

Estimating Intergenerational Mobility With Grouped Data: A Critique of Clark's *the Son Also Rises*

Florencia Torche¹ and Alejandro Corvalan²

Abstract

This article distinguishes three measures of intergenerational economic mobility that emerge when the population is divided into groups: overall individual mobility, within-group mobility, and between-group mobility. We clarify their properties and the relationship between them. We then evaluate Clark's use of surname between-group persistence as a preferred measure of intergenerational mobility in the book *The Son Also Rises: Surnames and the History of Social Mobility*. We show that aggregate surname-level intergenerational persistence cannot be compared with individual persistence because group-level income averages captures diverse individual-level and group-level factors impossible to disentangle without additional identifying information. Furthermore, measures of group persistence do not address the problem of measurement error leading to attenuation bias, which is Clark's rationale to study surname mobility. An empirical example partitioning the population into groups based on racial/ethnic origins and a simulation clarify the relationship between these different measures of mobility.

¹ Stanford University, Palo Alto, CA, USA

² Universidad Diego Portales, Santiago, Chile

Corresponding Author:

Florencia Torche, Stanford University, 450 Serra Mall, Stanford, CA 94305, USA.

Email: torche@stanford.edu

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Intergenerational mobility, measured by the strength of the association between parents' and children's socioeconomic status, is an important concern for scholars and policy makers alike because mobility is claimed to provide information about equality of opportunity in society (Torche 2015). Strong intergenerational persistence identifies a society in which individuals' adult status is largely shaped by advantages of birth, that is, limited mobility. In contrast, weak intergenerational persistence identifies a society with ample opportunity for mobility. Several measures of status have been used for the analysis of mobility including occupational status, income, earnings, education, and wealth. Much recent research comparing mobility across countries and over time uses income and earnings as measures of status, and so these are the measures referred to in this article. However, the discussion applies to any continuous measure of socioeconomic status such as wealth, schooling, or occupational status.

A challenge in the study of income mobility is the discrepancy between the underlying variable researchers are interested in—parents' long-term economic status, a unobserved construct believed to shape children's opportunities—and the variable researchers observe—income earned by individuals over a certain period of time, usually a year. Researchers address this challenge by taking averages of individual income across several years, which purportedly reduces measurement error contained in the year-specific observations and approaches the “true” measure of economic status. Economists call this averaged measure “permanent” or “lifetime” income to highlight that it is purged from temporal fluctuation. In the United States, measures of intergenerational persistence using across-year income averages reach between 0.4 and 0.6, much higher than the approximately 0.2 obtained with single-year income (Björklund and Jantti 2009; Black and Devereux 2011; Mitnik et al. 2015; Solon 1999).

An alternative approach to measure individual mobility has been recently proposed. This approach takes averages of a measure of economic status, such as occupational status, schooling, or income across groups organized by surname, and obtains the intergenerational association between surname averages for parents and children (Clark 2014:107-8; Clark and Cummins 2015; Clark et al. 2015). The rationale for using surname-level averages is

the same as the one for taking individual across-year averages: Clark claims that the surname-level averages capture the true social status of individuals, purged of measurement error. In his analysis, Clark selects high- and low-status surnames—he calls them “elite” and “underclass”—in different contexts and measures the surname-level intergenerational persistence of measures such as occupational status and schooling. For example, in the United States, “(T)he elite groups are the descendants of Ashkenazi and Sephardic Jews, the descendants of the wealthy individuals as of 1923–24 who had rare surnames, the descendants of individuals with rare surnames who graduated from Ivy League universities in or before 1850, and people of Japanese descent. The underclass groups are Native Americans, black Africans whose ancestors came to the United States before the Civil War, and, surprisingly, the U.S. descendants of the French settlers who came to the French colonies of North America between 1604 and 1759” (Clark 2014:45).

Selecting elite and underclass surnames, Clark finds that the surname-level intergenerational persistence is very high—around 0.75 or even higher—and surprisingly stable across contexts, including medieval England, Sweden since 1600, and Chile in the twentieth century. Based on these findings, Clark (2014) argues that intergenerational mobility of social status is extremely limited and stable across time and place: “this book suggests . . . a social law: there is a universal constant of intergenerational correlation of 0.75, from which deviations are rare and predictable” (p. 12).

Clark then goes on to equate social status transmitted across generations with individual social competence or ability, which he claims underlies partial measures of status, such as income, education, and occupation, and to suggest that competence is the product of exogenous genetic differences between individuals. He establishes a difference between genotype and phenotype, explaining that “The genotype is the set of genes carried by a single organism. Its phenotype comprises all of its observable characteristics, influenced by both by its genotype and its environment. Conventional studies of social mobility measure just the inheritance of particular aspects of the status phenotype. But families also have an underlying status genotype, which is inherited much more faithfully. Surname mobility estimates reflect this status genotype” (Clark 2014:12). Although Clark hastens to qualify this statement in a footnote indicating that “The term status genotype does not imply here that genes transmit status, just that the process looks similar in character to genetic transmission,” he then appears to bestow causal prevalence to a genetic explanation. First, he claims that “by and large, social mobility has characteristics that do not rule out genetics as the dominant connection between the generations” (Clark 2014:13) to then more strongly assert that

“Only if genetics is the main element in determining economic success, if nature trumps nurture, is there a built-in mechanism that explains the observed regression. That mechanism is the intermarriage of the children of rich and educated lineages with successful, upwardly mobile children of poor and uneducated lineages. Even though there is strong assortative mating—because this is based on the social phenotype created in part by luck—those of higher-than-average innate talent tend to mate with those of lesser ability and regress to the mean. Similarly, those of lower-than-average innate talent tend to marry unlucky offspring of higher average innate talent” (Clark 2014:14). He then reflects on the implications of his findings for parents: “What is the significance of these results for parents socially ambitious for their children? The practical implication is that if you want to maximize your children’s chances, you need to pay attention not to the social phenotype of your marriage partner but instead to his or her status genotype. That genotype is indicated by the social group your potential partner belongs to, as well as the social phenotype of their siblings, parents, grandparents, cousins, and so on to the *n*th degree of relatedness. Once you have selected your mate, your work is largely done. You can safely neglect your offspring, confident that the innate talents you secured for them will shine through regardless” (Clark 2014:14-15).

Not only parenting is unable to shape individual well-being, according to Clark. Institutions are also powerless to promote equal opportunity. As he asserts about the Swedish case, “The enlargement of the political franchise and the institutions of the extensive welfare state of modern Sweden, including free university education and maintenance subsidies to students, have done nothing to increase rates of social mobility” (Clark 2014:35)

In sum, based on his empirical finding of a strong surname-level intergenerational correlation in different contexts, Clark suggests that innate talents determine individual attainment and that intergenerational persistence is impervious to environmental exposures ranging from parenting to the welfare state, and it should better be left alone. Not surprisingly, this approach has elicited interest and controversy.

This article claims that Clark’s interpretation is incorrect. We show that using surname-level income averages is an inappropriate strategy if the intent is to understand mobility of individuals, and therefore the corollaries from the analysis are unwarranted. Surname-level income averages do not capture individual genetic endowments, or any individual attribute that can be passed across generations. We also show that taking group-level averages does not address the measurement error problem it intends to solve. Furthermore, we show that Clark’s findings of high and stable intergenerational persistence is an artifact of his selection of what he calls elite and underclass groups in the

contexts he examines. Using both an empirical example in the United States and simulated data, we show that the level of surname-aggregate persistence depends on the groups being chosen for the analysis and that it can be higher, of similar magnitude, or lower (or even have different signs) than estimates of individual-level persistence traditionally used by the mobility literature.

But our main contribution is not just to offer a critique of Clark's approach and putative implications. Rather, we generalize from the case of surname-based groups to any measure of group mobility and distinguish three different measures of intergenerational mobility that emerge when the population is divided into groups: overall individual mobility, within-group mobility, and between-group mobility. We explain how these measures relate to each other and what the implications of this distinction are for the understanding of mobility.

Populations, Groups, and Measures of Mobility

We consider N pairs of individuals¹ belonging to two generations, indexed by $i = 1, \dots, N$. Let y_i be a measure of socioeconomic well-being in the adult children's generation and x_i be the same measure for the parental generation. The overall sample means of these measures are denoted as \bar{y} and \bar{x} . In our discussion, we will assume that x and y measure family income.

The overall measure of individual intergenerational persistence is the parameter β in the following regression equation:

$$y_i = \alpha + \beta x_i + \varepsilon_i, \quad (1)$$

where ε_i is a classical error term. The estimation of β is given by:

$$\hat{\beta} = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sum_i (x_i - \bar{x})^2}. \quad (2)$$

Mobility analysts customarily use the logged version of family income. In this case, β is an elasticity and gives the proportion of a 1-percent difference in parents' income between families that is transmitted as income differences between their children. Because β captures intergenerational persistence, mobility is measured by $(1 - \beta)$. Empirical estimates of $\hat{\beta}$ usually fall between 0 and 1, implying that an initial income advantage will decline across generations (Blanden 2013). The economic mobility literature focuses on the overall individual coefficient $\hat{\beta}$ as a measure of intergenerational persistence.

We then assume that the population is partitioned into groups. Groups represent exogenous attributes that are preserved across generations, such as race, ethnicity, national origin, or surname. These attributes are experienced

as ascribed factors (Parsons 1951) or circumstances (Roemer 1998) by individuals. Let the groups be indexed by $g = 1, \dots, G$. Because groups may vary in size, we define π_g as the relative size of group g in the population.

The fact that the population can be partitioned into groups motivates two additional measures of intergenerational persistence. First, we can examine individual status persistence within each group. Second, we can focus on groups as units of analysis and examine how the average status level of each group persists across generations.

Within-group Estimator

In order to separate individual-level from group-level persistence, we introduce a set of group fixed-effects α_g as additional regressors to equation (1). These fixed effects absorb all covariation between groups, leaving only the individual-level intergenerational association that occurs within groups. The equation to be estimated is the following:

$$y_{ig} = \alpha_g + \beta_W x_{ig} + \varepsilon_{ig}, \quad (3)$$

where β_W is the intergenerational elasticity for individuals within groups. To obtain the within-group estimator $\hat{\beta}_W$, we define the estimator specific to the group g , $\hat{\beta}_{Wg}$, as the elasticity within that group and use the formulation in (2) to write:

$$\hat{\beta}_{Wg} = \frac{\sum_{i \in g} (x_{ig} - \bar{x}_g)(y_{ig} - \bar{y}_g)}{\sum_{i \in g} (x_{ig} - \bar{x}_g)^2}, \text{ for } g = 1, \dots, G \quad (4)$$

where the sum is overall the individuals in group g , and \bar{x}_g and \bar{y}_g are the sample means within group g . The within-group estimator for the entire sample $\hat{\beta}_W$ can be written as a weighted average of within-group estimators for each group $\hat{\beta}_{Wg}$ as follows:

$$\hat{\beta}_W = \frac{\sum_g \hat{\pi}_g \hat{\beta}_{Wg} \hat{\sigma}_{Wg}^2}{\sum_g \hat{\pi}_g \hat{\sigma}_{Wg}^2}, \quad (5)$$

where $\hat{\pi}_g$ is the relative size of group g in the sample, and $\hat{\sigma}_{Wg}^2$ is the estimated within-group variance of x such that group weights depend on their relative size and variance. The within-group estimator (also known as the fixed-effects estimator) is regularly used by researchers to remove the spurious associations driven by unobserved differences between groups. In an example applied to mobility research, Borjas

(1992, 1993) divides the U.S. population into racial/ethnic groups and predicts adult children's income using parents' income and group-level mean income capturing group fixed effects. In this case, the intergenerational income association net of group fixed effects is a within-group estimator.

Between-group Estimator

The second measure of mobility captures group-level persistence. The relevant unit of analysis is the group, and the number of observations is now G instead of N . We consider the linear regression of the group mean of y given the group mean of x , as follows:

$$\bar{y}_g = \alpha_B + \beta_B \bar{x}_g + \varepsilon_g. \quad (6)$$

The between-group estimator $\hat{\beta}_B$ is given by:

$$\hat{\beta}_B = \frac{\sum_g \hat{\pi}_g (\bar{x}_g - \bar{x})(\bar{y}_g - \bar{y})}{\sum_g \hat{\pi}_g (\bar{x}_g - \bar{x})^2}, \quad (7)$$

where each observation is weighted by the sample group size $\hat{\pi}_g$. The between-group estimator has been widely used by social scientists to capture ecological correlations. An application to mobility research is given by Sharkey (2008) who examines the neighborhood-level intergenerational association of economic status. The case of neighborhood of residence departs, however, from a standard definition of group because neighborhood is an endogenous attribute resulting from individual choice (within constraint) and thus sorting into group needs to be modeled.

The Relationship Between Group and Overall Individual Estimators of Persistence

We can write the estimator of overall individual-level persistence $\hat{\beta}$ given by (2) in terms of (5) and (7), as follows:

$$\hat{\beta} = \left(\frac{\hat{\sigma}_W^2}{\hat{\sigma}^2} \right) \hat{\beta}_W + \left(\frac{\hat{\sigma}_B^2}{\hat{\sigma}^2} \right) \hat{\beta}_B, \quad (8)$$

where $\hat{\sigma}^2$ is the estimated overall variance of x , $\hat{\sigma}_W^2 = \sum_g \hat{\pi}_g \hat{\sigma}_{Wg}^2$ is the group size-weighted average of within-group variances of x , and $\hat{\sigma}_B^2$ is the group size-weighted between-group variance of x given by $\sum_g \hat{\pi}_g (\bar{x}_g - \bar{x})^2$ (Duncan, Cuzzort, and Duncan 1961:64-67; Hertz 2008;

Raudenbush and Bryk 2002:137). A similar decomposition applies to the intergenerational correlation coefficient (see Hertz 2008), which is the measure favored by Clark.

This formulation makes clear that the overall individual intergenerational persistence $\hat{\beta}$ is a weighted average of the within-group component $\hat{\beta}_W$ and the between-group component $\hat{\beta}_B$. These components are weighted, respectively, by the proportion of the total variance in x that is within groups and by the proportion of the variance that is between groups (note that $\hat{\sigma}^2 = \hat{\sigma}_W^2 + \hat{\sigma}_B^2$).

“The Son Also Rises”: Using the Between-group Component to Study Mobility

While mobility researchers regularly use the overall individual estimator of persistence $\hat{\beta}$ as a measure of intergenerational mobility, in the book *The Son Also Rises: Surnames and the History of Social Mobility*, Clark (2014) sorts individuals into groups based on surnames, selects high- and low-status surnames in different national contexts, and focuses on only one mobility component, namely, the between-group intergenerational persistence parameter $\hat{\beta}_B$ described in equation (7).

Clark claims that $\hat{\beta}_B$ is a better estimator than $\hat{\beta}$ to measure intergenerational income persistence (or persistence of any other indicator of economic status) because taking the mean of income at the surname level eliminates the measurement error in the income measures. He claims that the surname level captures the underlying and unobserved “social competence” of individuals, purged of its random component (Clark 2014:107-8; Clark and Cummins 2015; Clark et al. 2015). He goes on to suggest that social competence captured by surname-level income means is the product of genetic differences between individuals and as such they are exogenous determinants of individual socioeconomic success.

We argue that these claims are unwarranted. The strategy of taking means over aggregate groups to reduce measurement error is not new. Mobility researchers use it regularly when they rely on panel data and take the mean of income measures across several years of observation to reduce measurement error in the form of transitory fluctuations in income. Mobility scholars argue that a single-year measure of income is an error-laden version of permanent or lifetime individual income. Such measurement error may emerge from luck (for example, being underemployed one year, or receiving an inheritance another year), preferences (choosing to work more hours one year, or to take more vacation another), or errors in reporting. Taking a

multi-year average is believed to reduce these sources of randomness and to approach parents' "permanent income," which is the variable assumed to determine children's resources and opportunities.²

The key difference between this practice and Clark's approach is that when researchers take a multi-year income mean for each individual, *individuals are the relevant unit of analysis*. Income measures are correctly grouped by individuals, and years of observation provide the within-group variation for each individual. By taking the group-level means and estimating a between-group regression of such means, mobility researchers appropriately focus on the individual as the unit of analysis and discard the within-group component, i.e. variation in income across years for each individual. As a result, mobility research can make claims about individual-level mobility.

In contrast, by grouping individuals by surnames and taking surname-level means, Clark effectively switches the unit of analysis from the individual to the group defined by surname. The surname-level estimate may be informative in its own right. However, it cannot be interpreted as or compared to an individual estimate. The reason is that the surname-level means capture a myriad of factors that cannot be disentangled without additional information. A seminal formulation of this problem can be found in the notion of "ecological fallacy" by Robinson (1950), where he explains that group-level correlations cannot, in most cases, be used as substitutes for individual-level correlations. As the literature that this contribution motivated explains, the coefficient associated with the group mean of any attribute in a regression model predicting individual outcomes is open to diverse interpretations, even when controlling for the individual-level attribute (Firebaugh 1978; Hauser 1970). First, the between-group coefficient could capture an unobserved variable at the individual level. Second, it could capture an observed or unobserved aggregate attribute. Third, it could capture emergent group-level properties, such as normative consensus or cultural climate (these emergent group attributes are variously termed contextual, structural, or compositional in the literature).³

Clark's claim that the surname-level means provide a measure of the underlying social competence of individuals amounts to assuming that the group mean only captures an unobserved individual-level attribute—that is, the first interpretation outlined above. However, the other two interpretations are, in principle, equally plausible. Without additional data, is it impossible to obtain the correct interpretation of $\hat{\beta}_B$.

Another way to understand the problem with Clark's approach is to use an instrumental variable interpretation: Clark's uses surname-level income averages as instruments for individual income.⁴ An instrument is a variable

correlated with outcome (children's socioeconomic status) only through the predictor affected by measurement error (parents' socioeconomic status) but which is not itself affected by measurement error. But in order to serve as an instrument, the surname-level income average needs to meet a critical assumption, namely, the exclusion restriction. The exclusion restriction requires that the entire effect of the instrument on the outcome be via an effect of the instrument on the predictor of interest (Angrist, Imbens, and Rubin 1996). In other words, the exclusion restriction requires that there are no alternative pathways of influence linking the instrument (surname-level average income) to the outcome (adult children's status) other than the predictor (parents' status).

The exclusion restriction is certainly violated in Clark's analysis: As explained, surname-level income averages capture factors other than individual attributes that are likely to affect children's income (Chetty et al. 2014; Lee and Solon 2009:footnote 3; Solon 1999:footnote 15; Solon 2015:footnote 13). Specifically, $\hat{\beta}_B$ likely captures group attributes emerging from the advantages and constraints that groups have historically faced, which says nothing about individual-level competence. The violation of the exclusion restriction is magnified by Clark's explicit selection of so-called elite and underclass groups, that is, groups that are likely to be shaped by widely diverging historical advantages and constraints. For example, Clark (2014) selects surnames identifying African Americans whose ancestors came to the United States before the civil war (read: who came as slaves) in chapter 3, Muslims in India in chapter 8, and *Mapuche* indigenous minorities in Chile in chapter 11. In all these cases, surname-level averages by construction capture historical disadvantages faced by these groups in their national contexts.

Let us delve into the case of Chile discussed by Clark (2014) in chapter 11 as an example. He distinguishes, among others, low-status surnames of *Mapuche* origin (*Mapuche* is the largest indigenous group in Chile) from high-status surnames from German and French origins. Since the Spanish conquest in the fifteenth century, *Mapuches* have experienced warfare, famine, and disease brought by the conquerors followed by land usurpation and displacement in the nineteenth century (Bengoia 2000, 2002; Boccara and Seguel-Boccara 1999). In contrast, German and French immigrants arriving in the nineteenth and early twentieth century benefitted from favorable treatment by the Chilean government in the form of subsidies and free land (Boccara and Seguel-Boccara 1999; Norambuena 1996). Furthermore, evidence suggests *Mapuches* have suffered from discrimination in domains such as education and employment (Merino et al. 2009; Zurita and Dresdner

2009). Claiming that surname-level income averages *only* identify individual-level competence, or any individual-level attribute, is patently incorrect in this case. In instrumental variable parlance, the exclusion restriction does not hold and so group-level averages do not provide valid instrument for individual-level status. In this context, it is not surprising that Clark consistently finds that the surname-level average estimate of persistence $\hat{\beta}_B$ is larger than the overall individual estimate $\hat{\beta}$ traditionally used by the mobility literature.

We do not claim that either interpretation of group-level estimates—observed and unobserved individual attributes, observed or unobserved group-level attributes, and emergent group-level properties—is the correct one in any particular case. Most likely, $\hat{\beta}_B$ captures all these components in varying proportions in different empirical instances. Given the multiple interpretations of the group-level intergenerational coefficient and the impossibility to adjudicate among them, Clark's claim that the group-level parameter captures only an unobserved attribute at the individual level—what he calls social competence—is simply unwarranted.

Comparing Between Group With Overall Intergenerational Mobility

Clark obtains surname-level means of status for parents and children in several contexts and compares the surname-level persistence $\hat{\beta}_B$ with the overall estimator $\hat{\beta}$ used by mobility scholars. He finds that $\hat{\beta}_B$ is much larger than $\hat{\beta}$. While $\hat{\beta}$ has been found to be in the 0.30 to 0.50 range by mobility scholars (Björklund and Jantti 2009; Black and Devereux 2011; Jantti and Jenkins 2015). Clark finds that $\hat{\beta}_B$ to range between .70 and .90. Based on this empirical finding, Clark argues that standard intergenerational persistence estimates $\hat{\beta}$ are artificially low because the individual data are affected by measurement error resulting in attenuation bias and that $\hat{\beta}_B$ captures the true level of intergenerational persistence, which is much higher than scholars have assumed.

We now show that this claim is unwarranted. In order to induce attenuation bias, measurement error needs to be classical in form, an assumption that is not met when surname-level groups are used. What Clark calls measurement error does not satisfy classical assumptions and consequently the standard mobility parameter $\hat{\beta}$ is not necessarily attenuated. In fact, we show that $\hat{\beta}$ can be smaller, larger, or the same magnitude as $\hat{\beta}_B$, and it can even differ in sign. This methodological issue has important substantive implications for the analysis of mobility. Given that the sort of measurement error Clark

refers to is not classical, the estimation of group-level persistence does not solve the individual-level “measurement error” issue that Clark attempts to address by de facto treating surname-level means as an instrumental variable.

Clark is right that measurement error in the predictor variable is an important problem for the analysis of mobility. Measurement error in the parental- and child-income variables implies that the values of x and y used in regression equation (1) are noisy measures of the true values x^* and y^* that satisfy the following relationship:

$$y_i^* = \alpha^* + \beta^* x_i^* + \mu_i, \quad (9)$$

where β^* is the true parameter of intergenerational persistence, and μ is a classical error term uncorrelated with x^* . The relationship between the true and the observed variables is given by:

$$y_i = y_i^* + \eta_i, \quad (10a)$$

$$x_i = x_i^* + v_i, \quad (10b)$$

where η_i and v_i are the measurement error components of y and x , respectively.

In order to assess the importance of measurement error, we can write $\hat{\beta}$ in terms of the estimator of the “real” parameter β^* by plugging equation (9) and relationships (10a) and (10b) in the definition of $\hat{\beta}$ given by (2).

$$\hat{\beta} = \left(\frac{\hat{\sigma}_{x^*}^2 + \hat{c}_{v,x^*}}{\hat{\sigma}_{x^*}^2 + 2\hat{c}_{v,x^*} + \hat{\sigma}_v^2} \right) \hat{\beta}^* + \left(\frac{\hat{c}_{x,\mu+\eta}}{\hat{\sigma}_{x^*}^2} \right), \quad (11)$$

where \hat{c} denotes the sample covariances between the subscript variables.⁵

The general formula (11) can be used to assess the consequences of different forms of measurement error, including the simplest classical form assumed by Clark. Classical measurement error assumes that η and v are purely random, which implies the following assumptions: First, η and v are uncorrelated with the true values of x^* and y^* ($c_{\eta,x^*} = 0$), ($c_{v,x^*} = 0$), ($c_{\eta,y^*} = 0$), ($c_{v,y^*} = 0$) and, therefore, uncorrelated with ε in equation (1). Second, η and v are uncorrelated with each other ($c_{\eta,v} = 0$). Under these classical assumptions, the probability limit of $\hat{\beta}$ becomes:

$$\text{plim } \hat{\beta} = \left(\frac{\sigma_{x^*}^2}{\sigma_{x^*}^2 + \sigma_v^2} \right) \beta^*. \quad (12)$$

Equation (12) shows that the asymptotic bias due to a classical measurement error is the proportion of the total variance in the predictor x that is due to the unobserved variable without measurement error x^* . Because this term is less than unity, the result is attenuation in the magnitude of $\hat{\beta}$ with respect to the real β^* . This is the standard “attenuation bias” problem due to a classical measurement error in the predictor variable (e.g., Wooldridge 2002).⁶

Let us now transfer these formulations to the analysis of mobility. Clark claims that by grouping observations by surname, the group-level means \bar{x}_g and \bar{y}_g provide a measure of true individual status purged of measurement error. This amounts to assuming that:

$$x_{ig}^* = \bar{x}_g, \quad (13a)$$

$$y_{ig}^* = \bar{y}_g, \quad (13b)$$

and consequently

$$v_i = x_{ig} - \bar{x}_g, \quad (14a)$$

$$\eta_i = y_{ig} - \bar{y}_g. \quad (14b)$$

Under these assumptions, the true coefficient β^* is equal to the group-level intergenerational persistence parameter $\hat{\beta}_B$ in equation (6), and $\sigma_{x^*}^2$ would be captured by the between-group variance $\hat{\sigma}_B^2$. If measurement error were classical, $\hat{\beta}$ would indeed be lower than $\hat{\beta}_B$ due to attenuation bias. However, the measurement error terms given by equations (14) do not meet all the classical measurement error assumptions. Examination of the sample covariances in (11) shows that the first assumption is indeed met: $\hat{c}_{\eta, x^*} = \hat{c}_{v, x^*} = 0$, since x^* is constant within groups and the sum of η and v is zero within groups. The same reasoning implies that $\hat{c}_{\eta, y^*} = \hat{c}_{v, y^*} = 0$. However, the second assumption is not met. The covariance between the measurement error component of y and x , given by $\hat{c}_{\eta, v}$ is not necessarily equal to zero. In contrast to the other requirements, *the definition of group means as the true measures of individual status does not impose any restriction on this term*. Allowing for this violation of the classical measurement error assumption in (11), we obtain the following relationship between $\hat{\beta}$ and $\hat{\beta}_B$:

$$\hat{\beta} = \left(\frac{\hat{\sigma}_B^2}{\hat{\sigma}_x^2} \right) \hat{\beta}_B + \left(\frac{\hat{\sigma}_v^2}{\hat{\sigma}_x^2} \right) \left(\frac{\hat{c}_{\eta, v}}{\hat{\sigma}_v^2} \right), \quad (15)$$

where the second term is multiplied and divided by $\hat{\sigma}_v^2$ to simplify its interpretation.

The first term in (15) captures the asymptotic attenuation bias described by (12). The ratio expresses the proportion of total variance in x that is due to the group means \bar{x}_g , which Clark uses as the true status variable x^* . But the relationship between $\hat{\beta}$ and $\hat{\beta}_B$ includes a second term emerging from the fact that η and v are not randomly distributed. Given that errors η and v are the group-demeaned versions of x and y given by (14a) and (14b), the second term in (15) is the least-square coefficient associated with the within regression given by equation (3) multiplied by the ratio between within and total variance of x . In other words, the formulation of $\hat{\beta}$ in (15) yields the same result as equation (8), showing that the overall intergenerational persistence is a weighted average of between-group and within-group persistence.

Attenuation bias is not the correct explanation for the difference in magnitude between $\hat{\beta}_B$ and $\hat{\beta}$ because it disregards the second term in (8) and (15), emerging from the violation of the classical measurement error assumption. Given this term, the group-level estimated persistence $\hat{\beta}_B$ is *not* necessarily larger in magnitude than individual persistence $\hat{\beta}$ and it can be smaller depending on the within-group component of persistence. Given that $\hat{\beta}$ is a weighted average of $\hat{\beta}_W$ and $\hat{\beta}_B$, $\hat{\beta}$ is by necessity bounded by the two group components. So, if $\hat{\beta}_B \geq \hat{\beta}_W$ then by necessity $\hat{\beta}_B \geq \hat{\beta}$, as found by Clark. A sufficient condition for this is that $\beta_B \geq \hat{\beta}_{Wg}$ for all groups, given that $\hat{\beta}_W$ is a weighted average of the group-specific β_{Wg} coefficients.

The substantive corollary of this methodological point is that the between-group estimator of persistence does not solve the individual-level measurement error issue that Clark claims to address, and thus it does not provide a suitable measure of individual-level mobility. The classical measurement error assumption may also be violated when mobility scholars take across-year means of individual income. Recall that the departure from classical measurement error emerges from the nonzero association between the group-demeaned versions of parents' income and children's income η and v . In the case of standard mobility analysis, across-year income observations are grouped by individual. In this case, η captures year-specific departures from the mean of parents' income, and v does the same for children's income. A nonzero correlation between η and v indicates that higher income in later years for parents is correlated with higher income in later years for children if positive, and an inverse relationship if negative. This correlation most likely emerges from life-course variation in income, for example, the income of both parents and children increases as they reach their peak occupational

years or decreases after retirement (if parents' and children's incomes are measured over the same stages of the life cycle). However, such life-course intergenerational correlation is likely minor if measurement for parents and children is centered around age 40.

The case is different when individuals are grouped by surnames. In this case, error terms η and v are the individual-level departures from the surname-level income mean in either generation. For example, η captures the departure for parent i with surname "Smith" from the mean income of all parents named Smith, and v captures the difference in the income for child i with surname Smith from the mean income of all children named Smith. The correlation between η and v captures, then, the extent to which the incomes of both parent and child i surnamed Smith are higher or lower than the Smith average. Given that this correlation is nonzero, *this component is a constituent element of the mobility process as experienced by individuals*, and it cannot be legitimately discarded in the analysis of mobility. To put it in a different way: even if intergenerational economic persistence were purely driven by the genetic transmission of cognitive competence, the extent to which our Smith father passes his good (or bad) genes to our Smith son, regardless of the Smith average, is very much a component of the mobility process that researchers want to capture. Eliminating this component in the analysis of mobility is inappropriate, regardless of the mechanisms accounting for it.

Empirical Example: Mobility by Ethnic/Racial Groups in the United States

To illustrate this discussion, we conduct an empirical analysis of intergenerational income mobility in the United States and a simulation analysis. In the empirical analysis, we group individuals by racial/ethnic origin and compare findings using the overall estimator of persistence traditionally used by the mobility literature to the between-group estimator. Data come from the National Longitudinal Survey of Youth 1979 (NLSY79), a nationally representative sample of 12,686 youths born between 1957 and 1964 who were 14 to 22 years old when they were first surveyed in 1979. These individuals have been interviewed annually through 1994 and biennially thereafter. We restrict the analysis to respondents 18 years old or younger in 1979 and combine parental information obtained in the first wave with adult children's information obtained from recent waves between 1996 and 2002, corresponding to the children's ages 31 to 45. Income measures include all sources

Table 1. Estimates of Intergenerational Income Mobility Among the U.S. Population Partitioned Into Racial/Ethnic Groups: Between-group, Within-group ($\hat{\beta}_{Wg}$), and Overall Intergenerational Persistence.

Race/Ethnic Group	All Sample	European Sample
	$\hat{\beta}_{Wg}$	$\hat{\beta}_{Wg}$
Black	0.2662	
English	0.4046	0.4046
French	0.3948	0.3948
German	0.2526	0.2526
Irish	0.2709	0.2709
Italian	0.3067	0.3067
Native American	0.5507	
Mexican American	0.1749	
Mexican	0.0915	
Puerto Rican	0.1953	
American	0.7668	
Other	0.3037	
$\hat{\beta}_{\text{Within group}}$.2875	.3354
$\hat{\beta}_{\text{Between group}}$.8392	.2982
$\hat{\beta}_{\text{Overall}}$.3915	.3353

Source: National Longitudinal Survey of Youth 1979 (NLSY79) Center for Human Resource Research (CHRR), The Ohio State University, 2016. Sample restricted to males of listed self-reported racial/ethnic origins.

Note: $\hat{\beta}_{Wg}$ is parameter estimate capturing intergenerational income association for each racial/ethnic group.

of monetary income for all household members. Income measures are averaged across pertinent years and logged.

For the purpose of this exercise, the sample is restricted to males. We group individuals by their reported racial/ethnic origin, based on the following questions asked in 1979: "What is your origin or descent"? The response categories included the following: Black, Chinese, English, Filipino, French, German, Greek, Hawaiian or Pacific Islander, Native American, Indian-Asian, Irish, Italian, Japanese, Korean, Cuban, Chicano, Mexican, Mexican American, Puerto Rican, Other Latino, Other Spanish, Polish, Portuguese, Russian, Scottish, Vietnamese, Welch, other, American (if volunteered), and none. We keep 12 ethnic/racial groups with largest sample sizes, namely, Black, English, French, German, Native American, Irish, Italian, Mexican American, Mexican, Puerto Rican, American, and other. Some of these

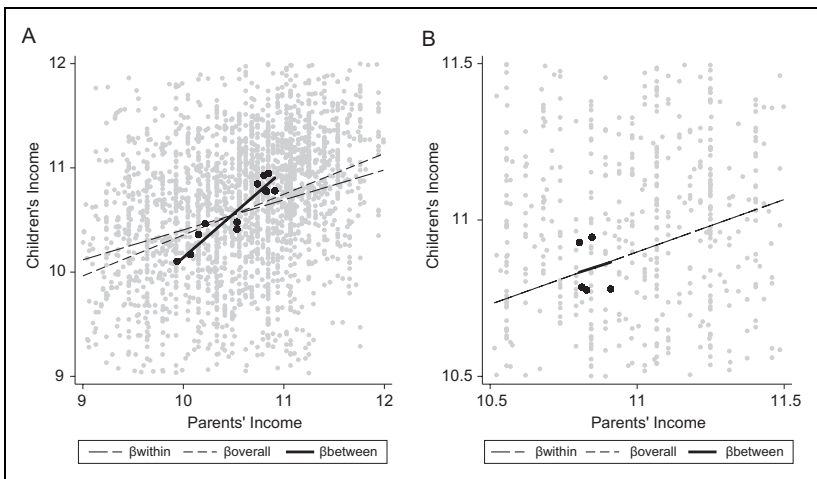


Figure 1. Estimates of intergenerational mobility in the United States. (A) Sample includes 12 ethnic-racial groups. (B) Subsample includes 5 ethnic-racial groups with European origins.

Source: Table 1 based on the National Longitudinal Survey of Youth 1979 (NLSY79). *Note:* Axes ranges are narrower in (B) than (A) for ease of display. Slopes β_{within} and β_{overall} are extremely similar in magnitude in (B) and thus they largely overlap. Gray dots identify individual-level observations, black dots identify group-level observations.

groups arguably do not capture racial or ethnic origin, and identification is likely endogenous (e.g., American and other). This is irrelevant in this case; the grouping strategy is solely intended to illustrate the concepts presented above. After imposing the explained sample restrictions and dropping observations with missing data, the analytical sample size is 2,740.

As reported in Table 1, the group-specific persistence coefficients $\hat{\beta}_{W_g}$ range from .0915 for Mexicans to .7668 for Americans. For this sample, $\hat{\beta}_W = .2875$, $\hat{\beta}_B = .8392$, and $\hat{\beta} = .3915$. These slopes are plotted in Figure 1A. This example closely replicates Clark's findings. Like Clark, we find that the group-level persistence estimate $\hat{\beta}_B$ is substantially greater than $\hat{\beta}$ signaling very limited intergenerational mobility according to Clark's reasoning. However, as in the case of surnames, we cannot claim that $\hat{\beta}_B$ provides an estimator comparable to $\hat{\beta}$. A portion of $\hat{\beta}_B$ plausibly captures underlying individual attributes that are passed across generations such as social competence—if such an attribute could be properly measured. However, $\hat{\beta}_B$ almost certainly also captures historical advantages accrued by different groups given different conditions and timing of migration,

institutional barriers to integration and human capital acquisition, discrimination, and collective resources such as social capital. In sum, $\hat{\beta}_B$ captures a myriad of individual-level and group-level factors that cannot be separated without additional information.

The second point we made is that $\hat{\beta}$ is not necessarily larger than $\hat{\beta}_B$ because measurement error is not necessarily classical in form. We can empirically test the properties of what Clark defines as measurement errors η and ν and the departures of individual-level income from the group-level mean income. In this case, $c_{\eta,\nu} = .159$ violating the classical measurement error assumption $c_{\eta,\nu} = 0$. Given this violation, we need to consider the within-group component of the intergenerational association to capture the proper relationship between $\hat{\beta}$ and $\hat{\beta}_B$. As shown, the value of $\hat{\beta}$ is a weighted average of $\hat{\beta}_B$ and $\hat{\beta}_W$, and given that the within-group component is strictly positive, it results in a larger value of $\hat{\beta}$ (and consequently a smaller difference between $\hat{\beta}$ and $\hat{\beta}_B$) than would be the case if the classical measurement error assumptions were met.

We also argued that the group-level estimate of persistence $\hat{\beta}_B$ is not necessarily larger than the overall individual-level estimate traditionally used by mobility research, $\hat{\beta}$. In other words, there is no “social law” capturing a “universal constant of intergenerational correlation of 0.75, from which deviations are rare and predictable” (Clark 2014:12). To show this, we restrict the sample to the subset of individuals with European ancestry in our sample—namely, those reporting English, French, German, Irish, and Italian origins. In this European-origins sample, the relationship between $\hat{\beta}_B$ and $\hat{\beta}$ reverses signs. Now $\hat{\beta}_W = .3354$, $\hat{\beta}_B = .2981$, and $\hat{\beta} = .3353$ (see Table 1 and Figure 1B). The reason for this reversal is that the between-group estimator is smaller than at least some of the group’s within-group estimators (see Chetty et al. 2014, appendix D for a similar empirical finding).

What explains the discrepancy between the findings using the entire sample and the European-only sample? The explanation lies in the baseline income differences between racial/ethnic groups. Specifically, it lies in the association between group income means and individual income, net of parents’ income. Remember that the group means capture diverse factors including unobserved individual attributes, historical processes shaping advantages and disadvantages for each group, and emergent group properties such as social capital. These factors are consequential for the ethnically diverse sample examined in Figure 1A partly because the ethnic groups included have faced widely different conditions and timing of migration (including forced migration and enslavement), institutional barriers to integration and human capital acquisition, and discrimination histories. These

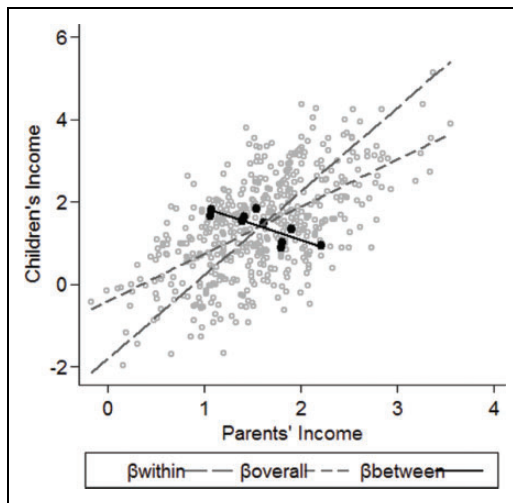


Figure 2. Estimates of intergenerational mobility using simulated data.

factors are less important in the European-origins sample. In this relatively homogeneous sample, ethnic differences appear not to contribute to individual well-being net of family background, and as a result the group fixed effects are close to zero.

Why did, then Clark consistently find large estimates of persistence (similar to Figure 1A)? The reason is his explicit selection of elite and underclass surname groups, that is, groups with widely different levels of economic advantage shaped by historical circumstances in different national contexts. By selecting advantaged and disadvantaged groups, Clark maximizes the impact of group-level income means on individual well-being and obtains very high estimates of between-group intergenerational persistence.

We then use simulated data to show that the relationship between $\hat{\beta}_B$ and $\hat{\beta}_W$ can in fact vary not only in terms of magnitude but also in terms of sign. Figure 2 displays the case in which the within-group intergenerational persistence is positive for all groups, but the between-group estimator $\hat{\beta}_B$ is negative because (by construction) the association between the group means of father's income and children's income is negative. We do not claim that these simulated data are realistic. A negative between-group intergenerational association would reflect an extreme form of "reverse mobility." We have not seen such empirical case, although major institutional interventions such as the cultural revolution in China appear to have induced some degree

of “status reversal” at the group level (Deng and Treiman 1997; Zhou and Hou 1999). Even if unrealistic, this example highlights the unsuitability of the between-group estimate to address the problem of measurement error, the indeterminacy in the association between $\hat{\beta}_W$ and $\hat{\beta}_B$, and the incommensurability of the group and individual estimates of mobility.

Conclusions

This article has distinguished three estimates of intergenerational persistence that emerge when populations are divided into groups—within-group, between-group, and overall individual intergenerational persistence—and establishes the relationship between them. Using this analytical apparatus, the article critically examines claims made by Clark (2014) in *The Son Also Rises*. Clark groups individuals by surname and uses the between-group estimator relating surname-level means of economic status across generations as a preferred measure of intergenerational persistence. He claims that the surname-based estimates are superior to individual-level estimates traditionally used by the mobility literature because surname averages of economic status eliminate the measurement error affecting individual measures. He asserts that the surname means provide a measure of underlying and unobserved social competence of individuals, purged of its random component. He also claims that surname estimates of persistence are consistently much greater than estimates from individual persistence and that conventional studies of social mobility underestimate the true association of underlying social status across generations.

We have argued that these claims are unwarranted. We show that the surname-level estimate of persistence used by Clark cannot be compared with the individual-level estimate traditionally used by mobility scholars. The reason is that the surname-level income averages capture diverse individual level and group level that cannot be unraveled without additional identifying information. These factors include unobserved individual attributes, observed and unobserved group attributes, and group emergent properties such as normative consensus and cultural climate.

We also show that taking surname-level means does not solve the measurement error problem that Clark attempts to solve because measurement error is not random and thus does not meet the classical assumptions. As a result, the within-surname group component of mobility needs to be considered. Given that measurement error is not classical, surname-level estimates can be of greater, smaller, or equal size as compared to individual-level ones depending on the magnitude of the within-group component of

intergenerational persistence. The reason why Clark found consistently high surname-level estimates of intergenerational persistence in the different contexts examined is because he explicitly chose elite and underclass surname groups, historically shaped by widely diverging historical advantages and constraints. For example, Clark selects surnames identifying African Americans whose ancestors came to the United States as slaves in the United States, Muslims in India in chapter 8, and *Mapuche* indigenous minorities in Chile. In all these cases, surname-level averages by construction capture historical disadvantages including land usurpation, forced labor, forced displacement, discrimination, and segregation among other barriers faced by these groups in their national contexts.

Our critique of the surname-level estimate of mobility does not mean that it is irrelevant or uninformative. On the contrary, group-level persistence provides important information about the role that ascribed attributes such as race/ethnicity, national origin, or surname may play in the transmission of advantage. As suggested by our empirical analysis of the United States, the fact that ethnic/racial group persistence is much greater than individual-level persistence suggests that being born into a particular race/ethnicity is a powerful determinant of one's fate, net of the impact of parental resources.

However, an intergenerational persistence at the group level does not provide useful or comparable information about the extent of mobility at the individual level. Nor does it allow us to adjudicate among the diverse factors driving group-level persistence, which include observed and unobserved individual attributes, historical factors shaping the opportunities and constraints faced by different groups, and emergent properties of groups such as social capital.

We hope this article has offered clarity about the distinct approaches to measuring intergenerational persistence and that it promotes much needed research examining both individual-level and group-level factors shaping the opportunity in different national contexts.

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Notes

1. Individual measures can be extended to households without loss of generality.
2. Even if these average measures may be inferior to the direct correction of errors of measurement (e.g., Bielby, Hauser, and Featherman 1977) and are sensitive to the number of years considered as well as the age in which income of parents and children are measured (Baker and Solon 2003; Haider and Solon 2006), they provide a widely used measure of lifetime economic status.
3. The interpretation of group means as emergent properties of the collectivity is familiar to sociologists, especially sociologists of education (Blalock 1984). A voluminous literature on the so-called school effects groups students by schools and uses the school-level means of parents' income, test scores, or other attributes to predict students' outcomes in addition to individual-level characteristics. This literature usually interprets the effect of these aggregate variables as resulting from "school climate," an emergent property of the collectivity distinct from the simple aggregation of individual attributes (e.g., Entwisle, Alexander, and Olson 1994; Lauen and Gaddis 2013; Willms 1986).
4. This is equivalent to using a set of surname- group indicator variables as the instruments.
5. To obtain (11), we start with (2) and apply definition of y^* in (9) as well as of x and y in (10a) and (10b):

$$\begin{aligned}\hat{\beta} &= \frac{\sum_i (x - \bar{x})(y - \bar{y})}{\sum_i (x - \bar{x})^2} = \frac{\hat{c}(x, y)}{\hat{\sigma}_x^2} = \frac{\hat{c}(x, \alpha^* + x^* \beta^* + \mu + \eta)}{\hat{\sigma}_{x^*}^2 + 2\hat{c}_{v, x^*} + \hat{\sigma}_v^2} \\ &= \frac{\hat{c}(x, x^*)}{\hat{\sigma}_{x^*}^2 + 2\hat{c}_{v, x^*} + \hat{\sigma}_v^2} \hat{\beta}^* + \frac{\hat{c}_{x, \mu + \eta}}{\hat{\sigma}_x^2} = \frac{c(x_i^* + v_i, x_i^*)}{\hat{\sigma}_{x^*}^2 + 2\hat{c}_{v, x^*} + \hat{\sigma}_v^2} \hat{\beta}^* + \frac{\hat{c}_{x, \mu + \eta}}{\hat{\sigma}_x^2} \\ &= \frac{\sigma_{x^*}^2 \hat{c}_{v, x^*}}{\hat{\sigma}_{x^*}^2 + 2\hat{c}_{v, x^*} + \hat{\sigma}_v^2} + \frac{\hat{c}_{x, \mu + \eta}}{\hat{\sigma}_x^2} .\end{aligned}$$

6. Note that measurement error in the dependent variable does not induce bias insofar as it is uncorrelated with the predictor and it would only potentially affect the estimation of the intercept (Wooldridge 2002:71).

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Author Biographies

Florencia Torche is a professor of sociology at Stanford University. Her scholarship examines stratification and mobility, educational inequality, assortative mating, and the early emergence of disadvantage.

Alejandro Corvalan is an assistant professor at the Department of Economics, Universidad Diego Portales, Chile. He is a member of the Millennium Institute for Market Imperfections and Public Policy.