Family-Specific Intergenerational Income Mobility

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Abstract

We propose an alternative measure of the degree to which income status is transmitted from one generation to another. Our indicator of intergenerational income mobility is based on a random coefficient model, which allows for the variation in the intergenerational correlation across the population of families due to multiplicative unobserved family-specific characteristics. This alternative measure of intergenerational mobility suggests that the intergenerational income persistence is stronger for a typical family than we might think when using a population correlation coefficient between fathers' and sons' earnings to measure intergenerational mobility.

1 Introduction

The extent of intergenerational income mobility has been a concern of policy analysts and theoretical economists for a long time. Studies conducted before the 1990s conclude that correlations between fathers' and sons' incomes in the USA are positive but quite small. These findings seem to suggest that the economic well-being of individuals is not restricted by their families' backgrounds. Since the early 1990s a lot of attention has been devoted to a discussion of possible biases in the previous estimates of the population correlation between long-run economic statuses of fathers and long-run economic statuses of sons. Accounting for some of the sources of inconsistency increases the estimated population correlation between fathers' and sons' long-run incomes. While measurement error and homogeneous samples have been acknowledged to overstate the extent of the intergenerational income mobility in the United States, other possible sources of inconsistency in the estimation of intergenerational income mobility have been paid less attention. Specifically, Bratsberg et al. (2007) emphasize that the appropriateness of correlation coefficients and elasticities as measures of intergenerational income mobility depends on the functional relationship between fathers' and sons' incomes being linear in logs. If the functional form is nonlinear, correlation coefficients and elasticities estimated using a linear model can be quite misleading. Further, nonlinearity of the functional form becomes especially problematic in the context of cross-country comparisons, since the functional forms are likely to differ across countries.

A natural extension of this thought is to consider whether the relationship between sons' and fathers' earnings contains an interaction term between fathers' earnings and some unobserved family-specific characteristic(s). This kind of empirical relationship can be reflected in a random coefficeint (RC) model. The RC model has been under constant attention by the theoretical econometricians over the last couple decades. Sadly, applied researchers seem to disregard the flexibility offered by this model. Indeed, one possibility for such a relation in a search for the true estimate of intergenerational income mobility could be driven by significant credit constraints that are faced by low-income households. Given these constraints, families at the bottom of income distribution are less able to invest in their children's human capital, making the intergenerational income correlation stronger for those whose parents had low income. As a more specific example, the following reasonning can be used as a justification for employing the RC model in this context. Let us consider sons from families with fathers who worked 48 hours a week and sons whose fathers worked 40 hours a week.

Further, let us assume these two types of fathers were earning the same total amount of money per week and their earnings were their only source of income. Given that the incomes of two types of families were the same (assuming mothers did not work for pay), it is reasonable to think that both types of sons will get equal years of higher education. On the one hand, it is quite possible that the former sons can earn more than the latter ones while adults because they are likely to work longer hours following the footsteps of their fathers. On the other hand, it is quite reasonable to think that when they were in college they studied more hours and, as a result, they accumulated a "better" human capital. Therefore, sons of "workaholic" parents are likely to be earning more when they are adults in comparison with sons of fathers who worked less hours. How informative would a correlation coefficient between these types of sons' and fathers' earnings be if we were to obtain one? What would this measure tell us about the income mobility between these two generations? Obviously, this example exploits only one possible unobserved by econometricians aspect of a family life disregarding many other unobserved family characteristics that ultimately effect sons' earnings. While being simple, following Bratsberg et al. (2007), this illustration does question the appropriateness of correlation coefficients and elasticities as measures of intergenerational income mobility. However, in contrast with Bratsberg et al. (2007), here we point out the importance of the functional form not only in observed fathers' earnings but also in some unobserved family-specific characteristics, which can enter the relationship between fathers' and sons' earning in a multiplicative way. Ignoring these unobserved family-specific characteristics can be especially damaging for cross-country comparisons due to potentially strong cultural differences among the countries unobservable by econometricians.

If the functional relationship between sons' and fathers' earnings does not depend on unobservables that vary across families, then the findings from the previous literature on intergenerational income mobility are quite reliable and directly interpretable. However, if there is a variation in the intergenerational correlation across the population of families due to some unobserved family-specific characteristics that enter the functional relationship between fathers' and sons' earnings multiplicatively with fathers' earnings, then the appropriateness of the estimates of the population correlation from earlier studies is rather questionable. Further, these estimates are inconsistent under assumption of family-specific income mobility, and, more importantly, potentially very misleading. Indeed, in the latter case the estimates of intergenerational correlations might be of little policy relevance, since (in addition to their inconsistency) they might be representative only of a small fraction of the population. As Angrist et al. (1996) show, the standard instrumental variables estimation produces a consistent estimate of the Local Average Treatment Effect, which is the average causal effect for only a subgroup of the population.

Solon (1992) addresses the issue of biases in the research on the intergenerational correlation before the 1990s. He finds the intergenerational income correlation in the US to be around 0.4, indicating that the Unites States is a much less mobile society than it has been considered previously. Björklund and Jäntti (1997) question whether cross-sectional and intergenerational inequalities are independent of each other. They compare the United States to Sweden, which has less cross-sectional income inequality, and conclude that the United States does not have higher intergenerational mobility than Sweden. Bratsberg et al. (2007) investigate patterns of intergenerational earnings mobility in Denmark, Finland, and Norway, and conclude that earnings mobilities in these countries are highly nonlinear in the parental earnings, while earnings mobilities across generations in the US and the UK are much closer to the linear form throughout the income distribution. If intergenerational income mobility is changing across families due to unobserved family characteristics, we should ask ourselves whether the cross-sectional income inequality is amplified by intergenerational income immobility or whether the former is reduced by the latter.

This paper illustrates how the RC model can be exploited to obtain an alternative measure of the degree to which income status is transmitted from one generation to another. Our indicator of intergenerational mobility allows for the variation in the intergenerational correlation across the population of families due to multiplicative unobserved family-specific characteristics. The measure of income mobility we get under assumption of multiplicative unobserved heterogeneity in the relationship between fathers' and sons' earnings is much more representative of a typical (or an average, as we refer to it throughout the paper) family. First, we provide theoretical calculations of the inconsistencies in the estimates from the OLS and the IV methods if the parameter of interest is our alternative measure but instead we employ methods that are used in the previous literature. Second, we consider the consequences of whether an instrumental variable used for the endogenous income of fathers is a valid instrument. Third, if the instrumental variable used is a valid instrument, this paper discusses the control function estimation, which is the only approach that provides consistent estimates of the intergenerational mobility averaged across the population of unobservables. Next, we obtain estimates of our alternative measure of intergenerational income mobility for the US based on the Panel Study of Income Dynamics using the OLS, the IV, and the CF methods. We compare our empirical findings with the empirical findings from the previous literature and contrast them with our theoretical predictions. Finally, we make three major conclusions. First, the only logical possibility for the empirical and theoretical discussions to be in compliance with each other is when there is a negative association between the income of fathers and the intergenerational mobility in their families. The higher the fathers' income, the higher the intergenerational income mobility, and vice versa. Second, if the instrumental variable employed is valid, the consistent estimate of the averaged correlation is above the estimates of the intergenerational correlations found in the previous literature. This finding emphasizes that the concerns raised by Bratsberg et al. (2007) about the appropriateness of the correlation coefficient as a measure of intergenerational mobility in a typical US family are legitimate. Third, if the instrumental variable cannot be trusted to be a valid instrument, the OLS estimate of the averaged correlation is its lower bound. The IV estimate can be either an upper or a refined lower bound for the averaged correlation depending on the degree of the correlation between fathers' income and family-specific mobility.

2 Estimation of Intergenerational Income Mobility

Let ρ_o be a true population correlation between the long-run economic statuses of fathers, y_{Fi}, and the long-run economic statuses of sons, y_{Si}. The traditional approach to estimation of ρ_o is based on OLS estimation of the following regression equation:

$$y_{Si} = \rho_o y_{Fi} + \varepsilon_i, \tag{1}$$

where y_{Si} and y_{Fi} are the natural logarithms of sons' and fathers' economic status, respectively, and ε_i is an idiosyncratic error.[1] Solon (1992) emphasizes dangers of biases implied by this estimation procedure. First, the difficulty of employing the OLS method for regression (1) arises due to the fact that permanent incomes of sons' and fathers' are not observed. Only annual incomes are available for researchers. Since econometricians are not able to observe the long-run economic statuses of fathers and sons directly, the traditional approach is to employ their current economic statuses

[1] This approach is based on the simplifying assumption that the variances of the long-run economic statuses of fathers and sons is the same $(\mathrm{Var}(y_{Fi}) = \sigma_F^2 = \sigma_S^2 = \mathrm{Var}(y_{Si}))$. If $\sigma_S^2 \neq \sigma_F^2$, then the estimated slope coefficient estimates $\rho \frac{\sigma_S}{\sigma_F}$.

instead. Second, unrepresentative samples also lead to the inconsistent OLS estimates of ρ_o. Solon suggests using data from the Panel Study of Income Dynamics, and time-averaging of the current economic incomes of fathers to alleviate the two problems. However, even if we follow his guidance, we might get uninformative estimates of the intergenerational income mobility if we do not account for a nonlinear functional relationship between sons' and fathers' earnings that depends on family-specific observables and unobservables. Indeed, if some unobserved (and observed) family-specific characteristics enter the functional relationship between fathers' and sons' earnings multiplicatively with fathers' earnings, then even the IV estimate of the intergenerational correlation from equation (1) is not only inconsistent but it also represents only a small fraction of the population. Angrist et al. (1996) point out that the IV estimator is consistent for the average causal effect for a subgroup of the population only, while Bratsberg et al. (2007) emphasize that the appropriateness of an estimate of the correlation coefficient from equation (1) as a measure of the intergenerational income mobility is rather questionable.

If we relax the assumption of a linear relationship between fathers' and sons' earnings in both observed covariates and unobserved characteristics that vary across families (pairs of fathers and sons), the population model becomes:

$$y_{Si} = \rho_i y_{Fi} + \varepsilon_i = \rho_o y_{Fi} + r_i y_{Fi} + \varepsilon_i, \tag{2}$$

where we call $\rho_i = \rho_o + r_i$ the family-specific intergenerational income mobility (or the family-specific correlation between the long-run economic status of fathers and sons), and $\rho_o = \mathrm{E}(\rho_i)$ is the population correlation between fathers' and sons' permanent incomes, averaged across the population of unobservables (from now on "averaged correlation" or "averaged intergenerational income mobility"). Let us understand what happens if we ignore the multiplicative unobserved heterogeneity and continue using the OLS estimation method.

Acknowledging the issues raised by Solon (1992), and combining family-specific intergenerational income mobility and annual measures of fathers' and sons' incomes, we get:

$$y_{Sit} = \rho_o y_{Fit} + r_i y_{Fit} + \varepsilon'_{it}, \tag{3}$$

where $y_{Fi} = y_{Fit} + v_{Fit}$, and $y_{Si} = y_{Sit} + v_{Sit}$. Then,

$$\operatorname*{plim}_{N\to\infty} \hat{\rho}_o^{OLS} = \frac{\mathrm{Cov}(y_{Sit}, y_{Fit})}{\mathrm{Var}(y_{Fit})} = \rho_o + \frac{\mathrm{Cov}(r_i y_{Fi}, y_{Fi}) - \sigma^2_{v_F}}{\sigma^2_F + \sigma^2_{v_F}}, \tag{4}$$

where $\sigma_F^2 = \text{Var}(y_{Fi})$, $\sigma_{v_F}^2 = \text{Var}(v_{Fit})$. Expression (4) is derived assuming that $\text{Cov}(y_{Fi}, v_{Fit}) = 0$ and $\text{Cov}(y_{Si}, v_{Sit}) = 0$. The direction of the inconsistency depends on the covariance term, $\text{Cov}(r_i y_{Fi}, y_{Fi})$. While it might be a challenge to see the sign of this term right away, a reasonable simplifying assumption clarifies the situation. Assume $\text{E}(r_i|y_{Fi}) = \alpha(y_{Fi} - \mu_F)$, where $\mu_F = \text{E}(y_{Fi}) > 0$, $\alpha \neq 0$. This form ensures that $\text{E}(r_i) = 0$. Assuming that $\text{E}(r_i|y_{Fi})$ is linear in y_{Fi} provides a direct link to the results from Bratsberg et al. (2007), since once this assumption is combined with equation (3) it is easy to see that the functional relationship between fathers' and sons' earnings becomes quadratic in fathers' earnings. The quadratic functional form is exactly the functional form which Bratsberg et al. (2007) conclude on for the USA and the UK.[2]

Using the Law of Iterated Expectations, $\text{Cov}(r_i y_{Fi}, y_{Fi}) = \alpha[\text{E}(y_{Fi})^3 - 2\mu_F\sigma_F^2 - \mu_F^3] = \alpha[M_3 + \mu_F\sigma_F^2]$, where M_3 is the third moment about the mean. Previous studies of properties of the income distribution in the US suggest that the US income has skewness either being very close to zero, or equal to a small positive number (see Adams (1960) as a possible example of the literature reasonably close to 1967 in time). This fact implies that $M_3 \geq 0$.[3] Thus, the OLS estimate of the averaged correlation between the economic statuses of fathers and the economic statuses of sons is downward-inconsistent if $\text{Cov}(r_i y_{Fi}, y_{Fi}) - \sigma_{v_F}^2 < 0$, and the OLS estimate of the averaged correlation, ρ_o, is upward-inconsistent if $\text{Cov}(r_i y_{Fi}, y_{Fi}) - \sigma_{v_F}^2 > 0$. When $\alpha < \frac{\sigma_{v_F}^2}{M_3 + \mu_F\sigma_F^2}$ the inconsistency of the OLS estimate of the averaged mobility is always negative, and it is positive if $\alpha > \frac{\sigma_{v_F}^2}{M_3 + \mu_F\sigma_F^2}$.

Interestingly, if $\alpha < 0$, the downward-inconsistency is larger than we might think if we ignore the family-specific nature of the intergenerational income mobility. If the true population model is (1) then the covariance term in (4) vanishes. In other words, ignoring the random coefficient nature of the model and using the OLS, we underestimate the averaged correlation between economic statuses of fathers and sons more than we think. Further, conclusion of downward-inconsistency based on the model with constant intergenerational income mobility might be wrong if $\alpha > \frac{\sigma_{v_F}^2}{M_3 + \mu_F\sigma_F^2}$.

Now, let us consider the IV estimation that is also extensively used in the literature. The traditional approach to the IV method in the context of intergenerational income mobility is to

[2] Thus, our choice of the US for an empirical investigation that follow later is in part motivatied by Bratsberg et al. (2007).

[3] Skewness equals $\frac{M_3}{\sigma^3}$, where M_3 is the third moment about the mean, and σ is the standard deviation. $M_3(x) = \text{E}[(x - \text{E}(x))^3]$

assume that instead of (2) the true population model is

$$y_{Si} = \gamma_1 y_{Fi} + \gamma_2 E_i + r_i y_{Fi} + \varepsilon_i, \tag{5}$$

where E_i is the fathers' education, and apply the IV method to equation (2) using E_i as an instrumental variable for y_{Fi}. Then, the IV estimator of the averaged correlation based on the annual measures of long-run economic statuses of fathers' and sons' is

$$\operatorname*{plim}_{N\to\infty} \hat{\rho}_o^{IV} = \frac{\text{Cov}(y_{Sit}, E_i)}{\text{Cov}(y_{Fit}, E_i)} = \rho_o + \gamma_2 \frac{(1-\lambda^2)\sigma_E}{\lambda\sigma_F} + \frac{\text{Cov}(r_i y_{Fi}, E_i)}{\text{Cov}(y_{Fi}, E_i)}, \tag{6}$$

where λ is the correlation between E_i and y_{Fi}, and $\sigma_E^2 = \text{Var}(E_i)$. Similar to the OLS case, expression (6) is derived assuming that $\text{Cov}(y_{Fi}, v_{Fit}) = 0$ and $\text{Cov}(y_{Si}, v_{Sit}) = 0$. In addition, we assume $\text{Cov}(v_{Fit}, E_i) = 0$. The covariance term, $\text{Cov}(r_i y_{Fi}, E_i)$, is the difference in the IV estimates based on the constant coefficient and the random coefficient models. Since as long as we are willing to assume that $\gamma_2 > 0$, $\gamma_2 \frac{(1-\lambda^2)\sigma_E}{\lambda\sigma_F}$ is positive as long as $0 < \lambda < 1$, the direction of inconsistency of the IV estimate of ρ_o depends on $\text{Cov}(r_i y_{Fi}, E_i)$. Once again, assume $\text{E}(r_i|y_{Fi}) = \alpha(y_{Fi} - \mu_F)$. Then, using the Law of Iterated Expectations, $\text{Cov}(r_i y_{Fi}, E_i) = \alpha[\text{Cov}(y_{Fi}^2, E_i) - \mu_F \text{Cov}(y_{Fi}, E_i)]$. It is reasonable to assume that $\text{Cov}(y_{Fi}^2, E_i)$ and $\text{Cov}(y_{Fi}, E_i)$ are both positive. The assumption about the second covariance simply states that education and income are positively correlated. Diminishing returns to education ensure that the assumption about the first covariance is true. However, even if we are willing to make these assumptions, they are not sufficient to answer the question about the sign of the inconsistency of the IV estimator of ρ_o. The sign of the covariance term in equation (6) depends on signs of both α and $[\text{Cov}(y_{Fi}^2, E_i) - \mu_F \text{Cov}(y_{Fi}, E_i)]$.

Say, $\text{E}(E_i|y_{Fi}) = \theta y_{Fi}$, $\theta \neq 0$. Then, $\text{Cov}(y_{Fi}, E_i) = \theta\sigma_F^2$, and $\text{Cov}(y_{Fi}^2, E_i) = \theta[M_3 + 2\mu_F\sigma_F^2]$, where M_3 is a third moment of y_{Fi}. Thus, $[\text{Cov}(y_{Fi}^2, E_i) - \mu_F \text{Cov}(y_{Fi}, E_i)] = \theta[M_3 + \mu_F\sigma_F^2]$, and $\frac{\text{Cov}(r_i y_{Fi}, E_i)}{\text{Cov}(y_{Fi}, E_i)} = \frac{\alpha[M_3 + \mu_F\sigma_F^2]}{\sigma_F^2}$. As long as $\theta > 0$, $[\text{Cov}(y_{Fi}^2, E_i) - \mu_F \text{Cov}(y_{Fi}, E_i)]$ is positive, since $M_3 > -\mu_F\sigma_F^2$ is always true if the skewness of the distribution of the fathers' incomes is non-negative. Based on Adams (1960), we can make this assumption about the skewness of the distribution of income in the US in approximately that period in time. In addition, to get empirical support on the sign of $[\text{Cov}(y_{Fi}^2, E_i) - \mu_F \text{Cov}(y_{Fi}, E_i)]$ we use two data sets provided with Wooldridge (2002). The first dataset, called WAGE1, is on the population of people in the workforce in 1976, where wage is measured in dollars per hour. It contains 526 observations. The second dataset, called WAGE2, is on the population of men in 1980, where the variable on wage is the monthly earnings. This dataset has 935 observations. For both datasets, using y_{Fit} as a proxy for y_{Fi}, we get that expression $[M_3 + \mu_F \sigma_F^2]$ is positive. Thus, relying on both the empirical findings and the theoretical derivations of the sign of the expression in question we can conclude the covariance term in equation (6) is positive if $\alpha > 0$ and negative otherwise. This implies that the inconsistency of the IV estimator of the averaged correlation is upward if $\alpha > 0$. In other words, if $\alpha > 0$, we are likely to overestimate the averaged correlation between permanent income of fathers and permanent income of sons more than we think. When $\alpha < 0$, the inconsistency can be either positive or negative.

As Solon (1992) points out the possibility that $\gamma_2 \simeq 0$ "is not out of the question." Research by Sewell and Hauser (1975) and Corcoran et al. (1992) is among the studies that support this possibility. If $\gamma_2 = 0$ and the population model is a model with constant across families intergenerational income mobility, then the IV estimate of the correlation between fathers' and sons' long-run incomes is consistent. If $\gamma_2 = 0$ and the population model is a random coefficient model, then the second term in (6) disappears, and the inconsistency of the IV estimate of ρ_o is upward when $\alpha > 0$, and it is downward when $\alpha < 0$. Table 1 contains the summary of the above discussion of the direction of inconsistency of the estimates of ρ_o.

Obviously, as previous derivations suggest, ignoring the multiplicative heterogeneity in the population model results in inconsistent estimates of ρ_o from either the OLS or the IV approaches. Instead, we can turn to a control function approach, which is pioneered by Smith and Blundell (1986) and Rivers and Vuong (1988) in the econometric literature. Wooldridge (2005) proposes using this method to deal with the random coefficients in the cross sectional models. The main idea of the control function approach is to add variables into the structural model to account for inconsistency. If there were no family-specific intergenerational income mobility, the estimate of ρ_o from the standard control function approach would coincide with the estimate of ρ_o from the instrumental variables approach. (The standard control function approach uses the OLS estimation of a regression that includes residuals from the first stage for the IV method as an additional explanatory variable along with the endogenous regressor.) A presence of multiplicative heterogeneity requires a modification of the standard control function approach and leads to different estimates of ρ_o. The control function approach results in consistent estimates of ρ_o when an instrumental variable used for the estimation is a valid instrument (i.e., the instrument is redundant in the structural equation). If the instrumental variable is not valid, i.e., $\gamma_2 \neq 0$ in (5), the control function method does not deliver a consistent estimate of the averaged intergenerational income mobility.

So, if we have a valid instrument we can apply a control function approach to equation

$$y_{Si} = \rho_o y_{Fi} + r_i y_{Fi} + \varepsilon_i = \rho_o y_{Fi} + u_i, \tag{7}$$

where $u_i = r_i y_{Fi} + \varepsilon_i$ is a new composite error. First, we traditionally assume a linear reduced form for y_{Fit}:

$$y_{Fi} = \delta_{20} + \delta_{21} E_i + v_{2i}, \tag{8}$$

where $\mathrm{E}(v_{2i}|E_i) = 0$. Second, we adopt an assumption about the distribution of (r_i, v_{2i}) conditional on E_i from Wooldridge (2005):

$$\mathrm{E}(r_i|E_i, v_{2i}) = (\pi_1 + \pi_2 E_i)v_{2i}. \tag{9}$$

Finally, we model the relationship between u_i and v_{2i} to be

$$\mathrm{E}(u_i|E_i, v_{2i}) = \theta v_{2i}. \tag{10}$$

The resulting estimating equation looks like:

$$\mathrm{E}(y_{Si}|E_i, v_{2i}) = \rho_o y_{Fi} + \pi_1 y_{Fi} v_{2i} + \pi_2 y_{Fi} E_i v_{2i} + \theta v_{2i}. \tag{11}$$

3 Data Description

The Panel Study of Income Dynamics (PSID) is a longitudinal survey conducted annually since 1968. The samples of fathers and sons are constructed generally following the guidelines from Solon (1992). As a clarification, we want to emphasize that while we use the approach outlined in Solon (1992) as a guideline for obtianing our samples, our ultimate goal is not to obtain traditional parameter estimates of the intergenerational income mobility that would be identical to the estimates from Solon (1992) or any other study. We use the obtained samples to show how the traditional estimational techniques would differ from the alternative approach we propose.

Following Solon (1992), we investigate the averaged intergenerational income mobility for fathers and their oldest sons and for fathers and all of their sons (multiple sons). The sample of fathers taken from 1968 contains 311 male heads of the households of age between 29 and 69 who had at least one biological or adoptive son. The survey from 1968 contains information on fathers' earnings in 1967. This sample is obtained from the Survey Research Center (SRC) component of the PSID. The sons in the oldest sons sample are oldest children from the original 1968 PSID households who reported positive annual earnings for 1984. The data on the annual earnings of sons in 1984 come from the 1985 survey. Sons are restricted to those who were born between 1951 and 1959 and who were heads of households in 1985. Panel A of Table 2 presents some summary statistics for the fathers and sons from the oldest sons sample. The multiple sons sample contains 404 multiple sons (either biological or adoptive) of the fathers from 1968 who met all the requirements mentioned above. Panel B of Table 2 reports summary statistics for sons from the multiple sons sample. Table 3 contains information about father-son pairs in each quintile of the distribution of fathers' and sons' earnings in 1967 and 1984, respectively. As it shows for both samples we employ, there is a higher income persistence in the low tail of the distribution of fathers' earnings. For example, for multiple sons almost 41% of all sons whose fathers were in the lowest quintile of the earnings distribution will end up in the lowest quintile of the distrbution of earings for their generation. Only 5% of sons whose father's earnings were in the bottom quintile will advance into the top quintile of the earnings distribution for their peers.

4 Empirical Results

Table 4 presents the estimated averaged intergenerational income mobility, ρ_o, using the OLS, the IV, and the CF methods. The instrument used in the IV and the CF approaches is fathers' years of education, which is provided in interval form by the PSID for 1968. The actual instrument is set at the midpoint of the reported interval for fathers' education. According to Table 4, if the instrumental variable employed is valid the consistent estimates of the averaged intergenerational mobility from the CF function approach are above the consistent IV estimates of the population correlation for both samples considered. Specifically, the CF estimate of the averaged mobility is 0.49 versus the IV estimate of the population correlation is 0.44 in the sample of oldest sons. This result supports the concerns raised by Bratsberg et al. (2007) about the appropriateness of the correlation coefficient as a measure of intergenerational mobility. Indeed, according to the estimates of the averaged intergenerational mobility, a typical US family shows more intergenerational persistence in income than is traditionally thought when interpreting the estimates of the population correlation between fathers' and sons' earnings. A test of the joint significance of the terms containing the residual in the CF approach indicates that these terms are jointly significant at 10% level ($p - value = 0.064$) for the sample of multiple sons. This result also suggests that there is statistical evidence (at least at 10% level) indicating that the random coefficient model is appropriate in this context.

In a general situation when γ_2 can take on any possible value ($\gamma_2 \neq 0$), none of the three methods results in a consistent estimate of the averaged intergenerational income mobility. Since $\underset{N\to\infty}{\text{plim}}\ \hat{\rho}_o^{OLS} - \rho_o = \frac{\alpha[M_3+\mu_F\sigma_F^2]-\sigma_{v_F}^2}{\sigma_F^2+\sigma_{v_F}^2}$ and $\underset{N\to\infty}{\text{plim}}\,\hat{\rho}_o^{IV} - \rho_o = \gamma_2\frac{(1-\lambda^2)\sigma_E}{\lambda\sigma_F} + \frac{\alpha[M_3+\mu_F\sigma_F^2]}{\sigma_F^2}$, basic algebraic calculations show that $\hat{\rho}_o^{OLS}$ can be smaller than $\hat{\rho}_o^{IV}$ in two cases. First, it is possible when both the IV and the OLS estimates are inconsistent downwards and the true averaged population correlation is above both of the estimates. The second case can occur in the opposite situation when both the OLS and the IV estimates are upward inconsistent and the true averaged population intergenerational mobility is below both of the two estimates. The first case is possible when $-A < \alpha < 0$, where $A = \frac{\gamma_2\frac{(1-\lambda^2)}{\lambda}\sigma_E\sigma_F(\sigma_F^2+\sigma_{v_F}^2)+\sigma_F^2\sigma_{v_F}^2}{[M_3+\mu_F\sigma_F^2]\sigma_{v_F}^2} > 0$. The second situation can happen when $\alpha > \frac{\sigma_{v_F}^2}{M_3+\mu_F\sigma_F^2} > 0$.

In a special case when we are willing to assume that a father's education is a valid instrument for a father's income, i.e., $\gamma_2 = 0$, $\hat{\rho}_o$ from the control function approach is the only consistent estimate of ρ_o. Further, if $\gamma_2 = 0$ in (5), $\underset{N\to\infty}{\text{plim}}\,\hat{\rho}_o^{IV} - \rho_o = \frac{\alpha[M_3+\mu_F\sigma_F^2]}{\sigma_F^2}$ and $\hat{\rho}_o^{OLS}$ can be smaller than $\hat{\rho}_o^{IV}$ in the two cases discussed above with A adjusted for $\gamma_2 = 0$. However, Table 1 suggests that the only situation when Table 4 contains results that are consistent among themselves for $\gamma_2 = 0$ is when $-A < \alpha < 0$.[4] Indeed, for $\alpha > \frac{\sigma_{v_F}^2}{M_3+\mu_F\sigma_F^2} > 0$ the true value of the averaged correlation is above the OLS estimate and it is consistently estimated by the IV method when $\gamma_2 = 0$. At the same time, the true averaged intergenerational mobility is below both the IV and the OLS estimates when $\gamma_2 \neq 0$. Thus, when $\alpha > \frac{\sigma_{v_F}^2}{M_3+\mu_F\sigma_F^2} > 0$ the model with $\gamma_2 = 0$ and the general model with $\gamma_2 \neq 0$ tell very different stories about the intergenerational correlation. Further, the model with $\gamma_2 = 0$ cannot be a special case of the general model when γ_2 can be different from zero. Contrary, $-A < \alpha < 0$ implies that the model with $\gamma_2 = 0$ is a special case of the model with $\gamma_2 \neq 0$. Indeed, for $-A < \alpha < 0$, the true value of the averaged intergenerational income mobility is above both the OLS and the IV

[4] We check the sign of expression $[\text{Cov}(y_{Fi}^2, E_i) - \mu_F \text{Cov}(y_{Fi}, E_i)]$ for the samples obtained from the PSID. This expression turns out to be positive as in the datasets WAGE1 and WAGE2 we use to assess the direction of the inconsistency of the IV estimate in Section 2.

estimates for either $\gamma_2 = 0$ or $\gamma_2 \neq 0$. Thus, negative α presents the only interesting situation.

What does negative alpha imply? If $\alpha < 0$, the correlation between fathers' and sons' permanent incomes is negative. In other words, the higher the long-run income of fathers, the lower the family-specific correlation between long-run economic statuses of a father and a son, ρ_i, and, equivalently, the higher the family-specific intergenerational income mobility. Assuming that a father's education is a valid instrument for a father's income, we estimate the averaged intergenerational income mobility to be 0.49. When a father's education is not a valid instrument for a father's income, we cannot consistently estimate the averaged correlation, ρ_o. Instead, when $\gamma_2 \neq 0$ we can rethink the OLS and IV estimates. The IV estimate of ρ_o can be either an upper bound or a lower bound of ρ_o depending on the value of α, which is unobserved. When $-A < \alpha < -\frac{\gamma_2 \frac{(1-\lambda^2)}{\lambda} \sigma_E \sigma_F}{M_3 + \mu_F \sigma_F^2}$, $\hat{\rho}_o^{IV}$ is upward inconsistent, and when $-\frac{\gamma_2 \frac{(1-\lambda^2)}{\lambda} \sigma_E \sigma_F}{M_3 + \mu_F \sigma_F^2} < \alpha < 0$, $\hat{\rho}_o^{IV}$ is downward inconsistent. Since we do not have any guidance on the magnitude of α, the best we can do is to use the OLS estimate of the averaged correlation as a lower bound for ρ_o. Thus, we would conclude that when $\gamma_2 \neq 0$ the averaged correlation between long-run economic statuses of fathers and long-run economic statuses of sons is at least 0.35. In both cases, when $\gamma_2 \neq 0$ and $\gamma_2 = 0$, higher long-run incomes of fathers imply higher family-specific intergenerational income mobility.

5 Conclusion

Previous studies devoted a lot of attention to discussion of possible biases in the estimates of the population correlation between long-run economic statuses of fathers and long-run economic statuses of sons. Measurement error and homogeneous samples have been acknowledged to exaggerate the extend of intergenerational income mobility in the United States. Because of the nonlinear functional relationship between fathers' and sons' incomes, the appropriateness of correlation coefficients and elasticities as measures of intergenerational income mobility has also been investigated. At the same time, a possibility of multiplicative unobserved heterogeneity in the relationship between fathers' and sons' earnings has been disregarded. If intergenerational income mobility does depend on unobserved family-specific characteristics, traditional estimates of correlation coefficients and elasticities are not representative of a typical family and, thus, can be quite misleading. The usual measures of intergenerational income mobility can be especially deceptive in a cross-country context. Therefore, an alternative measure of intergenerational income mobility should be considered.

This paper proposes an alternative measure of the degree to which income status is transmitted from one generation to another. Our indicator of intergenerational mobility is based on a random coefficient model, which allows for the variation in the intergenerational correlation across the population of families due to multiplicative unobserved heterogeneity in the relationship between fathers' and sons' earnings. Under this setting, estimates from the OLS and the IV methods that are used in the previous literature are shown to be inconsistent. Consequences of whether an instrumental variable used for the endogenous income of fathers is a valid instrument or not are discussed. The control function approach is suggested for consistent estimation of the intergenerational income mobility averaged across the population of unobservables when the instrumental variable used is a valid instrument. If the instrumental variable is not a valid instrument, none of the three estimation techniques considered – OLS, IV and CF – is consistent. In addition, in the latter case the OLS estimate of the averaged correlation is its lower bound, and the IV estimate can be either an upper or a refined lower bound for the averaged correlation depending on the degree of the correlation between fathers' incomes and family-specific mobility. Second, we obtain estimates of our alternative measure of intergenerational income mobility for the US based on the PSID using the OLS, the IV, and the CF methods. If the instrumental variable employed is valid, the consistent estimate of the averaged correlation is above the estimates of the intergenerational correlations from the previous literature. This finding emphasizes the legality of the concerns raised by Bratsberg et al. (2007) about the appropriateness of the correlation coefficient as a measure of intergenerational mobility in a typical family. If we use the averaged intergenerational correlation as a measure of intergenerational mobility in the US, we obtain that the intergenerational income persistence is stronger for a typical US family than when using a simple population correlation between fathers' and sons' earnings to measure intergenerational income mobility. Finally, investigating the empirical and theoretical findings, we can conclude that the three methods studied suggest that there is a negative association between the income of a father and the intergenerational mobility in his family. The higher the father's income is, the higher the intergenerational income mobility will be, and vice versa.

6 References

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Table 1. Direction of inconsistency of estimates of averaged correlation, ρ_o.

	OLS	IV	
		E_i is a valid IV	E_i is not a valid IV
$\alpha > 0$	upward/downward[1]	upward	upward
$\alpha < 0$	downward	downward	upward/downward[2]

[1] upward if $\alpha > \frac{\sigma^2_{v_F}}{M_3+\mu_F\sigma^2_F}$; downward if $\alpha < \frac{\sigma^2_{v_F}}{M_3+\mu_F\sigma^2_F}$.

[2] upward if $\alpha > -\frac{\gamma_2\frac{(1-\lambda^2)}{\lambda}\sigma_E\sigma_F}{M_3+\mu_F\sigma^2_F}$; downward if $\alpha < -\frac{\gamma_2\frac{(1-\lambda^2)}{\lambda}\sigma_E\sigma_F}{M_3+\mu_F\sigma^2_F}$.

Table 2. Samples' Characteristics.

Variable	Mean	St. Dev.	Min	Max
A: Oldest Sons[1]				
Son's earnings in 1984	23,492	15,367	19	147,656
Son's log earnings in 1984	9.80	0.93	2.94	11.90
Father's earnings in 1967[2]	28,813	17,437	405	186,660
Father's log earnings in 1967[2]	10.09	0.68	6.00	12.14
B: Multiple Sons[3]				
Son's earnings in 1984	22,665	14,297	19	147,656
Son's log earnings in 1984	9.78	0.89	2.94	11.90

[1] Panel A is based on 311 sons and fathers.

[2] Father's earnings in 1967 are in 1984 dollars.

[3] Panel B is based on 404 sons.

Table 3. Count of father-son pairs in each quintile of the distribution of father's and son's earnings.

	Oldest Sons						Multiple Sons					
Fathers	1	2	3	4	5	Total	1	2	3	4	5	Total
1	23	16	12	7	5	63	33	22	12	10	4	81
2	13	14	16	7	12	62	15	19	22	10	15	81
3	12	11	15	13	11	62	12	16	19	18	15	80
4	9	14	7	18	14	62	10	15	13	22	21	81
5	6	7	12	17	20	62	11	9	14	21	26	81
Total	63	62	62	62	62	311	81	81	80	81	81	404

Note: The lowest quintile of the distribution is denoted by 1, while the highest quintile is represented by 5.

Table 4. Estimated Averaged Intergenerational Correlation, ρ_o.

Year of father's log earnings	Sample size	(1) OLS	(2) IV	(3) CF
	Oldest Sons			
1967	311	0.354	0.440	0.490
		(0.075)	(0.123)	(0.156)
	Multiple Sons			
1967	404	0.352	0.434	0.480
		(0.064)	(0.102)	(0.129)

Notes: Education is an instrument for income. Standard errors are reported in parenthesis. Standard errors for the CF approach are bootstrapped standard errors based on 1000 replications. Tables with full regression results are available on request.