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Inequality of Educational Opportunity? Schools as Mediators of the Intergenerational Transmission of Income

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Abstract

Chetty et al. (2014) show that children from low-income families achieve much better adult outcomes, relative to those from higher-income families, in some places than in others. I use data from several national surveys to investigate whether children's educational outcomes (educational attainment, test scores, and non-cognitive skills) mediate the relationship between parental and child income. Commuting zones (CZs) with stronger intergenerational income transmission tend to have stronger transmission of parental income to children's educational attainment, as well as higher returns to education. By contrast, the CZ-level association between parental income and children's test scores is only weakly related to CZ income transmission, and is stable across grades. There is thus little evidence that differences in the quality of K-12 schooling are a key mechanism driving variation in intergenerational mobility. Access to college plays a somewhat larger role, but most of the variation in CZ income mobility reflects (a) differences in marriage patterns, which affect income transmission when spousal earnings are counted in children's income; (b) differences in labor market returns to education; and (c) differences in children's earnings residuals, after controlling for observed skills and the CZ-level return to skill. This points to job networks or the structure of the local labor and marriage markets, rather than the education system, as likely factors influencing intergenerational economic mobility.

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1 Introduction

Social scientists have long looked to the intergenerational transmission of income – the strength of the association between an adult's income and that of his or her parents – as a key dimension of social inequality. The stronger the association, the less likely it is that a child born into a disadvantaged family will succeed economically as an adult, and the further society is from equality of opportunity among children. The salience of intergenerational transmission has grown with the rise in income inequality, which makes it harder for families of modest incomes to keep up in the educational investment arms race (Chetty et al., 2014, 2016). Reardon (2011) has shown that the gap in test scores between students born to families in the top and bottom of the income distribution has grown in recent years as the income distribution has widened. Although we will not be able to observe the adult outcomes of recent cohorts of children for many years, Reardon's evidence at least suggests that economic mobility is likely to have declined.

While the measurement of intergenerational income transmission is the subject of long literatures spanning a number of social science disciplines,[1] little is understood about the channels by which this transmission occurs. Candidates include differences in parenting practices between high- and low-income families, differences in explicit investments in children's education, differences in access to educational or other public institutions, and labor market institutions (such as insider hiring or spatial mismatch) that advantage children from high-income families regardless of their skills.

Chetty et al. (2014, hereafter "CHKS") use data on the universe of U.S. tax filers to measure intergenerational income links at the fine geographic level, and reveal massive heterogeneity across space: The gap in adult earnings between children from high- vs. low-income families is nearly twice as large for children who grow up in Cincinnati as for those who grow up in Los Angeles. Although CHKS explore geographic correlates of this transmission, the mechanisms accounting for differences across areas are not well understood.

This paper probes these mechanisms, via an assessment of whether geographic areas with

[1] Some literatures focus on other dimensions of intergenerational transmission, such as transmission of occupational status. As data on incomes has improved, and as inequality of incomes even within narrowly defined occupations has risen, researchers increasingly focus on income transmission *per se*.

high intergenerational transmission of income – strong associations between parental and child incomes – also show high transmission of parental income into children's educational achievement and attainment. We would expect the two to be strongly correlated across space if human capital accumulation is an important mechanism by which one generation's advantage is transmitted into the next generation – for example, if variation in school quality or parenting practices is an important factor driving the variation in income transmission. On the other hand, if parental income primarily helps children by, for example, buying them access to better labor market networks, then areas where poor children do relatively well in school may not be areas where those children do relatively well in the labor market.

I also investigate the ages at which gaps in child outcomes appear. In the simple case where skill is uni-dimensional and is reflected both in children's achievement and adults' earnings, the age profile of the gap in achievement between children from high- and low-income families is indicative of the ages at which the relevant mechanisms operate. In more complex (and more realistic) models, the interpretation is not so straightforward, but it would nevertheless be useful to understand when, and in which types of outcomes, gaps arise. This would point to institutional factors likely to contribute to intergenerational transmission of income, and provide useful directions for future research.[2] For example, if in areas with high income transmission, gaps between high- and low-income children in test scores and other measures of child development are small at school entry but large at school exit, this would suggest that educational institutions are central to intergenerational transmission of advantage; on the other hand, if gaps are as large in Kindergarten as in adult outcomes, this would point away from schools and toward early childhood environments and services (e.g., prenatal and postnatal health care) as more likely contributory factors.

I rely on three panel surveys conducted by the National Center for Educational Statistics (NCES): the Education Longitudinal Survey (ELS), the Early Childhood Longitudinal Survey (ECLS), and the High School Longitudinal Survey (HSLS). Each is a representative national sample with information on parental income and children's achievement (test scores)

[2]Evidence on the developmental profile of family income gaps would also inform theories of child development such as Heckman's "skill-begets-skill" model (see, e.g., Carneiro and Heckman, 2003; Cunha and Heckman, 2007, 2008; Cunha et al., 2010), which posits that early investments are the key to closing gaps in eventual outcomes.

at various ages. Importantly, restricted-access versions of each sample can be geocoded to commuting zones (CZs), the unit of geography considered by CHKS.

The NCES samples each contain only about 15,000 respondents. This is far too few to support the construction of income-achievement transmission measures for individual CZs. I show below that this is not necessary in order to accomplish the more limited goal of measuring the across-CZ relationship between income-income transmission and income-achievement transmission. That relationship is identified even with small numbers of observations from each CZ – essentially, one can pool information from many CZs with similar income-income transmission to identify the average income-achievement transmission among them, even when the latter is not reliably estimated for any individual CZ. I develop an estimator for this, based on a mixed (random coefficients) model for the relationship between parental income and children's achievement. This yields an estimate of the "reverse" regression of income-achievement transmission on the known income-income transmission, which can then be transformed into the "forward" regression of interest.

I find that intergenerational income transmission in a CZ is reasonably strongly related to the strength of transmission from parental income to children's educational attainment. This reproduces a similar result for college enrollment in CHKS.[3] Income transmission is much less strongly related, however, to the transmission from parental income to children's achievement, as measured by standardized tests: While CZs vary substantially in the strength of parent income-to-child achievement transmission, this is only weakly correlated with income-to-income transmission. Moreover, the association between income-income and income-achievement transmission is approximately as strong when achievement is measured early in elementary school as when it is measured in 12th grade. This is strongly suggestive that differential inequities in access to good elementary and secondary schools are not an important mechanism driving the across-CZ variation in income transmission.

I also consider variation in the CZ-level labor market return to skill. Because children from low-income families complete less education (and acquire fewer skills) in every CZ

[3]The paper that is most similar to this one is Kearney and Levine (2016). Kearney and Levine (2016) find that high school dropout gaps by family status are stronger in more unequal states, which tend to have stronger income transmission by CHKS's measure. Kearney and Levine (2014) find that non-marital childbearing is more common among low-SES women in these states as well.

than do children from higher-income families, differences in the return to skill could produce differences in income transmission even if the distribution of skill acquisition were the same everywhere. Indeed, I find that the return to education varies substantially across CZs, and is more strongly associated with the strength of income transmission in the CZ than are either achievement or attainment gradients. This points to labor market institutions as a potentially important factor.

When I decompose children's family income into the child's own earnings and other components (spousal earnings and the family's non-labor income), and further decompose children's earnings into observed skill, the local returns to that skill, and the earnings residual, I find that spousal and unearned income accounts for more than one-third of the relative disadvantage of children from low-income families in high-transmission CZs. Another third operates through the child's residual earnings – that is, through variation in the relationship between parental income and child income conditional on the child's (observed) human capital. A majority of the remaining variation reflects differences across CZs in the return to skill; only 12% of the total is attributable to differences in children's skill accumulation (including both achievement and attainment).

It is important to emphasize that my results are purely observational; my estimates of the association between CZ-level income transmission and CZ-level transmission of parental income to children's test scores and other outcomes could be confounded by other CZ-level characteristics that are correlated with both.[4] Keeping this caveat in mind, my results indicate that human capital plays a relatively small role in the geographic variation in the intergenerational transmission of income. Much of this variation appears to reflect differences in adult earnings of children with similar skills, perhaps due to labor market institutions (e.g., unions, or other determinants of residual income inequality) or differences in access to good jobs (due, perhaps, to labor market networks or socially stratified labor markets). Differences in marriage markets, and particularly in the likelihood that an adult will have a working spouse, also play a large role. While this does not rule out an important role for educational interventions – particularly those governing college access – in raising mobility,

[4]Reverse causality is also possible: For example, CZs with more equal labor markets may make it easier to attract high quality graduates into teaching, leading to a causal path from economic mobility to gaps in children's outcomes.

it suggests that these other domains merit at least as much attention.

2 Conceptual framework

CHKS use tax data to construct various measures of intergenerational income mobility. I focus on what they call "relative mobility," the advantage that a child from a high-income family has, relative to a child from a low-income family in the same CZ, in achieving a high income as an adult. Letting p_{ic} represent the income of the parents of child i in CZ c, measured in national percentiles, and y_{ic} the child's adult income, again in national percentiles, CHKS's preferred relative mobility measure is the slope coefficient θ_c from a CZ-level bivariate regression:

$$y_{ic} = \alpha_c + p_{ic}\theta_c + e_{ic}. \tag{1}$$

CHKS have sufficient data to estimate θ_c extremely precisely without pooling information across CZs. Thus, they estimate that $\theta_c = 0.43$ in Cincinnati, meaning that a one percentile difference in parental income is associated with a 0.43 percentile difference in children's eventual income, on average, in that city, and that in Los Angeles $\theta_c = 0.23$, implying a relationship between parent and child income that is only a bit more than half as strong as in Cincinnati. Hereafter, I refer θ_c as the strength of *income transmission* in the CZ: Higher values correspond to *less*, rather than more, mobility across generations.

CHKS find substantial variation in transmission: While the (unweighted) average CZ has a slope measure of 0.33 – indicating intergenerational mean reversion (in percentiles) of about two-thirds – the standard deviation is 0.065. CHKS find that CZ-level income transmission is positively correlated with the fraction of black residents in the local population, with racial and economic segregation, and with income inequality. They also examine correlations with various policy measures, such as proxies for school quality. They find that intergenerational income transmission is negatively correlated with average test scores and high school completion, as well as with school expenditures, and is essentially unrelated to average class size. But these are merely between-CZ correlations; CHKS are unable to investigate the role played by *differences* in access to school quality between high- and low-income students.

Demographic and policy correlates are of limited value in identifying the channels responsible for differences across areas. The demographic correlates, for example, could indicate that segmented labor markets are an important factor, or they could reflect differences in the degree of stratification in the health or education systems, or differences in the pervasiveness of "poverty cultures." Another possibility is that local policies may be consequences, rather than causes, of either the area's demographic composition or its intergenerational transmission itself. For example, support for school spending may be higher in places with less economic stratification.

In this paper I analyze the channels by which income is transmitted across generations, with the goal of shedding light on the relevant mechanisms. For example, if school quality is a mechanism behind the geographic variation in income transmission, we would expect that CZs with high θ_c would also tend to be CZs in which the gap in educational outcomes between high- and low-income children is larger, while the gap in child incomes conditional on educational outcomes should be much smaller than the unconditional gap. Moreover, the timing with which any educational outcome gap emerges and grows over the child's development is informative about the particular mechanisms at work.

2.1 Test scores as mediators of intergenerational income effects

For simplicity, I assume that child outcomes s_{ict} (for "skills") for student i in commuting zone c are measured at two points, first at or around school entry ($t = 1$) and then again at school exit ($t = 2$). I also assume that skill (human capital) is uni-dimensional and measured perfectly at each stage. The framework can readily accommodate multiple dimensions of child outcomes (e.g. achievement as well as non-cognitive skill) as well as more than two time points.

Children's outcomes at $t = 1$ depend on their parents' income, as mediated by local conditions and institutions (including such factors as health care and early childhood systems as well as local culture): $s_{ic1} = f_{1c}(p_{ic})$. Outcomes at period 2 depend on the earlier outcomes as well as on subsequent inputs that may themselves depend on parental income, again as mediated by local conditions (including school quality): $s_{ic2} = f_{2c}(s_{ic1}, p_{ic})$. Finally, the adult income of child i depends on the child's skill in period 2. This is of course influenced by parental income, which may have a direct effect on the child's income as well: $y_{ic} = g_c(s_{ic2}, p_{ic})$.[5]

Figure 1 displays this framework graphically. It shows that there are several channels by which parental income influences children's income. Algebraically, we can write the reduced-form relationship as:

$$y_{ic} \equiv h_c(p_{ic}) \equiv g_c(f_{2c}(f_{1c}(p_{ic}), p_{ic}), p_{ic}). \tag{2}$$

CHKS's relative mobility measure (i.e., income transmission) is the (linearized) slope of this relationship in the CZ:

$$\theta_c \equiv \frac{dh_c}{dp_{ic}} = \frac{\partial g_c}{\partial s_2}\frac{\partial f_{2c}}{\partial s_1}\frac{\partial f_{1c}}{\partial p_{ic}} + \frac{\partial g_c}{\partial s_2}\frac{\partial f_{2c}}{\partial p_{ic}} + \frac{\partial g_c}{\partial p_{ic}}. \tag{3}$$

The three terms here represent three different channels, and implicate different mechanisms. The first reflects impacts of parental income on children's period-1 skill, multiplied by the effect of period-1 skill on later outcomes; the second reflects impacts of parental income on skill in period 2 conditional on skill in period 1, multiplied by the effect of period-2 skill on income; and the third represents direct effects of parental income on children's income conditional on period-2 skill. A large role for the first would point to early childhood institutions and parenting practices as likely mechanisms behind income transmission; the second to educational institutions and parental investment in school-aged children; and the third to labor market institutions such as networks and pay norms.

It is useful to assume that each of the f_1, f_2, and g functions is linear, with additive error terms deriving from inputs to skill accumulation that are orthogonal to parental income:

$$s_{ic1} = f_{1c}(p_{ic}) = \kappa_{1c} + p_{ic}\pi_{1c} + u_{ic1} \tag{4a}$$

$$s_{ic2} = f_{2c}(s_{ic1}, p_{ic}) = \kappa_{2c} + s_{ic1}\lambda_{2c} + p_{ic}\pi_{2c} + u_{ic2} \tag{4b}$$

$$y_{ic} = g_c(s_{ic2}, p_{ic}) = \kappa_{3c} + s_{ic2}\lambda_{3c} + p_{ic}\pi_{3c} + \epsilon_{ic}. \tag{4c}$$

[5] I assume here that early achievement s_{ic1} affects labor market outcomes y_{ic} only through later achievement s_{ic2}, but this is not essential.

Then we can write the reduced-form relationship between parental income and children's income as

$$\begin{aligned} h_c(p_{ic}) &= \kappa_{3c} + (\kappa_{2c} + (\kappa_{1c} + p_{ic}\pi_{1c} + u_{ic1})\lambda_{2c} + p_{ic}\pi_{2c} + u_{ic2})\lambda_{3c} + p_{ic}\pi_{3c} + \epsilon_{ic} \qquad (5) \\ &= (\kappa_{3c} + (\kappa_{2c} + \kappa_{1c}\lambda_{2c}))\lambda_{3c} + p_{ic}((\pi_{1c}\lambda_{2c} + \pi_{2c})\lambda_{3c} + \pi_{3c}) + ((u_{ic1}\lambda_{2c} + u_{ic2})\lambda_{3c} + \epsilon_{ic}), \end{aligned}$$

and income transmission as:

$$\theta_c = \frac{dh_c}{dp_{ic}} = \lambda_{3c}\lambda_{2c}\pi_{1c} + \lambda_{3c}\pi_{2c} + \pi_{3c}. \qquad (6)$$

With sufficient data, it would be possible to estimate each of the transmission coefficients $\Omega_c \equiv \{\pi_{1c}, \pi_{2c}, \pi_{3c}, \lambda_{2c}, \lambda_{3c}, \theta_c\}$ separately for each CZ. But this would require large representative samples in each CZ with measures not only of parental and child income (observed in CHKS's data) but also of children's intermediate developmental outcomes s_{ic1} and s_{ic2}. No such samples are available. Instead, I focus on understanding the distribution of Ω_c across CZs, and in particular the covariance and correlation between θ_c and the other elements of Ω_c. As I show in Section 4, this is feasible with much smaller samples.

I consider several longitudinal samples. No single panel is long enough to contain measures of s_{ic1}, s_{ic2}, and y_{ic} for the same individual. The ELS panel, my primary focus, begins when children are in high school, allowing me to observe s_{ic2} and y_{ic} but not s_{ic1}. Thus, I cannot distinguish direct influences of parental income on s_{ic2} from those operating through s_{ic1} in this panel. Equation (6) can be modified to reflect this:

$$\theta_c = \lambda_{3c}\pi'_{2c} + \pi_{3c}, \qquad (7)$$

where

$$\pi'_{2c} \equiv \lambda_{2c}\pi_{1c} + \pi_{2c} \qquad (8)$$

is the reduced-form transmission of parental income to children's period-2 achievement.

CHKS measure the CZ-level transmission of parental income into college enrollment. In my framework, college enrollment can be seen as the post-schooling skill measure s_{ic2}, and

CHKS's college transmission coefficient is thus π'_{2c}. CHKS find that π'_{2c} is quite variable across CZs, just as is θ_c, and that the two are highly correlated ($\rho = 0.68$). However, a back-of-the-envelope calculation suggests that π'_{2c} is not large enough in magnitude to be an important mechanism for intergenerational income transmission. The standard deviation of π'_{2c} across CZs is 0.0011. In data from the American Community Survey, pooling all CZs, those with some college or more have incomes about 19.2 percentile points higher than those without college, on average. (I discuss the sample used for this calculation below.) Taking this as an estimate of λ_{3c}, the impact of period-2 achievement on adult income, a one standard deviation increase in π'_{2c} would drive only a 0.02 increase in θ_c, or less than one-third of a standard deviation. Thus, although CZs with high θ_c tend also to have above-average π'_{2c}, CHKS's estimates suggest that the key mechanisms must operate through π_{3c}. My more detailed analyses with richer intermediate skill measures, below, confirm this conclusion.

The ECLS sample begins with younger children and follows them through middle school. The early achievement measures here can be seen as s_{ic1} and the later measures approximate s_{ic2}, but I do not observe adult earnings for this sample. I thus consider the decomposition (8), and compare the relationship of income transmission θ_c to reduced-form transmission to later achievement, π'_{2c}, with the relationship between income transmission and transmission into earlier achievement, π_{1c}. Insofar as educational institutions are contributing to inequality of opportunity, one would expect $\pi'_{2c} > \pi_{1c}$ and $\frac{\partial\theta_c}{\partial\pi'_{2c}} > \frac{\partial\theta_c}{\partial\pi_{1c}}$. This tendency could be offset, however, by high rates of decay of early achievement (i.e., by low λ_{2c}). In this case, unequal schooling may serve only to maintain early achievement gaps, which would have disappeared as children age had the children of rich and poor parents attended equal quality schools.

2.2 Exploiting and interpreting cross-CZ variation

Bradbury et al. (2015) estimate a system of equations similar to (4a) and (4b) at the national level. They find that reduced-form achievement gaps are roughly stable across ages (i.e., that π_1 is of comparable magnitude to π'_2), but that there is a sizable income gap in later achievement conditional on earlier achievement (i.e., that π_2 is not small). These are both possible because λ_2 is relatively small – there is substantial mean reversion between earlier and later achievement. Bradbury et al. interpret the π_2 result as evidence that post-Kindergarten investments account for an important share of the intergenerational transmission of parental income to children's achievement.[6]

There are a number of complications with interpreting mobility measures computed from national samples. One is that the measured transmission of parental income to children's achievement is likely to be quite sensitive to the quality of the achievement measures. If, for example, a particular age-t measure is directly related to parental income conditional on the child's actual skill, this will lead decompositions like that outlined above to overstate the importance of parental investments prior to t and understate the importance of post-t investments. This is not just a theoretical possibility. Many standardized tests, for example the SAT college entrance test, have been found to load too strongly onto family background relative to their information about students' human capital (see, e.g., Rothstein, 2004). Another concern is that differences in the measurement properties of the data sources used to construct each of the elements of the decomposition may confound the analysis. For example, data sources may differ in the degree of measurement error in family income (Rothstein and Wozny, 2013) or in the scaling of intermediate child outcome measures (Jacob and Rothstein, 2016; Bond and Lang, 2013; Nielsen, 2015). Even simple measurement error could confound the Bradbury et al. (2015) analysis: Mismeasurement of s_{ic1} would lead to attenuation of λ_2 and upward bias in π_2. Comparisons across CZs, using the same data sources and measures for each, can reduce these problems. So long as systematic or random measurement error or scaling problems are constant across CZs, they are unlikely to have much impact on between-CZ differences in the transmission coefficients Ω_c.

CHKS assess the importance of institutions to the transmission of inequality by comparing θ_c across CZs with different observed institutions. As they acknowledge, this observational analysis may be misleading relative to the causal effects of the particular institutions examined. This is of particular concern because the dependent variable θ_c is so far removed from the channels by which the institutions (e.g., primary school quality) operate.

[6] Bradbury et al. (2015) also compare results across four English-speaking countries, but measures are sufficiently different across measures to complicate interpretation.

I do not attempt to measure institutional quality directly. Rather, I investigate whether CZs that have high θ_c – strong transmission of parental income to children's income – also tend to have high transmission into earlier outcomes, as measured by π_{1c} and $\pi_{2c}^{'}$. As I discuss below, the available data do not permit me to measure π_{1c} and $\pi_{2c}^{'}$ directly, but they do allow me to measure their associations with θ_c. I report correlations of θ_c with π_{1c} and $\pi_{2c}^{'}$, as well as with π_{3c} and λ_{3c}.

It is worth reiterating that these associations are only suggestive – if across CZs, institutions that promote high values of π_{1c} are associated with institutions that promote high values of $\pi_{2c}\lambda_{3c} + \pi_{3c}$, π_{1c} might appear to be strongly associated with θ_c even though the key channels for the transmission of inequality are via post-school-entry experiences. We saw an example of this above: Income transmission (θ_c) is reasonably strongly correlated with education transmission ($\pi_{2c}^{'}$) in the CHKS data, but the magnitude of the latter is too small to account for more than a small share of the former. In Section 7, I present a decomposition of θ_c into components reflecting end-of-school human capital (s_{ic2}), returns to human capital (λ_{3c}), earnings residuals (ϵ_{ic}), and non-labor and spousal income, accounting for both correlations and magnitudes.

3 Data

CHKS explore several dimensions of intergenerational income transmission. As noted, I focus on their "relative mobility" measure, the coefficient of a regression, using data from CZ c, of the adult income of children born between 1980 and 1982 (y_{ic}) on the income of their parents (p_{ic}). Children's income is measured for their families (so includes spousal earnings as well as non-labor income) and averaged over the years 2011 and 2012, when the children are between 29 and 32. Children are linked to parents who claimed them as dependents after 1996, and p_{ic} is the average family Adjusted Gross Income (plus tax-exempt interest and non-taxable Social Security benefits) for those parents between 1996 and 2000. Both children's and parents' incomes are converted to national percentile ranks in the relevant distribution. Column 1 of Table 1 presents unweighted summary statistics for the CZ-level mobility (transmission) measure. The average of 0.33 indicates that in the average CZ, each one percentile increase in parental income is associated with one-third of a percentile increase in children's income. In 71 CZs, however, θ_c is less than 0.24, indicating parent income-child income relationships about one-quarter weaker than the average, while another 78 CZs have $\theta_c > 0.40$, about one-quarter larger than average.

As discussed above, CHKS also compute measures of the association between parental income and children's college attendance. These are based on a regression like (1) above, except that the dependent variable equals 100 for those who attend any college between ages 18 and 21 and 0 for those who do not. Column 2 presents statistics for this college transmission measure; as noted above, this is correlated 0.68 with the income transmission measure.

In the appendix, I also show results for two alternative measures of income transmission, θ_c. One, from CHKS, is based on the 1983-85 birth cohorts. Children's incomes are measured in 2011 and 2012, when these cohorts are 26-29 years old, so may not be reliable indicators of children's eventual labor market positions. Nevertheless, this measure (summarized in column 3 of Table 1) is correlated 0.84 across CZs with the measure for the earlier cohorts. The second is Chetty and Hendren's (2015) more plausibly causal estimate of CZ-level income transmission, based on children who move across CZs at different ages. This is measured relative to the average CZ, so has mean zero by construction. It is based on somewhat small samples and is noisy. Nevertheless, it – summarized in column 4 of Table 1 – is correlated 0.85 with CHKS's preferred estimates and 0.89 with the estimates from the later cohorts.

3.1 Samples

To measure the transmission of parental income to children's pre-college educational outcomes, I need data that contain each. For this, I rely on three nationally representative, longitudinal surveys conducted by the National Center for Education Statistics (NCES). Each covers a different birth cohort and age range.

My primary results are based on the Educational Longitudinal Study (ELS). This is a sample of just over 19,000 10th graders in 2002, corresponding roughly to the 1985-1986 birth cohorts. Respondents were surveyed in 2002 (10th grade), 2004 (12th grade), 2006 (two years after normal high school graduation), and 2012 (eight years after, when respondents were roughly 26). Children are geocoded to commuting zones based on their residential zip codes in the base year, supplemented with later information if the base year zip code is missing. As child outcome measures, I use scores from math and reading assessments administered in the first two waves, college completion and educational attainment from the 2012 survey, and non-cognitive skill measures (discussed in Section 5.3) measured in the initial survey. For comparability with income measures, test scores are converted to percentiles.[7] I also construct children's adult income, y_{ic}, as their self-reported 2011 family income (including spousal earnings and non-labor income when present, as in CHKS's construct, and also converted to percentiles), when children were 25 or 26 years old.

To examine earlier childhood outcomes, I use the Early Childhood Longitudinal Study, Kindergarten Cohort (ECLS-K). This survey sampled kindergarteners in 1998-9 and followed them through 8th grade in 2007. Child outcomes are math and reading scores, again converted to percentiles.[8] Students are assigned to CZs based on their 8th grade residences.[9] I also present some results from a third survey, the High School Longitudinal Study (HSLS). This has a similar structure to the ELS but represents children born in roughly 1994-1995, nearly the same cohort that is represented in the ECLS.

There are four limitations of the available samples for my purposes. Most importantly, each of the surveys is a national sample of only 15,000 - 20,000 observations. With 741 CZs in the country, this amounts to well under 100 observations per CZ. The surveys each use multi-stage sampling designs, with schools as one stage and then relatively large samples of students within each school.[10] This means that within-CZ heterogeneity is even more limited than the small sample sizes imply. A consequence is that it is necessary to pool information

[7] The ELS test scores are point estimates of student proficiency from an Item Response Theory model. Measurement error does not bias student performance on the original IRT scale, but will tend to compress gaps between groups on the percentile scale (Jacob and Rothstein, 2016). This will attenuate my estimates of income-to-achievement transmission, but should not bias the between-CZ comparisons that are my primary interest.

[8] The appendix also presents results for several non-cognitive skill measures from the ECLS-K 5th grade survey and the ELS 10th grade survey.

[9] Where 8th grade residences are unavailable, I use the location of the 8th grade school, then the 5th grade residence and school, then 3rd grade, and so on.

[10] The regressions below account for CZ-level (or within-CZ) clustering, but do not otherwise adjust for the survey designs. Most of my estimates are unweighted, for reasons discussed below, but results are generally robust to using student-level sampling weights.

across CZs in order to obtain any precision at all about the relationship between parental income and later outcomes (Gelman and Hill, 2006). This limits what I can measure: As I discuss below, I can estimate the distribution of π_{1c} and $\tilde{\pi}_{2c}$ across CZs c, and their association with other CZ-level measures such as the CHKS relative mobility measure θ_c, but I cannot estimate each CZ's π_{1c} and $\tilde{\pi}_{2c}$ separately.

Second, none of the available surveys provides outcomes across the full range of ages, ranging from Kindergarten through labor market entry. Thus, mapping out the age profile of student outcomes requires comparing ECLS and ELS results for different students. It is not possible to measure directly the impact of parental income on later achievement, controlling for earlier achievement (i.e., π_2 in equation (4b)).

Third, the samples represent different birth cohorts. CHKS compute relative economic mobility measures for children born in 1980-1982 and 1983-85; as noted above, they are very highly correlated. The latter measures are for nearly the same cohorts represented in the ELS, but the ECLS represents a later cohort, born around 1992-1993. My primary results use CHKS's income transmission measures for the 1980-1982 birth cohorts, though the appendix shows that results are nearly identical with other measures. To check whether differences between ELS-based results for older children and ECLS-based results for younger children are due to cohort rather than age differences,[11] I use the HSLS. I show that results for later-grade test scores are very similar for the ELS and for the HSLS, suggesting that cohort differences are not major contributors to any differences seen between ECLS early-grade and ELS later-grade results.

Finally, the parental income measures in the NCES surveys are extremely limited. In the ELS, parents report total family income in the base-year survey. This question is not asked in subsequent waves, so I cannot average over multiple years to better approximate the family's permanent income (Rothstein and Wozny, 2013; Mazumder, 2005) as in CHKS. Moreover, the parental income variable is binned into 13 categories. I assign each category to the midpoint of the national percentile range it represents. Measurement error in parental income likely attenuates the average relationship with child outcomes, but is not expected

[11] Chetty et al. (2014) find that national aggregate relative mobility has been quite stable across a range of birth cohorts (born 1971-1993), but CZ-level measures might in principle vary across cohorts with little variation in the national aggregate. See also Aaronson and Mazumder (2008).

to bias comparisons of this relationship across CZs. To address the average attenuation, I explore specifications that use predicted parental income based on parental education, occupation, and family structure. These in effect use the parents' other characteristics as instruments for their incomes, addressing measurement error concerns but imposing the assumption that parental education affects children's outcomes only through family income.

Parental income reporting is somewhat better in the ECLS and HSLS. ECLS parents were asked their family incomes three separate times, in Kindergarten, 1st grade, and 3rd grade, and the Kindergarted response is reported continuously (the 1st and 3rd grade responses again reported in 13 bins). I assign the bin midpoints for the 1st and 3rd grade surveys, average across the three waves, and construct percentiles of the distribution of averages. In the HSLS, family income is reported in each of the first two survey rounds, without binning. I average these and construct percentiles.

Summary statistics for the three ECLS samples are reported in Table 2. Summary statistics are not reported for children's test scores – all analyses here convert each to a percentile within the relevant sample, with mean 50.0 and standard deviation 28.9 by construction.

In addition to the NCES samples, I also present some results on the returns to education. These use American Community Survey (ACS) data. For maximum comparability with CHKS's measures, I use the 2010, 2011, and 2012 one-year public use microdata samples, and focus on the 253,852 individuals in these samples born between 1980 and 1982. For these individuals, I observe completed education as well as individual earnings and family income (but not parental income). Following CHKS, I convert family income to a national percentile within the ACS sample distribution. I do not have information about where respondents lived as children, so I assign them to the CZ where they live at the time of the survey.

3.2 National estimates

Figure 2 shows how average outcomes vary across the income bins in the ELS sample. Panel A shows the child's family income in 2011, when children were around age 25. Following CHKS, both parental and child income are scaled in national percentiles. As in CHKS's data, the percentile-percentile scatterplot is roughly linear, though there is some evidence of nonlinearity at the lowest parental incomes.[12]

Panel B repeats this exercise, using children's earnings but not their non-labor or spousal income. This is much closer to linear: Children from the lowest-income families reach the 40th percentile of the national earnings distribution, on average, while those from the highest-income families reach the 60th percentile. Panel C shows children's 12th grade math scores, again scaled as percentiles, while Panel D shows the average education, in years, of children from each parental income category. Panel C in particular shows some sign that the percentile-percentile relationship may not be perfectly linear. I nevertheless focus on linear models, though I explore specifications that re-scale parental income to ensure a linear relationship.

Table 3 presents preliminary estimates of the (linear) national relationship between each of my primary outcome measures and parental income. These estimates are likely attenuated due to measurement error in parents' incomes, with an attenuation factor that is constant within surveys but may vary across them. I discuss this further below.

The first rows present results for math and reading scores in grades Kindergarten through 8 from the ECLS. Each percentile increase in parental income is associated with an increase in Kindergarten scores of 0.41 percentiles in math and 0.37 percentiles in reading. Each of these is essentially unchanged when CZ fixed effects are added, in columns 2 and 5. Coefficients rise very slightly as students age; by 3rd grade, the coefficients are 0.44 and 0.45, and they do not change further between then and the end of the ECLS panel in 8th grade. The next rows present results for grades 9 and 11 from the HSLS, which has only math scores. Coefficients are smaller here than in the ECLS. Next, I show results from the ELS, first for test scores in grades 10 and 12 (math only) and then for non-test outcomes. Test score coefficients are quite similar to those from the HSLS, indicating that each parental income percentile is associated with 0.35 - 0.38 test score percentiles, with a somewhat smaller within-CZ relationship. Each parental income percentile is associated with increases in college enrollment and completion of 0.26 and 0.49 percentage points, respectively, and

[12]The plot uses a small "x" to indicate the 0.2 percent of respondents with reported parental incomes of zero. The plot suggests that these might best be thought of as missing parental income, as average child income is much higher than among families with small but positive reported parental income.

with an additional 0.02 years of education on average. It is also associated with an additional 0.18 percentiles of children's income at age 25-26. CHKS plot estimates of this coefficient, measuring children's income at various ages, in their Figure IIIA. Their coefficient is around 0.23 when children's income is measured at age 25, and rises to 0.33 at ages 29-32, the years used to compute their transmission measure.

4 Empirical framework: A random coefficients (mixed effects) model

The quantities of interest in my investigation are the role of children's developmental outcomes, s_{ic1} and s_{ic2}, in mediating the transmission of parental income p_{ic} to children's income y_{ic}. A traditional mediation analysis would include s_{ic1} and/or s_{ic2} as controls in the basic intergenerational transmission regression (1). But these permit only a national-level mediation analysis[13]; no existing samples contain all three of p_{ic}, y_{ic}, and s_{ic2} and provide large enough samples to permit CZ-level estimation of (4c).

A fallback approach might be to estimate the decomposition (6). This would require CZ-level measures of each of the components of Ω_c, potentially from different samples. Even this is not possible, however, as there is no sample containing useful measures of child skills and parental income that is large enough to permit this.

Instead, I set my sights on a more achievable target, regressions of income transmission θ_c on measures of transmission of parental income to earlier outcomes (i.e., on the various π_c coefficients). A sufficient statistic for these regressions is the variance-covariance matrix of Ω_c. The elements of this matrix are for the most part obtainable. Specifically, simple empirical models applied to the available NCES samples identify the "reverse" regressions of the π_cs on θ_c. The coefficients and residual variances of these regressions, each of which is identified, can then be used to infer $V(\Omega_c)$ and, in turn, the correlations of θ_c with the other transmission coefficients.

Consider the transmission of parental income into some child developmental outcome

[13] At the national level, adding controls for educational attainment and 12th grade math scores to the child income specification from Table 4, column 1, reduces the parental income coefficient from 0.18 to 0.07, indicating that a bit over half of income transmission is mediated by human capital.

w_{ic}:

$$w_{ic} = \kappa_c + p_{ic}\pi_c + u_{ic}. \tag{9}$$

For example, when the child outcome is the test score at school entry, this is equation (4a). Now consider the "reverse" projection of π_c, the transmission of parental income to the child's outcome, onto the intergenerational income transmission coefficient θ_c:

$$\pi_c = \gamma + \theta_c\beta + \eta_c, \tag{10}$$

where $\beta = {}^{cov(\theta_c,\pi_c)}/_{V(\theta_c)}$ is the across-CZ linear projection coefficient and η_c is orthogonal to θ_c. (I focus on identifying observational relationships; I do not give β a causal interpretation.) If the terms of (10) were known, it would be straightforward to obtain the regression of θ_c on π_c:

$$\frac{cov\left(\theta_c, \pi_c\right)}{V\left(\pi_c\right)} = \frac{cov\left(\theta_c, \pi_c\right)}{V\left(\theta_c\right)}\frac{V\left(\theta_c\right)}{V\left(\pi_c\right)} = \beta\frac{V\left(\theta_c\right)}{V\left(\theta_c\right)\beta^2 + \sigma_\eta^2}. \tag{11}$$

To obtain these terms, substitute (10) into (9). We obtain

$$w_{ic} = \kappa_c + p_{ic}\left(\gamma + \theta_c\beta + \eta_c\right) + u_{ic} \tag{12}$$

I estimate three types of regressions based on (12). First, Table 3, above, presented national regressions of children's outcomes on p_{ic}. These can be seen as restrictions on (12), with β and η_c each constrained to zero. Second, I estimate simple regressions of s_{ic1} on p_{ic} and its interaction with θ_c (which, recall, is measured with high precision by CHKS):

$$w_{ic} = \kappa_c + p_{ic}\gamma + \left(p_{ic}\theta_c\right)\beta + e_{ic}, \tag{13}$$

where the error term is $e_{ic} \equiv p_{ic}\eta_c + u_{ic}$ and standard errors account for clustering at the CZ level. (I explore various specifications for the CZ-level effect κ_c, and find that OLS, random effects, and fixed effects specifications are all quite similar.) The interaction coefficient identifies the projection slope β; failure to account for η_c sacrifices efficiency but does not bias this coefficient.

In order to compute $V\left(\pi_c\right)$ and thus the correlation between π_c and θ_c, we need not just

β but also $\sigma_\eta^2 \equiv V(\eta_c)$. (Because θ_c is observed, it is straightforward to compute $V(\theta_c)$ and thus to recover from β an estimate of the covariance between θ_c and π_c.) Thus, my third specification models the role of η_c directly. With the assumption that (κ_c, η_c) and u_{ic} are each normally distributed and i.i.d., (12) can be seen as a random coefficients model (also known as a "mixed" model, with fixed parameters γ and β and random effects variance-covariance matrix $V(\kappa_c, \eta_c)$), and can be estimated by maximum likelihood.[14] Common implementations of mixed models impose restrictions on the covariance between κ_c and η_c, but this is not necessary for identification. Identification does require, however, that we assume that κ_c and η_c are orthogonal to both θ_c and the CZ-level average of p_{ic}. This assumption is the same as the caveat mentioned above: I can identify the observational regression of π_c on θ_c (and vice versa), but have no basis for the exclusion restriction that would be needed to interpret either as causal.

There is no fully satisfactory way to handle sampling weights in mixed models. Accordingly, I estimate these models without weights. Fortunately, when I estimate simpler models (e.g., fixed effects models without random coefficients), estimates are nearly identical with and without weights, so this limitation is not likely to dramatically affect my results.

The CZ-specific intercept κ_c is a nuisance parameter, as my primary interest is the within-CZ relationship with parental income and how this varies across CZs. It is not computationally feasible to absorb κ_c via CZ fixed effects in the mixed model specifications, so it is included as a random effect. To ensure that any misspecification of this parameter does not influence the coefficients of primary interest, I divide p_{ic} into its CZ-level mean $\bar{p}_c$ and its deviation from that, $p_{ic} - \bar{p}_c$. It is the latter, which by construction is orthogonal to κ_c, that is allowed to interact with θ_c and to have a random coefficient in (12); a main effect for $\bar{p}_c$ is included, but it is not interacted with θ_c. Similarly, I de-mean θ_c before interacting with $p_{ic} - \bar{p}_c$ to permit interpretation of the $p_{ic} - \bar{p}_c$ main effect coefficient as reflecting the

[14] Gelman and Hill (2006) discuss the estimation of models like this, which are referred to variously as mixed, hierarchical, random coefficient, or multi-level models. In economics, it is common to estimate models like (12) in two steps: First, w_{ic} is regressed on p_i separately for each CZ c, to estimate π_c, and the resulting coefficients are then regressed on θ_c in a second step. This approach is unsuitable when the samples in each CZ are so small; mixed model methods obtain much better precision by pooling information from across CZs.

relationship in the average CZ.[15] The full mixed model is thus:

$$w_{ic} = \kappa_c + \bar{p}_c\phi + (p_{ic} - \bar{p}_c)\,\gamma + \left(\theta_c - \bar{\theta}\right)\delta + (p_{ic} - \bar{p}_c)\left(\theta_c - \bar{\theta}\right)\beta + (p_{ic} - \bar{p}_c)\,\eta_c + u_{ic}, \quad (14)$$

with ϕ, γ, δ, and β treated as fixed coefficients and κ_c and η_c as random. Standard errors are clustered at the CZ level. Of interest are β and σ_η, as these can be used to compute π_c.

4.1 Validating the method

Recall that my primary transmission measure is CHKS's relative mobility, the slope of child income with respect to parental income (measuring each in percentiles) in the CZ as measured in tax data. One way to validate my approach, as well as the use of the ELS data to extend CHKS's analyses of tax data, is to assess whether θ_c accurately captures the corresponding child income-parent income slopes in the ELS. Toward this end, Table 4 presents a number of analyses of intergenerational income transmission in the ELS. Column 1 repeats the specification from the final row of Table 3, without fixed effects. Column 2 separates parental income into the CZ-level sample mean and the deviation from that. The coefficient on the former is about double that of the latter. As I discuss below, this is likely a reflection of measurement error in parental income, which attenuates the within-CZ coefficient much more than the between-CZ coefficient.[16] Column 3 shows that each coefficient is robust to including CZ random effects.

Columns 4-7 explore heterogeneity in the within-CZ parental income coefficient. In column 4 I add an interaction with the CHKS income transmission measure. The interaction coefficient, 0.63, indicates that the ELS estimate of parental income - child income transmission is higher in CZs that CHKS estimate have higher parent-child income transmission, as expected. However, we can quite clearly rule out the null hypothesis that income transmission in the ELS is the same as in the CHKS tax data, which corresponds to a coefficient

[15] θ_c is de-meaned in the full sample of CZs, weighting each by its year-2000 population. Its mean in the regression samples differs slightly from zero.

[16] I have also estimated specifications that further decompose the deviation of parental income from the CZ mean into the deviation from the *school* mean and the difference between school and CZ means. The across-CZ and within-CZ, across-school coefficients are indistinguishable, and the within-school coefficient is much smaller. This is exactly what one would expect based on measurement error, but could also derive from sorting into schools based on unobservables or school-based peer effects.

of $\beta = 1$ on the income-θ_c interaction. (Recall that θ_c is defined as the slope of child income with respect to parent income in the CZ.) I return to this below.

Column 5 adds CZ fixed effects (and brings back sampling weights). I can no longer estimate ϕ, but the within-CZ parental income coefficient γ and its interaction β are the same as in column 4. Column 6 returns to the unweighted random effects specification but adds a random coefficient on parental income, allowing its coefficient to vary not just with CHKS's income transmission measure but also independently as in (14). The standard deviation of the random component of this coefficient is very small, just 0.01. A likelihood ratio test does not reject the hypothesis that $\sigma_\eta = 0$.[17] The lower part of the table shows the implied across-CZ standard deviation of $\pi_c = \theta_c\beta + \eta_c$, 0.038. 95% of the variation in π_c derives from the fixed component $\theta_c\beta$. Equivalently, the across-CZ return to parental income is correlated 0.97 with CHKS's transmission measure.

This high correlation is not surprising, of course, since θ_c is *defined* as the return to parental income in children's income, and the π_c obtained from the ELS sample differs from this only because the income measures and cohorts differ slightly. Thus, the high correlation serves to validate the use of the ELS sample for this exercise. However, the small coefficient β, 0.65 in Column 6 and similar in earlier columns, remains a concern. If the ELS and tax measures were perfectly comparable, this coefficient should equal one, a hypothesis that I can decisively reject.

One potential explanation for the smaller coefficient is that the ELS parental income measure is from only a single year and is reported in bins, so likely measures parents' permanent income with error. CHKS use a five-year average for their parental income measure, and the ELS coefficient may be attenuated relative to what would be obtained with a better income measure. To assess this, in Column 7 I replace the parental income percentile with a predicted percentile. This is obtained by regressing the measured parent income percentile on indicators for maternal education and occupation, for the presence of the father, and for paternal education and occupation when available, then taking the predicted values. This predicted percentile can be seen as an unbiased predictor of parents' permanent

[17] The null hypothesis that $\sigma_\eta = 0$ is on the boundary of the parameter space for the likelihood function, which is defined in terms of $\ln(\sigma_\eta)$. As a consequence, a Wald test cannot be used to test this null. The likelihood ratio test is based on the comparison of the fitted likelihoods of the models in columns 6 and 4.

income. When it is used in the mixed model specification, the interaction coefficient grows notably, with $\hat{\beta} = 1.46$ (SE 0.27).[18] I cannot reject the hypothesis that $\beta = 1$. Although I now reject the null hypothesis that $\sigma_\eta = 0$, the correlation between π_c and θ_c remains very strong.

Overall, this specification supports the view that analyses using the ELS parental income measure, without adjustment, are likely to yield attenuated estimates of π_c, but also that the parental income-child income relationship is essentially the same in the ELS as in CHKS's tax data once the measurement error in parental income is corrected. In most of the analyses below, I return to using the reported parental income, recognizing that the π_c coefficients will be attenuated by between one-third and one-half, though the appendix reports alternative estimates that use predicted parental income instead and the qualitative results are unchanged.[19]

I next turn to exploring a different aspect of the method, the measurement of children's income. In Table 4, I follow CHKS in focusing on children's family income, inclusive of spousal earnings and any non-labor income. However, for my investigation of educational outcomes as mediators of the parental income-child income relationship, it is important to understand the extent to which this relationship derives from differences in childrens' own earnings vs. differences in spousal earnings or unearned income. To explore this, in Table 5 I present a number of specifications parallel to that in Table 4, Column 7, but varying the measure of children's income. Column 1 repeats the earlier estimates for reference. Columns 2 and 3 present linear probability models for the child's marital status (column 2) or for the presence of a *working* spouse (column 3). In order to scale coefficients comparably to column 1, in these columns the dependent variable is set to 0 for those who are unmarried or who (in column 3) have a non-working spouse, and to 100 for others. Parental income is significantly more strongly associated with marriage and with the presence of spousal earnings in high-θ_c CZs than in low-θ_c CZs, though there is also independent across-CZ variation (i.e., $\sigma_\eta \neq 0$).

Columns 4-6 return to models for child income, using different income measures. In

[18] This can be seen as an IV specification, with parental education and occupation as instruments for parental income. Standard errors in Column 7 do not account for the estimation of the first-stage coefficients, however.

[19] This accords with other evidence that a single year's income has reliability around 0.5 as an estimate of permanent income. See, e.g., Rothstein and Wozny (2013).

column 4, only the child's own earnings are included. For comparability, this is scaled in terms of percentiles of the children's *family* income distribution, just as in column 1. Thus, a child with median earnings ($22,000 in the ELS sample) is assigned a percentile of 38, as $22,000 is the 38th percentile of the family income distribution used in column 1. The key interaction coefficient is about one-third smaller here than in column 1, suggesting that a substantial portion of the across-CZ variation in income transmission operates through channels other than the child's own earnings. Column 2 adds non-labor income for the child's family, again scaled as a percentile of the child total family income distribution. This brings the β coefficient up a bit, from 0.87 to 0.94, but it remains much less than the 1.46 in column 1. Evidently, spousal earnings are an important factor. This could reflect variation across CZs in the relative likelihood that children from high- and low-income families have working spouses, but it could also reflect differences in spousal earnings distributions conditional on work, as would occur if CZs vary in the degree of assortative mating. Column 6 offers one way to assess this. I compute the average earnings across the entire sample for working spouses, by gender – $27,000 for women and $41,000 for men – and assign this to every working spouse in the sample. The dependent variable in this column is constructed from the sum of the child's actual earnings, any non-labor income, and the imputed spousal income, set to the average for those with working spouses and to zero for those without. As before, this sum is converted to a percentile of the actual child family income distribution. Here, the β coefficient is substantially increased, 1.53. Thus, the difference between results for total family income and those based on childrens' own earnings and non-labor income is primarily due to differences (across parental income and across CZs) in the propensity to have a working spouse, not in the spousal earnings distribution conditional on work.[20]

In the investigation below, I examine transmission of parental income into children's educational outcomes, then variation across CZs in the returns to education. Part of the return to education may come through differences in the likelihood of having a working spouse, and Table 5 indicates that there may be important differences across CZs in this component of the return. I explore decompositions that account for this in Section 7.

[20] Appendix Table A7 reports estimates of these specification separately by child gender. Interestingly, the parental income main effects are quite different, but the β coefficients are quite similar for men and women.

5 Results: The transmission of parental income to children's human capital outcomes across CZs

This section contains the main results for the paper, examining the association across CZs between CHKS's parent income-child income transmission measure (θ_c) and measures from the ELS, ECLS, and HSLS of the transmission from parental income to children's human capital outcomes (π_c). I begin by examining students' test scores, then consider educational attainment and the return to education.

5.1 Transmission to children's test scores

Table 6 presents estimates of equation (14), using the ELS sample and the 12th grade math score as the dependent variable. As in the earlier analysis of child incomes, I scale test scores as percentiles in the ELS distribution; here, I return to the self-reported, noisy parental income measure rather than predicted parental income used in Table 5. Column 1 indicates that on average, each percentile of parental income is associated with about 0.38 percentiles of children's math scores. Columns 2 and 3 separate this into within- and between-CZ components. The within-CZ coefficient is 0.35 or 0.34, but the between-CZ coefficient is a fair amount larger. (As before, there is little distinction between between-CZ and within-CZ, across-school variation, but the association between income and achievement is only about half as strong within schools as between.) When I interact family income with CZ-level income transmission, in column 4 (random effects) and column 5 (fixed effects), the coefficients are 0.37 and 0.32, respectively. These are comparable in magnitude to the parental income main effect. Recall that in the analysis of child income in Table 4, the interaction coefficient was roughly quadruple the main effect.

Column 6 presents the mixed model. Here, the variance of the random component of the income coefficient is quite large, accounting for 90% of the total variance of π_c, and I can decisively reject the null hypothesis of $\sigma_\eta = 0$. The correlation between income-test score transmission π_c and income-income transmission θ_c is only 0.32. This is hard to reconcile with the hypothesis that test scores, or the knowledge and skill that they represent, are a key mechanism determining intergenerational income transmission, since there is evidently substantial variation in test score outcomes across CZs that does not translate into corresponding variation in income transmission. I explore this argument more formally below, in Section 7.

Table 7 presents mixed model estimates for each of the available test scores from the ECLS, ELS, and HSLS. The β coefficients in column 2 are comparable in magnitude across most of the specifications, though imprecisely estimated. The random component of the parental income coefficient (σ_η, in column 3) is meaningful in each specification, and column 6 indicates that the null hypothesis that $\sigma_\eta = 0$ is rejected in all but one case. This random component accounts for at least 80% of the overall variance of π_c (column 5).

The pattern of results has several implications. First, there is some indication from the β estimates (column 2) that the relative importance of parental income to student test scores in high-income-transmission CZs grows between kindergarten and high school, consistent with the hypothesis that differential access to school quality is a mechanism contributing to differential income transmission. This is based largely on the ECLS kindergarten and first grade results, however; there is much less evidence that coefficients rise after third grade. Moreover, even the post-kindergarten growth in these coefficients is quite small. Second, there is substantial heterogeneity across CZs in the transmission of parental income to children's test scores that is not associated with CZ-level income transmission (column 3), indicating that the institutions or other CZ characteristics that contribute to test score transmission differ from those determining income transmission. Put somewhat differently, there is only a weak correlation across CZs between income-income and income-test score transmission (column 5), so different influences must be at work. Finally, results are quite similar for the HSLS as for the ELS, suggesting that cohort differences are unable to explain the weak relationship of income-income and income-test score transmission in the HSLS and ECLS.

5.2 Transmission to children's educational attainment

Table 8 presents results from specifications like those in Table 6, except this time using measures of children's eventual educational attainment – an indicator for any college, an indicator for college graduation, and the number of years of education by age 26 – in place of test scores. The first measure corresponds to CHKS's analysis, while the other two are more conventional measures. Not surprisingly, parental income is strongly related to all three measures of children's attainment. The interaction coefficient β is substantial and statistically significant for college graduation and years of education, but is negative (though insignificant) in the models for any college.

Even numbered columns present the mixed model specification. A likelihood ratio test rejects the null hypothesis that the parental income random coefficient is zero (i.e., $\sigma_\eta = 0$) for the college attendance indicator but not for the other two outcomes. Even for these outcomes, however, point estimates indicate that three-quarters of the across-CZ variation in π is attributable to this random component rather than to CHKS's income transmission measure. (For the college attendance indicator, essentially all of the variation comes from the random coefficient.) As in the earlier analysis of test scores, the evidence does not point to a strong role for educational attainment as a mechanism driving variation in intergenerational income transmission.

It is not clear how to account for the particularly weak results in columns 1-2, where the dependent variable is an indicator for some college or more. This is the only attainment construct that CHKS were able to measure in their tax data, and they found that the transmission of parental income to children's college enrollment (π_c in my notation) was highly positively correlated ($\rho = 0.68$) with income-to-income transmission. To explore this further, Appendix Table A1 repeats the analysis in Table 8, this time using the CHKS parental income to college enrollment transmission measure in place of their income-to-income transmission measure. With this switch, the β coefficient becomes positive and statistically significant even for college enrollment. But the relationship remains quite weak, with a coefficient far below the value ($\beta = 1$) we would expect under the null hypothesis that income-to-college transmission is identical in the ELS as in the tax data. Moreover, each of the other educational attainment measures is much more strongly related to CHKS's college transmission measure than is the simple college enrollment indicator. The most straightforward explanation seems to be that CHKS's measure, which is based on the payment of tuition at any college on a student's behalf, is capturing a different phenomenon than are traditional survey-based measures of college enrollment, based on respondents reporting some educational attainment (including attendance at college without a degree) beyond high school.[21]

Returning to the results for years of completed education, it is worth considering the magnitude of the effects in Table 8 via a calculation like that in Section 2.1. In the ACS sample described above, each additional year of education is associated with an additional 4.1 percentiles of children's family income.[22] Column 6 of Table 8 indicates that the standard deviation across CZs of the parental income coefficient in a model for children's educational attainment (i.e., σ_{π_2}) is 0.0026. Thus, a one standard deviation increase in π_{2c} would be expected to generate an increase in θ_c of 0.0026*4.1 = 0.01 operating through educational attainment. This is under one-sixth of a standard deviation of θ_c. Moreover, this calculation uses the total variation in the parental income coefficient (π_{2c}), not just the part that is collinear with income transmission ($\theta_c\beta$). A one-standard deviation increase in the latter is only 0.0013. This implies that differences in the transmission of parental education into educational attainment can account for less than one-twelfth of the variation (in standard deviation terms) across CZs in income transmission.

5.3 Robustness and additional results

The results above indicate that CZs in which the transmission of parental income to children's income is stronger tend not to be CZs in which there is strong transmission of parental income to children's test scores, either early or late in schooling careers. They are, on average, CZs with stronger transmission of parental income into children's educational attainment, but even here the relationship is not very strong.

Appendix Table A2 explores the sensitivity of these results to the choice of an income transmission measure. It presents mixed model specifications for three outcomes – child income, 12th grade math scores, and years of education. In columns 1, 4, and 7, the

[21] Note that the ELS sample reports a surprisingly high college enrollment rate – 84% of the sample reports some postsecondary attendance or degree by age 26, where CHKS identify only 59% of their sample as having attended college (using a somewhat different definition) by age 21. In ACS data, 58% have some college or more, with 17% having some college but no degree. A possible, partial explanation is that some of the ELS respondents attend institutions not captured by the CHKS data. Fully 31% of the ELS sample reports "Some PS attendance, no PS credential," the lowest category that I count as college enrollment.

[22] This rises to 5.9 when very low and very high values of attainment are trimmed. This would have little effect on the calculation here.

transmission measure is CHKS's preferred measure for the 1980-82 birth cohorts, as in the results above. In columns 2, 5, and 8, CHKS's alternative measure for the 1983-85 birth cohorts is used, while in columns 3, 6, and 9 the more plausibly causal measure from Chetty and Hendren (2015) are used. Results are quite similar across measures: I find that all three measures of θ_c from tax data are strongly correlated with the θ_c from the ELS data, weakly correlated with π_{2c} when the educational outcome is the 12th grade math score, and more strongly correlated when the outcome is educational attainment. The sole exception is the educational attainment model based on the Chetty-Hendren transmission measure, where the correlation is somewhat weaker but I cannot reject a perfect correlation.

CHKS document that their income transmission (relative mobility) measure is quite strongly correlated with the fraction black in the CZ. Although they also find that an alternative measure computed solely from zip codes with very few black residents is quite similar, this nevertheless raises the possibility that race is an important confounding factor. In Appendix Table A3, I add to the main mixed model specifications controls for the child's own race and gender, as well as interactions of race and gender with θ_c. This weakens the income transmission and test score transmission results (such as they were), but has little effect on the educational attainment results. There is absolutely no indication that failure to account for race or gender in my earlier specifications has led me to understate the role of educational achievement in income transmission.

Another concern, raised by Figure 2, above, is that my linear mixed model specification misspecifies the relationship between parental income and children's outcomes, particularly test scores. To address this, I rescale parental income as $\tilde{p}_{ic} \equiv E\left[s_{ic2}|p_{ic}\right]$, where s_{ic2} is the child's 12th grade test score. This ensures that $E\left[s_{ic2}|\tilde{p}_{ic}\right]$ is linear in $\tilde{p}_{ic}$. (This could also be accomplished by rescaling s_{ic2}, but as there is not a unique scaling that would accomplish this I do not pursue it.) As Figure 2 indicates, the transformation from p_{ic} to $\tilde{p}_{ic}$ somewhat compresses the lower middle of the parental income distribution (around the 15th-20th percentiles) relative to the tails. Appendix Table A4 reproduces Table 6 using the new parental income measure. The rescaling of course changes the scale of the parental income coefficients, but does little to the relative magnitude of the interaction coefficient β and does not alter the substantive conclusion that income transmission is not strongly related to test score transmission. Appendix Table A5 uses predicted parental income (on the original scaling), as in Table 4, column 7, for the main specifications. This does not change the qualitative results for educational achievement or attainment.

Overall, the basic results on achievement, attainment, and income transmission appear quite robust. They are suggestive that learning in school is not a key channel determining the across-CZ variation in income transmission, but that access to higher education may be more important.

One possibility not yet considered is that elementary and secondary schools do matter, but that math and reading test scores do not capture their impacts. A growing literature in recent years has documented the importance of non-cognitive skills as a component of the learning process. Both the ECLS and the ELS contain batteries of questions aimed at identifying children's non-cognitive skills, and I use these to assess whether high-income-transmission CZs tend to be CZs with large gaps in non-cognitive skills between children from high- and low-income families. Appendix Table A6 presents specifications for non-cognitive skill outcomes measured in the ELS 10th grade survey (Panel A) and the ECLS 5th grade survey (Panel B), each converted to z-scores. Unfortunately, measures differ somewhat across surveys. For about half of the measures, there is statistically significant variation across CZs in the return to parental income (i.e., $\sigma_\eta \neq 0$), and the random component (η_c) generally accounts for nearly all of the across-CZ variation. The β coefficient on the parental income - CZ income transmission interaction is generally small and not statistically significant, and frequently has the wrong sign. Overall, there is little indication that non-cognitive skills are important mediators of income-to-income transmission. Panel C, however, tells a somewhat different story. Like Panel B, this is based on the ECLS 5th grade wave, but in this case the outcome variables derive from teachers' reports of children's non-cognitive skills rather than from the children's own responses. For these measures, there is evidence of parental income-CZ income transmission interactions (i.e., of $\beta \neq 0$), which account for more of the overall variation in π_c. It is not clear how to account for the discrepancy between these results and those from the student self-reports in Panel B – even when the concepts overlap (e.g., for externalizing problem behaviors), results are quite different. This may indicate that high-transmission CZs tend to be CZs in which teachers are more biased in their assessments of low-income children, but this is quite speculative.

6 Results: Returns to education

The above results have concerned the role of skills – achievement, attainment, and non-cognitive skills – as mediators of the intergenerational transmission of income. In terms of Figure 1, the results suggest that π_{1c} and π_{2c} are not primary mechanisms influencing reduced-form transmission θ_c. This in turn implies that much of the variation in income transmission must be due to direct effects of parental income on children's income, controlling for human capital (i.e., to π_{3c}), or to differences in the *returns* to human capital (i.e., in λ_{3c}).

To investigate this, I turn to the ACS samples of 28-32 year olds surveyed in 2010-2012. As before, I estimate mixed models, in this case allowing the return to education (specified as percentiles of income per year of completed education) to vary both with the CHKS income transmission measure and independently across CZs.

Results are presented in Table 9. Column 1 shows that each year of education is associated with 4.1 percentiles of family income. Column 2 shows that this association is a bit smaller within CZs, 3.9, and this is not much affected by the inclusion of random effects (column 3) or fixed effects (column 5). Column 4 presents a simple interacted model with CZ random effects but fixed coefficients. It indicates that the return to education is larger in high-income-transmission CZs – the interaction coefficient is comparable in magnitude to the income main effects (though recall that the transmission measure has standard deviation 0.065, so most CZs have returns to education within about 10% of the average shown in columns 1-2). Column 6 presents the mixed model. There is also substantial, statistically significant variation across CZs in the return to education conditional on the CHKS income transmission measure, which accounts for less than one-quarter of the total across-CZ variation in λ_{3c}. The overall variability in returns to education across CZs (i.e., in λ_{3c}) is substantial, with a coefficient of variation of 16%.

7 Decomposing the variation in CZ-level income-income transmission

The results thus far indicate that CZs with relatively strong intergenerational income transmission tend to have stronger relationships between parental income and children's educational attainment, only slightly stronger associations between parental income and children's test scores, and higher returns to education. Some preliminary calculations indicate that the educational attainment relationships are not large enough to be primary channels in overall income transmission, but I have not yet quantified the contributions of the test score or returns to education effects. In this section, I explore decompositions of the across-CZ variation in the income-income relationship. I begin with three components: (a) children's skill accumulation by the end of school; (b) returns to skills; and (c) relationships between parents' incomes and the component of children's incomes that is not attributable to observed human capital. I then consider a second decomposition separates out a fourth component corresponding to non-labor income and spousal earnings.

Suppose that z_{ic} is a scalar measure of the human capital of child i from CZ c. We can project children's incomes onto this separately for each CZ:

$$y_{ic} = z_{ic}\psi_c + \nu_{ic}, \tag{15}$$

where ψ_c is the return to human capital in CZ c and ν_{ic} is the income residual. Thus, the relationship between children's incomes and parents' incomes in CZ c is:

$$\frac{dy_{ic}}{dp_{ic}} = \frac{\partial z_{ic}}{\partial p_{ic}}\psi_c + \frac{\partial \nu_{ic}}{\partial p_{ic}}. \tag{16}$$

This is the definition of θ_c, the income transmission measure. I label it θ_c^{ELS} to indicate that this relationship may differ somewhat based on the sample used to compute it. Now consider how this varies with the CHKS transmission measure, θ_c:

$$\frac{d\theta_c^{ELS}}{d\theta_c} = \frac{d^2 y_{ic}}{dp_{ic}d\theta_c} = \frac{\partial^2 z_{ic}}{\partial p_{ic}\partial\theta_c}\psi_c + \frac{\partial z_{ic}}{\partial p_{ic}}\frac{\partial \psi_c}{\partial \theta_c} + \frac{\partial^2 \nu_{ic}}{\partial p_{ic}\partial\theta_c}. \tag{17}$$

The left side of this equation was estimated in column 6 of Table 4 as 0.65. (Recall that this is attenuated due to measurement error in the ELS parental income variable.) The right side has three components. The first term represents variation in human capital accumulation gaps between high- and low-income families. This might occur, for example, if high-θ_c CZs offer less equal school quality to children from different family backgrounds. The analysis in Section 5 concerned this component. The second term in (17) reflects covariance of the CZ-level return to skill with CZ-level income transmission, scaled by the overall average difference in skill accumulation between high- and low-income families. For example, high-θ_c CZs may have fewer unions or just a more unequal income distribution, generating a higher return to skill and thus producing better outcomes for children from high-income families. This component was the focus of Section 6. The third term reflects differences in the transmission of parental income to children's incomes holding skills constant. This might be large if high-θ_c CZs have more stratified labor (or marriage) markets or employment networks that allow high-income parents to ensure good outcomes for their children regardless of the children's skills.

To implement this decomposition, I need a scalar index of human capital. I form this by estimating a regression of children's income percentiles on their educational attainment and their 12th grade math scores, with CZ fixed effects, in the ELS sample. My human capital index is the predicted value from this regression (neglecting the fixed effects). Note that this method of forming z_{ic} normalizes $\psi = 1$ in the average CZ.

Column 1 of Table 10 repeats the basic random effects regression of children's income percentiles on parents' income and its interaction with CZ-level income transmission, from Table 4, Column 6. (The sample differs slightly from the one used earlier, as I exclude observations with missing test scores or educational attainment.) The interaction coefficient is 0.62.

In Column 2, I repeat the specification but use the child skill index z_{ic} as the dependent variable. Not surprisingly given the earlier results, the interaction terms, which represents the first term of the decomposition (17), is small and not statistically significant. The point estimate of 0.09 implies that skill accumulation accounts for only 15% ($= {}^{0.09}/_{0.62}$) of the differences in ELS income transmission between cities with low and high values of the CHKS transmission measure.

Column 3 explores the role of returns to skill. Here, the dependent variable is the child's income percentile, but explanatory variables are the child's skill index and its interaction with the CZ-level income transmission. This interaction coefficient estimates $\frac{\partial \psi_c}{\partial \theta_c}$; the second term of the decomposition (17) can then be obtained by multiplying it by the average effect of parental income on children's skill, which by column 2 is 0.10. Thus, the second term is 0.21, indicating that differences in returns to skill account for 34% of the variation in income transmission.

Column 4 returns to the specifications from columns 1 and 2, but here the dependent variable is the residual from the column 3 regression (representing ν_{ic} in (15)). The interaction coefficient here is 0.31, indicating that half of the variation in income transmission is attributable to differences in the transmission of parental income to child income controlling for the child's observable skills and for CZ-level differences in the returns to these skills.

The decomposition in Table 10 uses the child's family income. A portion of the return to skill component estimated in column 3 might reflect returns to skill on the marriage market – higher skill children may be more likely to have working spouses in high-transmission CZs, or might have spouses with higher earnings. Similarly, a portion of the residual component in column 4 might reflect a relationship between parental income and spousal earnings or family non-labor income conditional on the child's skill accumulation. To explore this, I decompose the child's family income into his/her earnings and the remainder, reflecting spousal earnings and non-labor income. As in Table 5, child earnings are scaled in terms of percentiles of the child family income distribution, and the remainder is measured as the increase in percentiles when the other components of family income are included.

Results are in Table 11. Columns 1-4 are the same as in Table 10, though now only the child's own earnings are permitted to contribute to the returns to skill (column 3) or the earnings residual (column 4). The contribution of returns to skill is halved relative to Table 10, and the contribution of residual income transmission by about one-third. Column 5 presents results for the non-earnings component of family income. This accounts for about one-third of the variation across CZs in parent income - child family income transmission. Based on Table 5, this primarily reflects differences in the relative propensity of children from high- and low-income families to have working spouses, rather than differences in non-labor income or in spousal earnings conditional on work.

A natural question is whether this decomposition differs by gender. Interestingly, when I implement the decomposition in Table 11 separately for boys and girls, in Appendix Table A8, the non-earnings component (column 5) is quite similar for both. The primary difference between the two is that the skill accumulation (column 2) and return to skill (column 3) components are much smaller for girls than for boys, while the earnings residual component (column 4) is much larger. Even for boys, however, skill accumulation accounts for less than one-fifth of the variation in income transmission, and returns to skill for one-third, with over half operating through earnings residuals and spousal and non-labor income.

8 Conclusion

Chetty et al.'s (2014) pathbreaking work showed that there is dramatic variation in intergenerational income mobility across geographic areas within the United States. This raises the intriguing possibility that we can identify policies that account for this variation and, by exporting these policies from high- to low-mobility areas, move closer to equality of opportunity.

CHKS presented suggestive correlations that indicated that school quality might be an important contributing factor. This paper has investigated this suggestion further, by asking whether high- and low-income children's academic outcomes are more equal in areas where their adult economic outcomes are more equal – that is, in areas with more intergenerational mobility. I find that there is statistically significant variation across commuting zones in the gradients of educational attainment, academic achievement, and non-cognitive skills with respect to parental income. Intergenerational income transmission is reasonably strongly correlated with the educational attainment gradient and with the labor market return to education, but does not covary strongly with either academic achievement or non-cognitive skill gradients (with the exception of gradients computed from teacher reports of children's non-cognitive skills).

I find that only about one-tenth of the across-CZ variation in intergenerational income mobility is attributable to differences in children's earnings deriving from differences in skill accumulation. A slightly larger share is attributable to differences in the labor market returns to children's skills. About one-third is attributable to differences in the labor market return to parental income holding skills (and the returns to skills) constant. The remaining, largest portion derives from differences in spousal and non-labor income, primarily reflecting differences in the likelihood of having a working spouse.

Although this evidence is observational rather than causal, it strongly suggests that differences in elementary and secondary school quality are not an important determinant of variation in income mobility. (This is not to say that school quality is not important for other reasons, of course, or even that it does not contribute to overall mobility in a way that is roughly constant across CZs.) There appears to be more of a role for access to higher education in driving economic mobility, though even here the contribution is not large relative to the overall variation. Further investigation into the determinants of local intergenerational mobility should focus on differences in the returns to education, in the returns to family income conditional on children's human capital, and in the relative propensity of children from high- and low-income families to have working spouses. Plausible factors driving the former might include institutions determining local income inequality, such as state income taxation and union density. The second, reflecting direct effects of parental income on children's earnings conditional on children's human capital, might reflect variation in the importance of labor market networks or in spatial or social stratification of the labor market. The third seems to reflect differences in the likelihood of marriage rather than variation in assortative mating; insofar as this reflects differences across CZs in the likelihood that romantic partners will be formally married rather than differences in the likelihood of partnership, it may not represent meaningful variation in equality of opportunity.

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Figure 1: Academic achievement as mediator of the effect of parental income on children's income

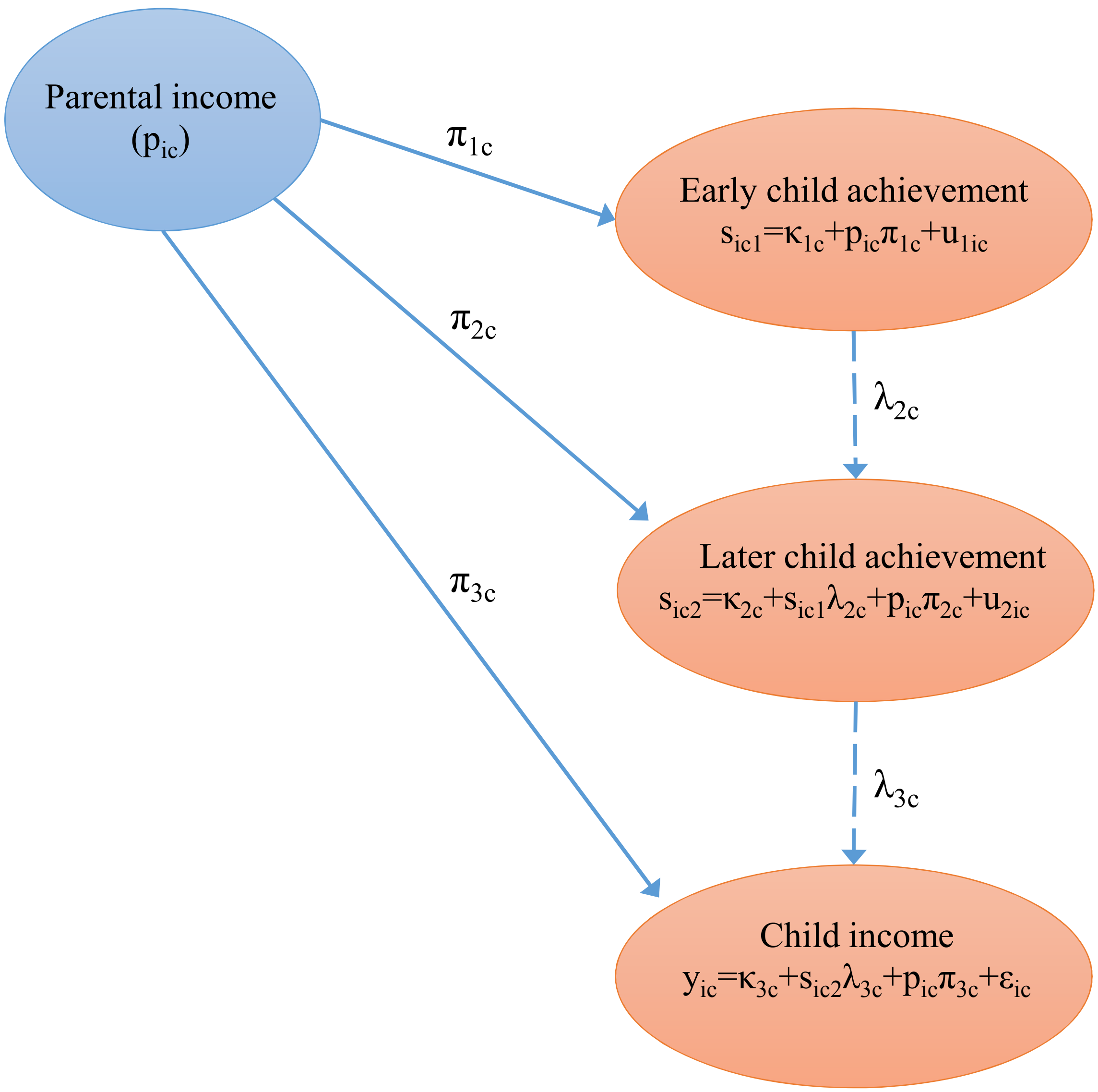
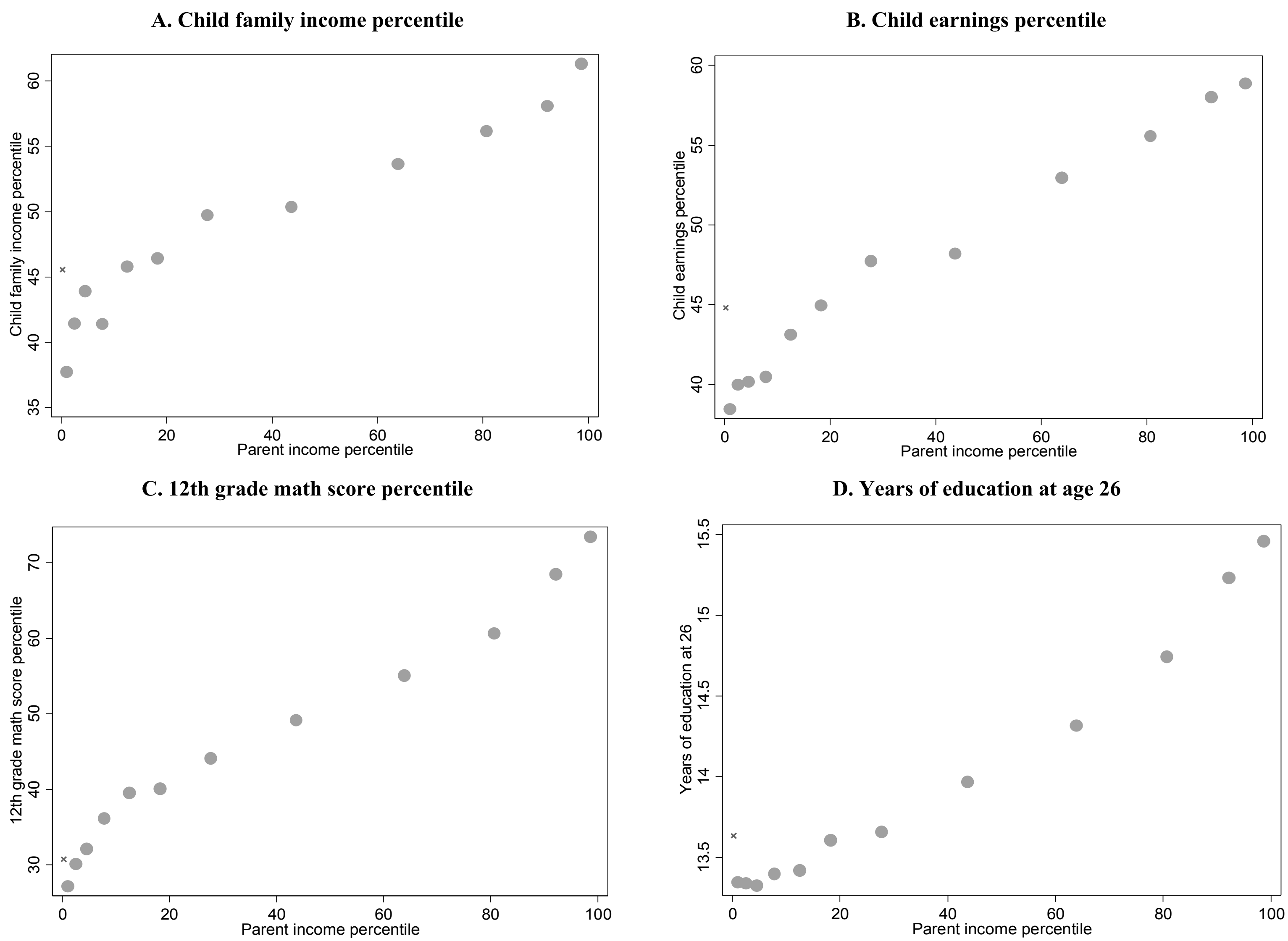


Figure 2. Average ELS outcomes by parent income



Note : Each point represents a response to the ELS parental income question, converted to a percentile (and assigned to the midpoint of the relevant range). The small "x" represents the average outcome for the 0.2% of observations reporting zero parental income. Child family income, earnings, and 12th grade math scores are each measured as percentiles of the relevant national distribution.

Table 1. Measures of income transmission at the CZ level from tax data.

	Slope of:			
	child income percentile (0-100)	**child college enrollment (0/100)**	**child income percentile (0-100)**	**child income percentile (0-100)**
	with respect to parent income percentile (0-100)			
	(1)	**(2)**	**(3)**	**(4)**
Birth cohorts	1980-1982	1980-1982	1983-1985	1980-1991
Identification	observational	observational	observational	movers
N	709	709	708	718
Mean	0.33	0.68	0.31	0.00
Standard deviation	0.06	0.11	0.07	0.07
10th percentile	0.24	0.53	0.21	-0.08
90th percentile	0.40	0.80	0.39	0.09
Correlations				
(1)	1	0.68	0.84	0.85
(2)		1	0.62	0.61
(3)			1	0.89
(4)				1

Notes : Columns 1, 3, and 4 report on "relative mobility" measures from Chetty et al. (2014) (columns 1 and 3) and Chetty and Hendren (2015) (column 4). Column 2 reports on the slope of college attendance between 18 and 21 on parental income percentile (scaled from 0 to 1), from Chetty et al. (2014). Summary statistics are computed across commuting zones, unweighted. The mobility measure in column 4 is computed relative to the average CZ, so has (weighted) mean zero.

Table 2. Summary statistics for NCES samples

	Early Childhood Longitudinal Study (ECLS)	High School Longitudinal Study (HSLS)	Educational Longitudinal Study (ELS)
	(1)	**(2)**	**(3)**
Birth year	1992-1993	1994-1995	1985-1986
N	19,940	21,440	15,240
# of CZs	365	295	312
Demographics			
Female	0.48	0.50	0.50
Black	0.18	0.17	0.14
Hispanic	0.19	0.22	0.16
Asian	0.03	0.03	0.04
Other non-white	0.02	0.08	0.05
Parent income	51,789	77,730	61,417
	(47,419)	(128,331)	(50,312)
Parent income percentile	48.9	49.6	50.0
	(29.0)	(29.0)	(28.5)
Test scores available for grades	K,1,2,3,5,8	9,11	10,12
Post-high school outcomes (from 2012 follow-up survey)			
Any college			0.84
College completion			0.33
Years of education			14.0
			(1.8)
Income at age 26			36,095
			(35,238)
Income percentile at age 26			50.0
			(28.9)

Note : Sample sizes and demographics are computed for the base-year sample for each survey, and use sampling weights. Sample sizes are rounded to the nearest 10. Standard deviations in parentheses.

Table 3. Cross-sectional regressions of child outcomes on parental income

	Math			Reading		
			Number of observations			**Number of observations**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
CZ FEs	N	Y		N	Y	
ECLS-K						
K (spring)	0.41	0.40	19,190	0.37	0.36	18,500
	(0.01)	(0.01)		(0.01)	(0.01)	
G1 (spring)	0.40	0.41	16,370	0.38	0.37	16,080
	(0.01)	(0.01)		(0.01)	(0.01)	
G3	0.44	0.42	14,180	0.45	0.43	14,090
	(0.01)	(0.01)		(0.01)	(0.01)	
G5	0.45	0.43	11,140	0.45	0.43	11,130
	(0.02)	(0.02)		(0.02)	(0.02)	
G8	0.44	0.42	9,210	0.46	0.44	9,150
	(0.02)	(0.02)		(0.02)	(0.02)	
HSLS						
G9	0.36	0.32	20,170			
	(0.01)	(0.01)				
G11	0.35	0.31	20,460			
	(0.01)	(0.01)				
ELS						
G10	0.37	0.34	15,240	0.35	0.32	15,240
	(0.01)	(0.01)		(0.01)	(0.01)	
G12	0.38	0.35	13,650			
	(0.01)	(0.01)				
Any college (*100)	0.26	0.24	13,250			
	(0.01)	(0.01)				
College completion (*100)	0.49	0.45	13,250			
	(0.02)	(0.02)				
Years of education (*100)	2.04	1.87	13,250			
	(0.07)	(0.07)				
Income at 26	0.18	0.16	11,510			
	(0.01)	(0.01)				

Notes : Each entry represents the coefficient from a separate weighted least squares regression of the child's outcome on family income. Columns 2 and 5 add fixed effects for commuting zones. Parental incomes, test scores, and child incomes are measured in percentile units, scaled 0-100. Any college and college completion are binary, but scaled as 0/100 for readability; years of education is multiplied by 100 for the same reason. Sample sizes in columns 3 and 6 are rounded to the nearest 10.

Table 4. Parent income - child income relationships in the ELS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Parental income	0.18						
	(0.01)						
Parental income - CZ mean		0.16	0.17	0.17	0.16	0.17	0.24
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
CZ mean parental income		0.32	0.35	0.35		0.35	0.48
		(0.04)	(0.04)	(0.04)		(0.04)	(0.05)
(Parental income - CZ mean) *				0.63	0.64	0.65	1.46
CZ income transmission				(0.16)	(0.20)	(0.16)	(0.27)
SD of parental income random						0.01	0.10
coefficient (η)						(0.02)	(0.03)
Parental income measure	Actual	Actual	Actual	Actual	Actual	Actual	Pred.
CZ controls	None	None	RE	RE	FE	RE	RE
SD of total parental income coefficient (π)						0.038	0.127
Share of variance attributable to CZ income transmission						95%	42%
p-value, share of variance = 100% (LR test)						0.86	0.01
Corr(tax data income transmission, ELS π)						0.97	0.65

Notes: Dependent variable in each column is the child's family income at age 26, in percentile units (0-100). Parental income is also measured in percentiles (0-100). CZ income transmission is the observational relative mobility measure for the 1980-82 birth cohorts from Chetty et al. (2014), demeaned across CZs. Column 7 uses the predicted parental income percentile in place of the reported value, for both main effects and interactions. Parental income is predicted based on a (weighted) regression of the reported income percentile on indicators for mother's years of education, mother's occupation, and father's years of education and occupation (interacted with an indicator for father presence). Specifications labeled "RE" and "FE" include CZ random effects and fixed effects, respectively; columns 4, 6, and 7 also include main effects for CZ income transmission. Specifications in columns 1, 2, and 5 are weighted using ELS sampling weights; others are unweighted. Standard errors are clustered at the CZ level. p-values in columns 6-7 are for likelihood ratio tests of the mixed models against random effects models with fixed coefficients (as in column 4). Number of observations (rounded to the nearest 10) = 11,510 (10,950 in column 7).

Table 5. Parent income - child income relationships in the ELS

	Child family income	Marital status (0/100)	Working spouse (0/100)	Child earnings	Child earnings + nonlabor income	Child earnings + non-labor income + imputed spousal earnings
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Parental income - CZ mean	0.24	-0.01	0.02	0.23	0.27	0.22
	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
CZ mean parental income	0.48	-0.01	0.12	0.43	0.48	0.42
	(0.05)	(0.12)	(0.11)	(0.05)	(0.05)	(0.05)
(Parental income - CZ mean) *	1.46	1.17	1.14	0.87	0.94	1.53
CZ income transmission	(0.27)	(0.47)	(0.50)	(0.26)	(0.24)	(0.27)
SD of parental income random	0.10	0.13	0.15	0.07	0.06	0.10
coefficient (η)	(0.03)	(0.05)	(0.05)	(0.04)	(0.03)	(0.03)
SD of total parental income coefficient (π)	0.127	0.150	0.159	0.083	0.080	0.132
Share of variance attributable to CZ income transmission	42%	19%	16%	35%	44%	43%
p-value, share of variance = 100% (LR test)	0.01	0.10	0.05	0.45	0.61	<0.01
Corr(tax data income transmission, ELS π)	0.65	0.44	0.40	0.59	0.66	0.66

Notes: All specifications are unweighted linear regressions with fixed coefficients, a CZ random effect, a main effect for CZ income transmission, and a random coefficient on parental income that varies at the CZ level, as in Table 4, column 7. Only the dependent variable changes across columns. In columns 1, 4, 5, and 6, dependent variable is a measure of child income, with varying definitions, scaled as percentiles of the child total family income distribution; in columns 2 and 3, dependent variable is an indicator for being married or for having a working spouse, multiplied by 100. In all columns, parental income is the predicted percentile, described in notes to Table 4. CZ income transmission is the observational relative mobility measure for the 1980-82 birth cohorts from Chetty et al. (2014), demeaned across CZs. Standard errors are clustered at the CZ level. p-values are for likelihood ratio tests of the mixed models against random effects models with fixed coefficients (as in Table 4, column 4). Number of observations (rounded to the nearest 10) = 10,940.

Table 6. Parental income and children's 12th grade math achievement in the ELS

	(1)	(2)	(3)	(4)	(5)	(6)
Parental income	0.38					
	(0.01)					
Parental income - CZ mean		0.35	0.34	0.34	0.35	0.33
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
CZ mean parental income		0.69	0.71	0.71		0.71
		(0.04)	(0.04)	(0.04)		(0.04)
(Parental income - CZ mean) *				0.37	0.32	0.41
CZ income transmission				(0.15)	(0.21)	(0.17)
SD of parental income random coefficient (η)						0.07
						(0.02)
CZ controls	None	None	RE	RE	FE	RE
SD of total parental income coefficient (π)						0.07
Share of variance attributable to CZ income transmission						10%
p-value, share of variance = 100% (LR test)						<0.01
Corr(tax data income transmission, ELS π)						0.32

Notes : Dependent variable in each column is the 12th grade math score, in national percentile units (0-100). Parental income is also measured in percentiles (0-100). CZ income transmission is the observational relative mobility measure for the 1980-82 birth cohorts from Chetty et al. (2014), demeaned across CZs. Specifications labeled “RE” and “FE” include CZ random effects and fixed effects, respectively; columns 4 and 6 also include main effects for CZ income transmission. Specifications in columns 1, 2, and 5 are weighted using ELS sampling weights; others are unweighted. Standard errors are clustered at the CZ level. p-value in column 6 is for a likelihood ratio test of the mixed model against the random effects model with fixed coefficients in column 4. Number of observations (rounded to the nearest 10) = 13,650.

Table 7. Variation in parental income - child achievement relationships across grades, cohorts, and subjects

		Parental income - CZ mean	Parental income * CZ income transmission	SD of parental income random coefficient (η)	SD of total parental income coefficient (π)	Explained share of variance	p-value, share of variance = 100%
		(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Math scores							
ECLS	K (spring)	0.38	0.16	0.08	0.08	0.01	<0.01
		(0.01)	(0.23)	(0.01)			
ECLS	G1 (spring)	0.38	0.23	0.06	0.06	0.05	<0.01
		(0.01)	(0.22)	(0.01)			
ECLS	G3	0.40	0.41	0.06	0.07	0.14	<0.01
		(0.01)	(0.21)	(0.02)			
ECLS	G5	0.39	0.50	0.06	0.07	0.19	<0.01
		(0.01)	(0.21)	(0.01)			
ECLS	G8	0.39	0.34	0.04	0.05	0.17	0.17
		(0.01)	(0.21)	(0.02)			
HSLS	G9	0.30	0.30	0.05	0.05	0.10	0.02
		(0.01)	(0.17)	(0.01)			
HSLS	G11	0.28	0.59	0.07	0.07	0.18	<0.01
		(0.01)	(0.17)	(0.01)			
ELS	G10	0.31	0.36	0.06	0.07	0.09	<0.01
		(0.01)	(0.17)	(0.01)			
ELS	G12	0.33	0.41	0.07	0.07	0.10	<0.01
		(0.01)	(0.17)	(0.02)			
Panel B: Reading scores							
ECLS	K (spring)	0.35	0.33	0.08	0.08	0.06	<0.01
		(0.01)	(0.26)	(0.01)			
ECLS	G1 (spring)	0.35	0.07	0.06	0.06	0.01	<0.01
		(0.01)	(0.24)	(0.01)			
ECLS	G3	0.42	0.13	0.08	0.08	0.01	<0.01
		(0.01)	(0.23)	(0.01)			
ECLS	G5	0.39	0.32	0.09	0.09	0.04	<0.01
		(0.01)	(0.26)	(0.01)			
ECLS	G8	0.41	0.24	0.07	0.07	0.04	<0.01
		(0.01)	(0.22)	(0.02)			
ELS	G10	0.30	0.24	0.08	0.08	0.03	<0.01
		(0.01)	(0.18)	(0.01)			

Notes : Each row presents a single mixed model regression pertaining to a different test score (for a given sample, grade, and subject), each scaled as national percentile units (0-100). Specifications are as in Table 6, column 6; see that table for details. Number of observations (rounded to the nearest 10) varies from 9,200 (ECLS-K, 8th grade math) to 20,430 (HSLS, 11th grade math).

Table 8. Parental income - children's educational attainment relationships in the ELS

	Any college (0/100)		College graduation (0/100)		Years of education at 26 (*100)	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Parental income - CZ mean	0.22	0.24	0.45	0.45	1.85	1.86
	(0.01)	(0.01)	(0.02)	(0.02)	(0.06)	(0.06)
CZ mean parental income	0.50	0.49	1.01	1.01	4.12	4.14
	(0.05)	(0.05)	(0.06)	(0.06)	(0.26)	(0.26)
(Parental income - CZ mean) *	-0.11	-0.19	0.64	0.74	2.28	2.39
CZ income transmission	(0.20)	(0.21)	(0.30)	(0.29)	(1.12)	(1.09)
SD of parental income random coefficient (η)		0.10		0.08		0.23
		(0.02)		(0.03)		(0.13)
SD of total parental income coefficient (π)		0.10		0.09		0.26
Share of variance attributable to CZ income transmission		1%		23%		26%
p-value, share of variance = 100% (LR test)		<0.01		0.15		0.36
Corr(tax data income transmission, ELS π)		-0.10		0.48		0.51

Notes : Specifications are as in Table 6, columns 4 (odd numbered columns here) and 6 (even numbered columns). See notes to that table for details. Dependent variables in columns 1-4 are scaled as 0 for failures and 100 for successes; in columns 5-6, dependent variable is years of education multiplied by 100. Standard errors are clustered at the CZ level. Number of observations (rounded to the nearest 10) = 13,250.

Table 9. Returns to education in American Community Survey (ACS) data

	(1)	(2)	(3)	(4)	(5)	(6)
Years of education	4.12					
	(0.07)					
Years of education - CZ mean		3.94	3.99	4.03	4.02	3.84
		(0.06)	(0.05)	(0.04)	(0.04)	(0.04)
CZ mean education		9.36	5.59	5.54		5.23
		(0.87)	(0.28)	(0.27)		(0.27)
(Education - CZ mean) *				4.92	4.91	5.12
CZ income transmission				(0.66)	(0.68)	(0.77)
SD of education random coefficient (η)						0.55
						(0.04)
CZ controls	None	None	RE	RE	FE	RE
SD of total education coefficient (π)						0.62
Share of variance attributable to CZ income transmission						22%
p-value, share of variance = 100% (LR test)						<0.01
Corr(tax data income transmission, ELS λ)						0.47

Notes : Sample consists of individuals born 1980-1982 in the ACS 2010-2012 one-year public use microdata samples (N=253,852). Respondents are assigned to their CZ of current residence. Dependent variable in each specification is the child's family income percentile (0-100). Years of education is naturally coded. CZ income transmission is the observational measure for the 1980-82 birth cohorts from Chetty et al. (2014), demeaned across CZs. Specifications labeled "RE" and "FE" include CZ random effects and fixed effects, respectively; columns 4 and 6 also include main effects for CZ income transmission. Specifications in columns 1 and 2 are weighted using ACS sampling weights; others are unweighted. Standard errors are clustered at the CZ level. p-value in column 6 is for a likelihood ratio test of the mixed model against the random effects model with fixed coefficients in column 4.

Table 10. Decomposition of the variation in intergenerational income transmission

Mechanism	**Total transmission**	**Skills**	**Return to skills**	**Residual**
Dependent variable	**Child income**	**Child skill index**	**Child income**	**Child income residual**
	(1)	**(2)**	**(3)**	**(4)**
Parental income - CZ mean	0.16	0.10		0.07
	(0.01)	(0.00)		(0.01)
CZ mean parental income	0.33	0.21		0.05
	(0.04)	(0.01)		(0.02)
CZ income transmission	1.57	-3.79	-0.62	-2.85
	(7.55)	(1.90)	(7.54)	(3.57)
(Parental income - CZ mean) *	0.62	0.09		0.31
CZ income transmission	(0.17)	(0.05)		(0.15)
Skill index - CZ mean			0.98	
			(0.04)	
CZ mean skill index			1.25	
			(0.13)	
(Skill index - CZ mean) *			2.24	
CZ income transmission			(0.59)	
d skills / d parental income (scale factor)			0.10	
Scaled component		0.09	0.21	0.31
Share of total	100%	15%	34%	50%

Notes : Sample consists of 9,980 observations (rounded to the nearest 10) from the ELS sample with complete information on 12th grade math scores, educational attainment and family income at age 25, and parental income. All specifications are unweighted random effects models with fixed coefficients, main effects for CZ income transmission (demeaned across CZs), CZ random effects, and standard errors clustered at the CZ level, as in Table 4, column 4. Child income in column 1 is child family income, including own and spousal earnings plus non-labor income, scaled as national percentiles (0-100). The skill index in columns 2 and 3 is the predicted value from a CZ fixed effects regression of children's family income percentiles on 12th grade math scores and indicators for years of schooling completed, estimated using third follow-up (2012) sampling weights. The child income residual is the residual from the regression in column 3. Parental income is measured in percentiles (0-100).

Table 11. Decomposition of the variation in intergenerational income transmission using child earnings

Mechanism	**Total transmission**	**Skills**	**Return to skills**	**Residual**	**Non-labor and spousal income**
Dependent variable	**Child income**	**Child skill index**	**Child earnings**	**Child earnings residual**	**Family income less own earnings**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Parental income - CZ mean	0.16	0.09		0.05	0.02
	(0.01)	(0.00)		(0.01)	(0.01)
CZ mean parental income	0.33	0.19		0.08	-0.01
	(0.04)	(0.01)		(0.03)	(0.03)
CZ income transmission	1.57	-4.34	6.15	-3.33	-6.51
	(7.55)	(1.72)	(5.13)	(5.00)	(6.64)
(Parental income - CZ mean) *	0.62	0.08		0.20	0.23
CZ income transmission	(0.17)	(0.06)		(0.14)	(0.10)
Skill index - CZ mean			0.98		
			(0.04)		
CZ mean skill index			1.35		
			(0.12)		
(Skill index - CZ mean) *			1.10		
CZ income transmission			(0.61)		
d skills / d parental income (scale factor)			0.09		
Scaled component	0.62	0.08	0.10	0.20	0.23
Share of total	100%	12%	16%	31%	36%

Notes : Specifications and samples are as in Table 10; number of observations (rounded to the nearest 10) = 9,980. Dependent variable in column 3 is the child earnings, scaled as percentiles of the child family income distribution (0-100). In column 4, dependent variable is the residual from the column 3 regression. In column 5, dependent variable is the increment to the child's family income percentile from including spousal earnings and non-labor income in the family income, measuring both child earnings and full family income against the national full family income distribution.

Appendix A: Additional results

Appendix Tables A1-A8 present additional specifications and results not included in the main tables.

Table A1 presents results for the three ELS educational attainment measures considered in Table 8, but replaces the income transmission (relative mobility) measure with CHKS's education mobility measure, defined as the slope of college enrollment at age 18-21 (scaled as 0 for non-enrollment and 100 for enrollment) with respect to parental income (in percentiles, 0-100).

Table A2 explores two alternative income transmission (relative mobility) measures. One is the alternative measure computed by CHKS for the younger, 1983-5 birth cohorts, with adult incomes measured at younger ages. The second is the measure constructed by Chetty and Hendren (2015) based on families that move from one CZ to another. Three dependent variables are considered: Children's adult family income (in percentiles, 0-100), children's 12th grade math scores (also in percentiles), and the child's years of completed education as of age 26 (multiplied by 100).

Table A3 considers the same three outcomes and the baseline CHKS mobility measure for the 1980-2 cohorts, but adds to the base specification indicators for the child's race and gender and, in columns 3, 6, and 9, interactions of these with the income transmission measure.

Table A4 explores the potential impact of nonlinearity in the child test score - parental income relationship. I rescale parental income by replacing each value with the sample average test score among all observations with the same reported parental income. This ensures that the relationship is perfectly linear, on average.

Table A5 reports my main mixed specifications for the three primary outcomes, comparing those that use reported parental income with those that use predicted parental income based on maternal education and occupation, the presence of the father, and the paternal education and occupation (when present).

Table A6 reports estimates for a variety of non-cognitive measures from the ELS and ECLS. These measures are described in Appendix B.

Table A7 reports specifications from Table 5, separately for male and female children. Table A8 repeats this exercise for Table 11.

Appendix B: Non-cognitive skill measures

Appendix Table A6 presents results for several different measures of non-cognitive skills from the ELS 10th grade survey and the ECLS 5th grade student and teacher surveys. I describe these measures here.

ELS 10th grade survey. Each of the measures used is created by principal factor analysis from student responses to questions of the form "How often do these things apply to you?", with response options "almost never," "sometimes," "often," and "almost always." Quotations are from National Center for Education Statistics (undated).

Instrumental motivation. Intended to capture "motivation to perform well academically in order to satisfy external goals like future job opportunities or financial security." Based on three responses about whether the student studies in order to achieve long-run success.

General effort and persistence. Based on five questions characterizing effort put into studying.

General control beliefs. Intended to capture "expectations of success in academic learning." Based on four responses characterizing the student's self-perceived ability to achieve desired academic outcomes.

Self efficacy, math. Based on five responses characterizing the student's self-perceived ability to succeed in math classes and his/her views about the importance of innate ability in math.

Self efficacy, reading. Based on five responses characterizing the student's self-perceived ability to succeed in reading classes.

ECLS 5th grade student survey. Students rated 42 statements about their perceptions of themselves as "not at all true," "a little bit true," "mostly true," and "very true." These were averaged into several scales. Quotations are from Tourangeau et al. (2006).

Perceived interest / competence in reading. Eight statements concerning "reading grades, the difficulty of reading work, and [the student's] interest in and enjoyment of reading."

Perceived interest / competence in math. Eight statements concerning "mathematics grades, the difficulty of mathematics work, and [the student's] interest in and enjoyment of mathematics."

Perceived interest / competence in all school subjects. Six statements concerning "how well [the student] do[es] in 'all school subjects' and [the student's] enjoyment of 'all school subjects."'

Perceived interest / competence in peer relations. Six statements concerning "how easily [the student] make[s] friends and get[s] along with children as well as their perception of their popularity."

Externalizing problem behaviors. Six statements concerning "externalizing problem behaviors such as fighting and arguing 'with other kids,' talking and disturbing others, and problems with distractibility."

Internalizing problem behaviors. Eight statements concerning "internalizing problem behaviors such as feeling 'sad a lot of the time,' feeling lonely, feeling ashamed of mistakes, feeling frustrated, and worrying about school and friendships."

ECLS 5th grade teacher survey. Teachers rated 26 statements about how often students exhibited certain social skills and behaviors as "never," "sometimes," "often," and "very often." These were averaged into several scales. Quotations are from Tourangeau et al. (2006).

Approaches to learning. "Measures behaviors that affect the ease with which children can benefit from the learning environment." Based on seven items relating to "the child's attentiveness, tax persistence, eagerness to learn, learning independence flexibility, [] organization ... [and] child follows classroom rules."

Self control. "Four items that indicate the child's ability to control behavior by respecting the property rights of others, controlling temper, accepting peer ideas for group activities, and responding appropriately to pressure from peers."

Interpersonal skills. "Five items that rate the child's skill in forming and maintaining friendships; getting along with people who are different; comforting or helping other children; expressing feelings, ideas, and opinions in positive ways; and showing sensitivity to the feelings of others."

Peer relations. This is a combination of the self-control and interpersonal scales.

Externalizing problem behaviors. This scale "includes acting out behaviors": six items "rate the frequency with which a child argues, fights, gets angry, acts impulsively, [] disturbs ongoing activities ... [and] talks during quiet study time."

Internalizing problem behaviors. Four items ask about "the apparent presence of anxiety, loneliness, low self-esteem, and sadness."

For all of the non-cognitive items, I reverse-code so that higher values are better, then convert to percentiles. To form overall indices from each survey, I convert each listed scale to a z-score, average them, then convert the average to percentiles.

Table A1. Parental income - children's educational attainment relationships and CZ-level education mobility

	Any college (0/100)		College graduation (0/100)		Years of education at 26 (*100)	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Parental income - CZ mean	0.22	0.23	0.46	0.45	1.86	1.85
	(0.01)	(0.01)	(0.02)	(0.02)	(0.06)	(0.06)
CZ mean parental income	0.50	0.48	1.01	1.01	4.13	4.15
	(0.05)	(0.04)	(0.07)	(0.06)	(0.26)	(0.26)
(Parental income - CZ mean) *	0.31	0.31	0.59	0.66	2.68	2.85
CZ education transmission	(0.15)	(0.13)	(0.19)	(0.18)	(0.78)	(0.70)
SD of parental income random coefficient (η)		0.10		0.07		0.19
		(0.01)		(0.03)		(0.11)
SD of total parental income coefficient (π)		0.10		0.09		0.31
Share of variance attributable to CZ education transmission		7%		39%		64%
p-value, share of variance = 100% (LR test)		<0.01		0.22		0.59
Corr(tax data education transmission, ELS π)		0.26		0.63		0.80

Notes : Specifications are as in Table 8, except that Chetty et al.'s education relative mobility measure, computed as the slope of college enrollment at age 18-21 (measured as 0 or 100) with respect to parent income percentile (measured from 0 to 100), is used in place of their baseline income mobility measure. See notes to Tables 6 and 8 for details. Standard errors are clustered at the CZ level. Number of observations (rounded to the nearest 10) = 13,250.

Table A2. ELS Results using alternative mobility measures

	Child income			12th grade math score			Years of education at 26 (*100)		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Parental income - CZ mean	0.17	0.17	0.17	0.33	0.33	0.33	1.86	1.86	1.87
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.06)	(0.06)	(0.06)
CZ mean parental income	0.35	0.35	0.35	0.71	0.71	0.70	4.14	4.15	4.17
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.26)	(0.26)	(0.26)
(Parental income - CZ mean) *	0.65	0.62	0.59	0.41	0.26	0.18	2.39	2.47	1.54
CZ income transmission	(0.16)	(0.15)	(0.18)	(0.17)	(0.16)	(0.18)	(1.09)	(1.07)	(1.15)
Income transmission measure	CHKS	CHKS (83-5)	CH	CHKS	CHKS (83-5)	CH	CHKS	CHKS (83-5)	CH
SD of parental income random	0.008	0.013	0.003	0.068	0.070	0.071	0.225	0.233	0.257
coefficient (η)	(0.017)	(0.018)	(0.017)	(0.015)	(0.016)	(0.016)	(0.126)	(0.126)	(0.131)
SD of total parental income coefficient (π)	0.038	0.039	0.031	0.072	0.072	0.072	0.262	0.275	0.270
Share of var. attributable to CZ income transmission	95%	90%	99%	10%	5%	2%	26%	28%	9%
p-value, share of variance = 100% (LR test)	0.86	0.73	0.98	<0.01	<0.01	<0.01	0.36	0.37	0.27
Corr(tax data income transmission, ELS π)	0.97	0.95	0.99	0.32	0.22	0.13	0.51	0.53	0.30

Notes : Columns 1, 4, and 7 correspond to columns 2, 4, and 6, respectively, of Table 8. Columns 2, 5, and 8 replace the Chetty et al. (2014) preferred income transmission (relative mobility) measure for the 1980-82 cohorts with a measure computed for the 1983-85 cohorts. Columns 3, 6, and 9 use instead the Chetty and Hendren (2015) causal mobility measure. Standard errors are clustered at the CZ level. Number of observations (rounded to the nearest 10) = 11,510 for child income, 13,650 for 12th grade test scores, and 13,250 for years of education.

Table A3. Parental income - child outcome relationships in the ELS, adding controls for race and gender

	Child income			12th grade math score			Years of education at 26 (*100)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Parental income - CZ mean	0.17	0.15	0.14	0.33	0.28	0.28	1.86	1.73	1.73
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.06)	(0.06)	(0.06)
CZ mean parental income	0.35	0.29	0.28	0.71	0.58	0.58	4.14	3.78	3.79
	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.26)	(0.28)	(0.28)
(Parental income - CZ mean) *	0.65	0.44	0.38	0.41	0.13	0.20	2.39	2.00	2.18
CZ income transmission	(0.16)	(0.15)	(0.16)	(0.17)	(0.16)	(0.18)	(1.09)	(0.97)	(1.02)
SD of parental income random coefficient (η)	0.01	0.00	0.00	0.07	0.06	0.06	0.23	0.18	0.18
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.13)	(0.14)	(0.15)
Race and gender		X	X		X	X		X	X
Race and gender X income transmission			X			X			X
SD of total parental income coefficient (π)	0.038	0.025	0.022	0.072	0.057	0.058	0.262	0.215	0.216
Share of var. attributable to CZ income transmission	95%	99%	99%	10%	2%	4%	26%	27%	32%
p-value, share of variance = 100% (LR test)	0.86	0.99	0.99	<0.01	0.02	0.02	0.36	0.22	0.23
Corr(tax data income transmission, ELS π)	0.97	0.99	0.99	0.32	0.13	0.19	0.51	0.52	0.57

Notes : Columns 1, 4, and 7 correspond to columns 2, 4, and 6, respectively, of Table 8. Columns 2, 5, and 8 add indicators for black, Hispanic, and female; columns 3, 6, and 9 also add interactions of these variables with CZ-level income transmission. Standard errors are clustered at the CZ level. Number of observations (rounded to the nearest 10) = 11,510 for child income, 13,650 for 12th grade test scores, and 13,250 for years of education.

Table A4. Parental income and children's 12th grade math achievement in the ELS, with parental income replaced by E[achievement | parental income]

	(1)	(2)	(3)	(4)	(5)	(6)
Parental income	1.03					
	(0.03)					
Parental income - CZ mean		0.95	0.91	0.90	0.95	0.88
		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
CZ mean parental income		1.78	1.88	1.89		1.88
		(0.11)	(0.09)	(0.09)		(0.09)
(Parental income - CZ mean) *				0.97	0.82	1.04
CZ income transmission				(0.38)	(0.50)	(0.43)
SD of parental income random coefficient (η)						0.15
						(0.04)
CZ controls	None	None	RE	RE	FE	RE
SD of total parental income coefficient (π)						0.161
Share of variance attributable to CZ income transmission						13%
p-value, share of variance = 100% (LR test)						0.04
Corr(tax data income transmission, ELS π)						0.367

Notes : Sample and specifications are as in Table 6, except that parental income is rescaled as the average 12th grade math score across all respondents with the same reported 12th grade family income. Number of observations (rounded to the nearest 10) = 13,590.

Table A5. Parental income - child outcome relationships in the ELS, using predicted parent income

	Child income		12th grade math score		Years of education at 26 (*100)	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Parental income - CZ mean	0.17	0.24	0.33	0.63	1.86	3.97
	(0.01)	(0.02)	(0.01)	(0.02)	(0.06)	(0.10)
CZ mean parental income	0.35	0.48	0.71	1.11	4.14	6.28
	(0.04)	(0.05)	(0.04)	(0.06)	(0.26)	(0.40)
(Parental income - CZ mean) *	0.65	1.46	0.41	0.49	2.39	2.45
CZ income transmission	(0.16)	(0.27)	(0.17)	(0.30)	(1.09)	(1.89)
SD of parental income random	0.01	0.10	0.07	0.10	0.23	0.43
coefficient (η)	(0.02)	(0.03)	(0.02)	(0.02)	(0.13)	(0.21)
Parental income measure	Actual	Pred.	Actual	Pred.	Actual	Pred.
Number of observations (rounded to nearest 10)	11,510	10,950	13,650	12,880	13,250	12,570
SD of total parental income coefficient (π)	0.038	0.127	0.072	0.100	0.262	0.455
Share of variance attributable to CZ income transmission	95%	42%	10%	8%	26%	9%
p-value, share of variance = 100% (LR test)	0.86	0.01	<0.01	<0.01	0.36	0.10
Corr(tax data income transmission, ELS π)	0.97	0.65	0.32	0.28	0.51	0.30

Notes : Specifications in columns 1, 3, and 5 are those in Table 4, column 6; Table 6, column 6; and Table 8, column 6, respectively. Columns 2, 4, and 6 replace the parental income measure with predicted parental income, as in Table 4, column 6. Standard errors are clustered at the CZ level.

Table A6. Parental income and children's non-cognitive skills in the ELS

	Parental income - CZ mean	Parental income * CZ income transmission	SD of parental income random coeff. (η)	SD of total parental income coeff. (π)	Explained share of variance	p-value, share of variance = 100%
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: ELS (10th grade)						
Instrumental motivation	0.09	0.08	0.02	0.02	0.04	0.30
	(0.01)	(0.15)	0.01			
General effort and persistence	0.09	-0.04	0.06	0.06	0.00	0.02
	(0.01)	(0.21)	(0.02)			
General control beliefs	0.14	-0.21	0.05	0.05	0.05	<0.01
	(0.01)	(0.19)	(0.03)			
Self-efficacy - Math	0.11	0.17	0.03	0.03	0.12	0.25
	(0.01)	(0.14)	(0.01)			
Self-efficacy - Reading	0.14	-0.45	0.07	0.07	0.14	0.02
	(0.01)	(0.23)	(0.02)			
Index of five measures	0.14	-0.15	0.05	0.05	0.03	<0.01
	(0.01)	(0.18)	(0.02)			
Panel B: ECLS-K 5th grade student survey						
Perceived interest / competence	0.05	-0.18	0.05	0.05	0.04	0.02
in reading	(0.01)	(0.21)	(0.01)			
Perceived interest / competence	0.02	0.07	0.04	0.04	0.01	0.45
in math	(0.01)	(0.16)	(0.02)			
Perceived interest / competence	0.08	0.11	0.05	0.06	0.02	0.04
in all school subjects	(0.01)	(0.21)	(0.01)			
Perceived interest / competence	0.07	-0.34	0.04	0.05	0.20	0.11
in peer relations	(0.01)	(0.17)	(0.02)			
Externalizing problem behaviors	0.19	0.03	0.01	0.01	0.04	0.79
	(0.01)	(0.12)	(0.01)			
Internalizing problem behaviors	0.18	-0.38	0.05	0.06	0.16	<0.01
	(0.01)	(0.17)	(0.01)			
Index of six measures	0.20	-0.26	0.03	0.04	0.18	0.19
	(0.01)	(0.17)	(0.02)			

Table continued on next page

Table A6 (continued)

	Parental income - CZ mean	Parental income * CZ income transmission	SD of parental income random coeff. (η)	SD of total parental income coeff. (π)	Explained share of variance	p-value, share of variance = 100%
	(1)	(2)	(3)	(4)	(5)	(6)
Panel C: ECLS-K 5th grade teacher survey						
Approaches to learning	0.19	0.58	0.06	0.07	0.25	0.02
	(0.01)	(0.18)	(0.02)			
Self-control	0.15	0.72	0.06	0.08	0.32	0.02
	(0.01)	(0.18)	(0.02)			
Interpersonal skills	0.15	0.22	0.05	0.05	0.06	0.16
	(0.01)	(0.17)	(0.02)			
Peer relations	0.15	0.52	0.06	0.06	0.24	0.03
	(0.01)	(0.18)	(0.01)			
Externalizing problem behaviors	0.11	0.48	0.03	0.04	0.50	0.05
	(0.01)	(0.12)	(0.02)			
Internalizing problem behaviors	0.11	-0.02	0.07	0.07	0.00	<0.01
	(0.01)	(0.20)	(0.01)			
Index of six measures	0.21	0.61	0.07	0.08	0.23	0.02
	(0.01)	(0.21)	(0.02)			

Notes : Each row presents a single mixed model regression, estimated without sampling weights. Dependent variables are discrete responses, scaled so that higher numbers are better and then converted to percentiles between 0 and 100 (with discrete responses assigned to the midpoint of the relevant range). Indexes are constructed by reversing the original response scale as necessary, converting to z-scores, averaging across responses and then converting to percentiles. Standard errors are clustered at the CZ level.

Table A7. Parent income - child income relationships in the ELS by gender

	Child family income	Marital status (0/100)	Working spouse (0/100)	Child earnings	Child earnings + nonlabor income	Child earnings + non-labor income + imputed spousal earnings
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Men						
Parental income - CZ mean	0.17	-0.08	-0.02	0.14	0.18	0.15
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
CZ mean parental income	0.31	-0.03	0.15	0.21	0.29	0.30
	(0.06)	(0.14)	(0.13)	(0.06)	(0.06)	(0.07)
(Parental income - CZ mean) *	1.30	1.22	1.00	0.72	0.91	1.26
CZ income transmission	(0.43)	(0.55)	(0.61)	(0.48)	(0.44)	(0.44)
SD of parental income random	0.13	0.05	0.09	0.16	0.14	0.13
coefficient (η)	(0.04)	(0.05)	(0.13)	(0.04)	(0.03)	(0.04)
SD of total parental income coefficient (π)	0.147	0.086	0.103	0.169	0.149	0.144
Share of variance attributable to CZ income transmission	25%	65%	30%	6%	12%	24%
p-value, share of variance = 100% (LR test)	0.16	0.60	0.67	<0.01	0.02	0.15
Corr(tax data income transmission, ELS π)	0.50	0.80	0.55	0.24	0.35	0.49
Panel B: Women						
Parental income - CZ mean	0.31	0.02	0.05	0.28	0.33	0.28
	(0.02)	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)
CZ mean parental income	0.66	0.00	0.07	0.63	0.66	0.56
	(0.08)	(0.14)	(0.14)	(0.06)	(0.06)	(0.08)
(Parental income - CZ mean) *	1.33	1.25	1.21	0.76	0.74	1.51
CZ income transmission	(0.42)	(0.56)	(0.58)	(0.38)	(0.39)	(0.40)
SD of parental income random	0.10	0.07	0.04	0.08	0.07	0.09
coefficient (η)	(0.04)	(0.13)	(0.19)	(0.05)	(0.04)	(0.04)
SD of total parental income coefficient (π)	0.127	0.098	0.078	0.089	0.085	0.125
Share of variance attributable to CZ income transmission	35%	52%	76%	23%	24%	46%
p-value, share of variance = 100% (LR test)	0.07	0.94	0.81	0.36	0.46	0.09
Corr(tax data income transmission, ELS π)	0.59	0.72	0.87	0.48	0.49	0.68

Notes : Sample and specifications are as in Table 5, but with models estimated separately by gender. N (rounded to the nearest 10) = 5,090 in Panel A; 5,850 in Panel B.

Table A8. Decomposition of the variation in intergenerational income transmission using child earnings by gender

Mechanism	**Total transmission**	**Skills**	**Return to skills**	**Residual**	**Non-labor and spousal income**
Dependent variable	**Child income**	**Child skill index**	**Child earnings**	**Child earnings residual**	**Family income less own earnings**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Panel A: Men					
Parental income - CZ mean	0.13	0.09		0.03	0.03
	(0.01)	(0.00)		(0.01)	(0.01)
CZ mean parental income	0.23	0.19		0.02	0.04
	(0.04)	(0.01)		(0.04)	(0.02)
CZ income transmission	7.55	-2.23	7.59	-1.37	-1.70
	(10.52)	(2.41)	(8.53)	(8.59)	(4.91)
(Parental income - CZ mean) * CZ income transmission	0.53	0.10		0.08	0.23
	(0.23)	(0.06)		(0.22)	(0.11)
Skill index - CZ mean			0.77		
			(0.06)		
CZ mean skill index			0.86		
			(0.12)		
(Skill index - CZ mean) * CZ income transmission			2.01		
			(1.01)		
d skills index / d parental income (scale factor)			0.09		
Scaled component	0.53	0.10	0.17	0.08	0.23
Share of total	100%	19%	33%	15%	44%

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Table A8 (continued)

Mechanism	Total transmission	Skills	Return to skills	Residual	Non-labor and spousal income
Dependent variable	**Child income**	**Child skill index**	**Child earnings**	**Child earnings residual**	**Family income less own earnings**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Panel B: Women					
Parental income - CZ mean	0.19	0.09		0.06	0.03
	(0.01)	(0.00)		(0.01)	(0.01)
CZ mean parental income	0.42	0.19		0.12	-0.04
	(0.05)	(0.01)		(0.03)	(0.04)
CZ income transmission	-6.09	-6.75	11.10	-4.17	-9.87
	(9.53)	(1.95)	(6.78)	(4.25)	(9.80)
(Parental income - CZ mean) *	0.64	0.04		0.25	0.29
CZ income transmission	(0.24)	(0.08)		(0.17)	(0.16)
Skill index - CZ mean			1.14		
			(0.05)		
CZ mean skill index			1.66		
			(0.13)		
(Skill index - CZ mean) * CZ income transmission			0.16		
			(0.78)		
d skills index / d parental income (scale factor)			0.09		
Scaled component	0.64	0.04	0.01	0.25	0.29
Share of total	100%	7%	2%	39%	45%

Notes : Sample and specifications are as in Table 11, but with models estimated separately by gender. N = 4,630 in Panel A; 5,350 in Panel B.