 | .48 |
| | (.276) | (.329) | (.496) |
| West | 1.3** | -1.53*** | .653 |
| | (.628) | (.447) | (.798) |
| Ocean coast | .347 | -.455 | -.0186 |
| | (.29) | (.397) | (.43) |
| Small town | -.769 | 1.04 | -.679 |
| | (.857) | (1.45) | (1.46) |
| Small urban | -.111 | -.817 | .375 |
| | (.499) | (.937) | (.704) |
| Large urban | .312 | -.125 | -.325 |
| | (.517) | (.712) | (.763) |
| Small metro | .0629 | -.0499 | .0256 |
| | (.364) | (.552) | (.584) |
| Medium metro | .267 | -.104 | .45 |
| | (.294) | (.415) | (.544) |
| Jan temp | -.00158 | -.0122 | -.0453 |
| | (.0149) | (.0201) | (.0301) |
| July temp | .0284 | -.0113 | .0289 |
| | (.0246) | (.0427) | (.0632) |
| Ann. Snow | .00764* | -.0217** | -.0031 |
| | (.00445) | (.00942) | (.00817) |
| Wage tax | -.0816** | .132** | .0501 |
| | (.0403) | (.0663) | (.0524) |
| Ln(college subsidy) | .232 | -.471 | -.323 |
| | (.165) | (.345) | (.309) |
| College enroll/Pop | 2.32** | 1.47 | -.509 |
| | (.967) | (3.9) | (2) |
| No college | .15 | .343 | -.258 |
| | (.657) | (.941) | (.979) |
| % BA | .0276* | -.0013 | -.0071 |
| | (.0144) | (.0254) | (.0256) |
| % Manufacturing | -.0129 | .0529*** | .0271 |
| | (.0134) | (.0195) | (.0192) |
| Ln(population) | .909*** | -.53*** | -.219 |
| | (.12) | (.175) | (.194) |
| Distance | -.00236*** | | |
| | (.000268) | | |
| Distance$^2$ | 2.69e-07*** | | |
| | (3.29e-08) | | |
| BY CZ Col enroll/Pop × Dest. Ln(pop) | 1.44 | | |
| | (1.26) | | |
| BY CZ Col enroll/Pop × Dest. Ln(col enroll) | -23.1 | | |
| | (31.5) | | |
| Observations | 2724 | | |

*** p<0.01, ** p<0.05, * p<0.1. Results are from a single logit estimation of destination CZ choice. Columns represent interactions between column heading and row variable. Robust standard errors in parentheses.

Table B.4: Destination CZ Choice Logit, Medium-High Skilled

| VARIABLES | (1) No interaction | (2) Home × | (3) Rural Origin × |
|---|---|---|---|
| $\ln(\bar{W})$ | -1.04 | | |
| | (.716) | | |
| Home | 11.7*** | | |
| | (3.95) | | |
| South | .561*** | -.136 | 1* |
| | (.201) | (.425) | (.574) |
| Midwest | .374* | -.298 | .75 |
| | (.2) | (.304) | (.547) |
| West | 1.93*** | -1.3*** | -.103 |
| | (.335) | (.399) | (.696) |
| Ocean coast | -.113 | -.00449 | .214 |
| | (.246) | (.292) | (.413) |
| Small town | 1.47 | 1.5 | -2.11 |
| | (.964) | (1.24) | (1.37) |
| Small urban | .0815 | -.208 | .321 |
| | (.492) | (.828) | (.867) |
| Large urban | -.025 | .246 | .628 |
| | (.409) | (.815) | (.782) |
| Small metro | .0875 | -.357 | 1.2 |
| | (.328) | (.417) | (.779) |
| Medium metro | .085 | .149 | .0273 |
| | (.217) | (.292) | (.416) |
| Jan temp | -.00924 | -.00501 | -.00363 |
| | (.0114) | (.0192) | (.0207) |
| July temp | .0275 | -.00974 | -.0392 |
| | (.0215) | (.037) | (.035) |
| Ann. Snow | -.00244 | .00167 | -.00257 |
| | (.00462) | (.00633) | (.00753) |
| Wage tax | -.0839** | .0379 | .00879 |
| | (.0383) | (.0674) | (.0788) |
| Ln(college subsidy) | .424** | -.184 | -1.26*** |
| | (.205) | (.372) | (.373) |
| College enroll/Pop | -4.28* | 7.64 | .2 |
| | (2.38) | (5.7) | (5.15) |
| No college | -1.8** | -2.47*** | 2.75*** |
| | (.816) | (.839) | (.954) |
| % BA | .0558*** | -.0904*** | -.0258 |
| | (.0124) | (.0253) | (.023) |
| % Manufacturing | -.0112 | .0445** | -.0236 |
| | (.0117) | (.0175) | (.0194) |
| Ln(population) | .921*** | -.465*** | .0763 |
| | (.103) | (.169) | (.175) |
| Distance | -.00254*** | | |
| | (.00019) | | |
| Distance$^2$ | 2.96e-07*** | | |
| | (2.19e-08) | | |
| BY CZ Col enroll/Pop × Dest. Ln(pop) | 1.44 | | |
| | (1.16) | | |
| BY CZ Col enroll/Pop × Dest. Ln(col enroll) | -27.8 | | |
| | (54.1) | | |
| Observations | 2771 | | |

*** p<0.01, ** p<0.05, * p<0.1. Results are from a single logit estimation of destination CZ choice. Columns represent interactions between column heading and row variable. Robust standard errors in parentheses.

Table B.5: Destination CZ Choice Logit, High Skilled

| VARIABLES | (1)<br>No interaction | (2)<br>Home × | (3)<br>Rural Origin × |
|---|---|---|---|
| $\ln(\bar{W})$ | -.659 | | |
| | (.486) | | |
| Home | 7.15** | | |
| | (3.33) | | |
| South | .403* | -.402 | -.282 |
| | (.223) | (.391) | (.432) |
| Midwest | .238 | -.516* | .00436 |
| | (.182) | (.29) | (.38) |
| West | 1.44*** | -1.2*** | -.378 |
| | (.268) | (.351) | (.511) |
| Ocean coast | .0838 | -.706*** | -.506 |
| | (.167) | (.256) | (.308) |
| Small town | -1.11 | -.797 | 2.03* |
| | (.852) | (.92) | (1.1) |
| Small urban | -.406 | .1 | .471 |
| | (.585) | (.505) | (.745) |
| Large urban | -.303 | -.506 | .859 |
| | (.323) | (.523) | (.555) |
| Small metro | -.635*** | .439 | .649 |
| | (.234) | (.355) | (.414) |
| Medium metro | -.0974 | -.0509 | .426 |
| | (.173) | (.259) | (.283) |
| Jan temp | -.000947 | .0000477 | -.0235* |
| | (.00849) | (.0159) | (.0139) |
| July temp | .0137 | -.00846 | .023 |
| | (.0198) | (.0258) | (.0295) |
| Ann. Snow | -.00353 | -.00807 | .00791 |
| | (.00374) | (.0059) | (.00611) |
| Wage tax | -.0647** | .139*** | -.0151 |
| | (.0294) | (.0514) | (.0519) |
| Ln(college subsidy) | .389** | -.72*** | .231 |
| | (.175) | (.255) | (.237) |
| College enroll/Pop | .76 | 2.21 | -1.62 |
| | (.776) | (3.34) | (2.34) |
| No college | .091 | .94 | -.262 |
| | (.623) | (.752) | (.797) |
| % BA | .0745*** | -.0866*** | -.0421** |
| | (.0123) | (.0168) | (.0181) |
| % Manufacturing | .0107 | .0143 | -.00692 |
| | (.0104) | (.0158) | (.0142) |
| Ln(population) | .828*** | -.399*** | .15 |
| | (.0783) | (.11) | (.141) |
| Distance | -.00224*** | | |
| | (.000152) | | |
| Distance$^2$ | 2.70e-07*** | | |
| | (1.84e-08) | | |
| BY CZ Col enroll/Pop × Dest. Ln(pop) | -.283 | | |
| | (.749) | | |
| BY CZ Col enroll/Pop × Dest. Ln(col enroll) | -13.4 | | |
| | (30.1) | | |
| Observations | 3069 | | |

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Results are from a single logit estimation of destination CZ choice. Columns represent interactions between column heading and row variable. Robust standard errors in parentheses.

Table B.6: Parameter Estimates for States, Census

| State | (1) $S_{jt-1}$ | (2) $K_{jt}$ | (3) $K_{jt}\Lambda_{jt}$ | (4) $S_{jt}$ | (5) $\Lambda_{jt}M_{jt}$ |
|---|---|---|---|---|---|
| Alabama | .7 | .68 | .52 | .67 | .99 |
| Alaska | 1.68 | .81 | .45 | .79 | .98 |
| Arizona | 1.18 | .74 | .54 | 1.09 | 1.47 |
| Arkansas | .65 | .59 | .45 | .55 | .93 |
| California | 1.39 | 1.01 | .99 | 1.33 | 1.31 |
| Colorado | 1.5 | 1.11 | .92 | 1.53 | 1.37 |
| Connecticut | 1.39 | 1.41 | 1.02 | 1.45 | 1.03 |
| Delaware | .93 | 1.03 | .63 | .98 | .95 |
| District of Columbia | .71 | 1.31 | .39 | 1.53 | 1.17 |
| Florida | .88 | .74 | .55 | .88 | 1.19 |
| Georgia | .71 | .64 | .5 | .9 | 1.39 |
| Hawaii | 1.47 | 1.06 | .72 | .92 | .87 |
| Idaho | 1.22 | .98 | .69 | .85 | .87 |
| Illinois | 1.03 | 1.24 | 1.06 | 1.28 | 1.04 |
| Indiana | .79 | .87 | .63 | .75 | .87 |
| Iowa | .98 | 1.25 | .77 | .86 | .69 |
| Kansas | 1.17 | 1.13 | .85 | 1.1 | .97 |
| Kentucky | .71 | .71 | .52 | .64 | .9 |
| Louisiana | .83 | .64 | .45 | .56 | .87 |
| Maine | .84 | .83 | .5 | .74 | .89 |
| Maryland | 1.05 | .96 | .69 | 1.18 | 1.23 |
| Massachusetts | 1.23 | 1.63 | 1.37 | 1.76 | 1.08 |
| Michigan | 1 | 1.08 | .85 | .92 | .85 |
| Minnesota | 1.25 | 1.4 | 1.13 | 1.36 | .98 |
| Mississippi | .61 | .53 | .39 | .49 | .92 |
| Missouri | .85 | .97 | .7 | .85 | .88 |
| Montana | 1.16 | 1.14 | .68 | .72 | .64 |
| Nebraska | 1.12 | 1.32 | 1 | 1.05 | .8 |
| Nevada | .81 | .78 | .55 | .7 | .9 |
| New Hampshire | 1.18 | .99 | .69 | 1.18 | 1.19 |
| New Jersey | 1.18 | 1.44 | 1.14 | 1.47 | 1.02 |
| New Mexico | 1.06 | .73 | .42 | .74 | 1.02 |
| New York | 1.13 | 1.46 | 1.12 | 1.27 | .87 |
| North Carolina | .6 | .65 | .51 | .81 | 1.24 |
| North Dakota | 1.13 | 1.33 | .79 | .85 | .64 |
| Ohio | .91 | .99 | .73 | .85 | .86 |
| Oklahoma | .99 | .96 | .64 | .71 | .74 |
| Oregon | 1.25 | .91 | .73 | .96 | 1.05 |
| Pennsylvania | .86 | 1.09 | .74 | .87 | .8 |
| Rhode Island | .96 | 1.27 | .88 | 1.12 | .89 |
| South Carolina | .56 | .55 | .38 | .61 | 1.11 |
| South Dakota | 1.15 | 1.14 | .7 | .78 | .68 |
| Tennessee | .69 | .71 | .52 | .7 | 1 |
| Texas | 1 | .73 | .65 | .95 | 1.31 |
| Utah | 1.52 | 1.3 | 1.08 | 1.28 | .99 |
| Vermont | 1.13 | .82 | .47 | .92 | 1.12 |
| Virginia | .95 | .79 | .53 | 1.15 | 1.47 |
| Washington | 1.38 | 1.08 | .95 | 1.21 | 1.12 |
| West Virginia | .9 | .77 | .51 | .57 | .74 |
| Wisconsin | .97 | 1.18 | .85 | .92 | .78 |
| Wyoming | 1.31 | .99 | .51 | .67 | .68 |

# C Model estimation with the NELS:88 and states as locations

Model estimation with states as locations is an aggregation of the method applied to CZs. The model estimation described above yields estimates for each CZ of the high- and low-skilled populations of a first generation as adults, a second generation as children, those children who stayed in their origins, and the second generation as adults. I sum each of these populations within states to get state populations of high- and low-skilled people.[15] I then take ratios to calculate $S_{jt-1}$, $K_{jt}$, $K_{jt}\Lambda_{jt}$, and $S_{jt}$ for each state $j$. I calculate $\Lambda_{jt} = (K_{jt}\Lambda_{jt})/K_{jt}$ and $M_{jt} = S_{jt-1}/(K_{jt}\Lambda_{jt})$.

Tables C.1 and C.2 show the resulting estimates. Table C.1 displays summary statistics of model estimates describing the distribution of skills across states. These estimates are similar to those from the Census accounting exercise (Table 2). One difference is that the increase in skewness from child to adult skill distributions comes both through differential native retention and in-migration with the NELS:88, rather than just the former in the Census. The skewness of $\Lambda_{jt}$ is negative with the Census but positive in the model estimation. The ranges of $\Lambda_{jt}$ and $M_{jt}$ are similar between the two methods, except that the maximum $M_{jt}$ from the NELS:88 method is substantially higher than the maximum from the Census.

Table C.2 lists correlations between model components that are comparable to those in Table 3 from the Census accounting exercise. There are some differences, but they seem less notable than the similarities. The largest difference is that the correlation between $M_{jt}$ and $K_{jt}/S_{jt-1}$ changes sign. The main correlations of interest are similar between the two tables. In particular, the correlation between parent skills ($S_{jt-1}$) and skill gains through intergenerational transmission $K_{jt}/S_{jt-1}$ is negative and very similar in both specifications. Also, the correlation between $S_{jt-1}$ and skill gains through migration ($\Lambda_{jt}M_{jt}$) is

[15] For CZs crossing state lines, I assign their populations to the state with the higher share of CZ population.

close to zero. These two correlations reflect the persistence findings in Figure 2 and Figure 3, respectively.

In general, model estimation with the NELS:88 induces more variability in estimates of the geographic mobility of skills than is present in the Census accounting exercise. This is perhaps to be expected, since there is an extra layer of estimation from the model, relative to the Census method, and the underlying sample for measuring migration and intergenerational transmission is smaller than the Census sample. However, the NELS:88 approach has enough precision to replicate findings in the Census and add to the understanding of the geographic distribution of human capital.

Table C.1: Accounting for Skills across States, NELS:88

| Description | Variable | (1) Mean | (2) StDev | (3) Skew | (4) Min | (5) Max |
|---|---|---|---|---|---|---|
| Parent gen. skill ratio | $S_{jt-1}$ | 1 | .26 | 1.06 | .64 | 1.87 |
| Child skill ratio | $K_{jt}$ | 1.16 | .33 | .48 | .61 | 1.95 |
| Stayers skill ratio | $K_{jt}\Lambda_{jt}$ | .74 | .25 | 1.05 | .28 | 1.51 |
| Adult skill ratio | $S_{jt}$ | 1.12 | .4 | 1.61 | .56 | 2.59 |
| | | | | | | |
| Intergenerational factor | $K_{jt}/S_{jt-1}$ | 1.18 | .35 | 2 | .64 | 2.77 |
| Native retention factor | $\Lambda_{jt}$ | .64 | .11 | 1.25 | .47 | 1.03 |
| In-migration factor | $M_{jt}$ | 1.6 | .82 | 5.39 | .98 | 6.89 |
| Total migration factor | $\Lambda_{jt}M_{jt}$ | 1 | .38 | 4 | .52 | 3.21 |

Table C.2: Correlations between Accounting Exercise Characteristics of States, NELS:88

| | (1) $S_{jt-1}$ | (2) $K_{jt}$ | (3) $K_{jt}\Lambda_{jt}$ | (4) $S_{jt}$ | (5) $K_{jt}/S_{jt-1}$ | (6) $\Lambda_{jt}$ | (7) $M_{jt}$ | (8) $\Lambda_{jt}M_{jt}$ |
|---|---|---|---|---|---|---|---|---|
| $S_{jt-1}$ | 1 | | | | | | | |
| $K_{jt}$ | .496 | 1 | | | | | | |
| $K_{jt}\Lambda_{jt}$ | .542 | .841 | 1 | | | | | |
| $S_{jt}$ | .557 | .528 | .584 | 1 | | | | |
| | | | | | | | | |
| $K_{jt}/S_{jt-1}$ | -.352 | .618 | .378 | .062 | 1 | | | |
| $\Lambda_{jt}$ | .205 | -.022 | .493 | .148 | -.235 | 1 | | |
| $M_{jt}$ | -.076 | -.274 | -.341 | .454 | -.223 | -.319 | 1 | |
| $\Lambda_{jt}M_{jt}$ | .019 | -.302 | -.184 | .565 | -.34 | .036 | .929 | 1 |