sociological science

Is College Really "the" Equalizer? New Evidence Addressing Unobserved Selection

Haowen Zheng,[a] Robert Andersen[b], Anders Holm[b], Kristian Bernt Karlson[c]

a) University of Michigan; b) Western University; c) University of Copenhagen

Abstract: Influential research shows that college graduates achieve similar labor market outcomes regardless of socioeconomic origin, leading to the view that a college degree is a "great equalizer." Still, other evidence suggests that family background continues to shape labor market outcomes long after graduation, implying that college's equalizing effect may largely reflect the characteristics of those who pursue higher education. However, the role of unobserved selection into college has rarely been examined. After formally illustrating how this unobserved selection can bias estimates of the college effect, we present new analyses that correct for this bias using an instrumental-variable approach on white male respondents in the 1979 cohort of the National Longitudinal Survey of Youth. The selection-corrected results suggest that intergenerational mobility is similar among college graduates and nongraduates. Although college yields substantial returns for all, these returns do not differ by family background. We conclude that for higher education to serve as a true equalizer, it must become both less selective and more accessible to students from disadvantaged backgrounds.

Keywords: social mobility; education; stratification; college; inequality

Reproducibility Package: A replication package is available at https://osf.io/ne23f/. It includes all code used for data cleaning and analysis as well as a cleaned data set derived from the public-use NLSY79 data. Part of the analysis relies on restricted geographic data obtained through a data contract with the BLS (see https://www.bls.gov/nls/request-restricted-data/nlsy-geocode-data.htm). This is not included in the replication package but can be accessed through a BLS application. The instrumental variables were drawn from the replication package of Carneiro, Heckman, and Vytlacil (2011) (see https://www.openicpsr.org/openicpsr/project/112467/version/V1/view).

Citation: Zheng, Haowen, Robert Andersen, Anders Holm, and Kristian Bernt Karlson. 2026. "Is College Really "the" Equalizer? New Evidence Addressing Unobserved Selection" Sociological Science 13: 242-272.

Received: October 6, 2025

Accepted: December 12, 2025

Published: March 3, 2026

Editor(s): Arnout van de Rijt, Jeremy Freese

DOI: 10.15195/v13.a10

The influence of family origin and formal education on socioeconomic attainment has been a central focus of sociological research for decades (Blau and Duncan 1967; Duncan, Featherman, and Duncan 1972; Jencks et al. 1972). Numerous studies document a weak or nonexistent association between family background and labor market outcomes among college graduates in the United States (Hout 1988; Torche 2011; Pfeffer and Hertel 2015; Brand 2023; Streib 2023) and in other modern societies (Breen and Jonsson 2007; Breen and Müller 2020; Vallet 2020; see also an edited version by Breen 2004). Based on the empirical observation that higher education neutralizes the influence of parental background on occupational attainment, many have credited college as the "great equalizer."

In recent years, this dominant view has been challenged. Scholars increasingly argue that the observed higher intergenerational mobility for college graduates is driven by selection bias. In other words, the commonly observed "equalizer effect" in previous research largely reflects a failure to account for the possibility that college graduates and nongraduates differ in characteristics that affect labor market outcomes independently of socioeconomic background (Witteveen and Attewell 2017; Karlson 2019; Zhou 2019; Fiel 2020; Yu and Elwert 2025; Yu and Zhao 2025). Academic performance and college success are linked to a wide range of attributes that are also rewarded in the labor market, including cognitive ability (Deary et al. 2007; Allensworth and Clark 2020; O'Connell and Marks 2021), future expectations (Sewell, Haller, and Portes 1969; Morgan 2004), and personality traits (Tross et al. 2000; Furnham, Chamorro-Premuzic, and McDougall 2003; Cucina and Vasilopoulos 2005; Komarraju, Karau, and Schmeck 2009; Poropat 2009; Trapmann et al. 2007; Corazzini et al. 2021; Mammadov 2021). Because many of these factors cannot be adequately measured in survey data, failing to account for them may overstate the effect of higher education on social mobility.

Even if all relevant traits could be measured without error, no single data set could capture every factor influencing both college graduation and adult SES attainment (Young 2018; Engzell and Mood 2023). It is unsurprising, then, that unobserved selectivity in college graduation has been underexplored in studies of intergenerational mobility. Past studies that did adjust for selection have reported inconsistent results (e.g., Karlson 2019; Zhou 2019), and are based on observed characteristics, often implicitly assuming that college completion is "as good as random" once measured variables are controlled for. As we formally demonstrate below, this assumption is difficult to determine *a priori*. To date, no study has explicitly corrected mobility estimates for unobserved selection into college graduation.

Our analysis re-examines the "college as equalizer" thesis using an identification strategy that directly accounts for unobserved selectivity in college completion. Building on Carneiro et al.'s (2011) study of the causal effects of college on earnings, we employ instrumental variables (IVs) and a variant of the Heckman sample selection model (Heckman 1979; Winship and Mare 1992) that imposes no distributional assumptions on the unobserved variables. Our models are estimated on a sample of white men born between 1957 and 1964 in the National Longitudinal Survey of Youth (NLSY) 1979. We restrict the analysis to white men because the IVs required for identification are available only for this group. Although this limits the generalizability of our findings, it allows direct comparison with prior studies that used the same data set, often analyzing men and women separately (Torche 2011; Karlson 2019; Zhou 2019; Yu and Elwert 2025; Yu and Zhao 2025).

Our findings challenge the conventional belief that a college degree equalizes the influence of socioeconomic background on occupational and income attainment. After we adjust for unobserved heterogeneity, the association between parental SES and adult outcomes is strikingly similar for college graduates and nongraduates. This pattern holds for intergenerational mobility in rank income, log income, and occupational status. Individuals from disadvantaged backgrounds receive substantial returns to a college degree but not larger returns than their more advantaged peers. Thus, a college degree does little to offset the enduring influence of parental background. In short, although college improves labor market outcomes, it does not function as a "great equalizer."

Does a College Degree Hold Meritocratic Power?

Education is widely viewed as playing a central role in the association between family background and labor market outcomes (Breen and Jonsson 2005; Hout and DiPrete 2006). Hout’s (1984, 1988) seminal studies, for example, find no association between occupational origins and destinations among U.S. college degree holders, a result largely confirmed by Torche’s (2011) comprehensive re-analysis. Other research likewise underscores the role of education in promoting income mobility (Chetty et al. 2017; Bloome, Dyer, and Zhou 2018; van de Werfhorst 2024) and occupational mobility across modern societies (Erikson and Jonsson 1998; Vallet 2004; Breen and Jonsson 2007; Breen 2010). The prevailing interpretation of these findings is that a college degree enables students from low-SES backgrounds to overcome socioeconomic disadvantage and achieve labor market outcomes comparable to their high-SES peers.

The mechanisms through which a college degree might act as an equalizer remain understudied. Social theory suggests that a college degree enhances human, social, and cultural capital, signals productivity, and promotes a meritocratic labor market that limits class-based discrimination (Arcidiacono, Bayer, and Hizmo 2010; Clark and Martorell 2014). Some scholars argue that college education equalizes earnings across SES backgrounds by amplifying the role of chance and uncertainty in labor market outcomes (Streib 2023). Nevertheless, even without considering potential changes in the role of higher education over recent decades (see, e.g., Breen and Müller 2020), the “college as equalizer” thesis is open to both theoretical and methodological critique.

The College “Selectivity Problem”

A central concern is that failing to account for characteristics that distinguish college graduates from nongraduates may bias estimates of intergenerational social mobility by college status. Many of these factors are difficult to measure. College graduates represent a highly selected group who must successfully navigate a series of educational transitions in adolescence and early adulthood (Mare 1981, 1993). Although family background shapes these decisions, cognitive skills, personality, motivation, and other difficult-to-observe traits and characteristics also play meaningful roles (Tross et al. 2000; Furnham et al. 2003; Cucina and Vasilopoulos 2005; Deary et al. 2007; Komarraju et al. 2009; Poropat 2009; Trapmann et al. 2007; Allensworth and Clark 2020; Corazzini et al. 2021; Mammadov 2021; O’Connell and Marks 2021).

Estimates of the effect of college education on mobility are particularly vulnerable to bias arising from the differential influence of resources and personality traits on college entry across SES backgrounds. First-generation students from low-SES families often lack the cultural expectations for attending college, economic resources, and social support that their high-SES peers enjoy. As a result, they may rely more heavily on personality traits such as diligence, goal orientation, self-efficacy, and maturity (Collins 1971; Bourdieu 1977; Naumann, Bandalos, and Gutkin 2003; Wilkins 2014; Castilla and Poskanzer 2022). For example, conscientiousness—one of the big five personality traits—positively impacts both college degree attainment and SES afterward (Alderotti, Rapallini, and Traverso 2023). If conscientiousness is omitted from models predicting mobility, the estimated effect of college education is likely overstated (Cameron and Heckman 1998; Karlson 2019).

The Hidden Impact of Family Background

Family background continues to shape socioeconomic outcomes even after college graduation. It is widely accepted, for example, that class-based social capital plays a critical role in employment and other labor market outcomes (Granovetter 1973; Lin 1999; Fernandez and Fernandez-Mateo 2006; DiMaggio and Garip 2012). The social networks of low-SES families often provide useful information about low-wage job opportunities but are typically unhelpful for high-SES positions (Huang and Western 2011). In contrast, high-SES networks are more likely to include information about job openings in higher paying positions that require a college education (Lin, Ensel, and Vaughn 1981; Erickson 2001; McDonald 2011). This disparity is compounded by the greater diversity of high-SES networks relative to lower-SES networks (Campbell, Marsden, and Hurlbert 1986; Erickson 1996; McPherson, Smith-Lovin, and Cook 2001). These patterns are consistent with research indicating that middle-class young adults possess greater knowledge of how societal institutions function than their lower-income peers (Lareau 2015).

Institutional and cultural forces also help sustain a high-SES advantage after college graduation. Employers often discriminate based on race, gender, and social class through hiring (Ortiz and Roscigno 2009; Pager, Western, and Bonikowski 2009; Rivera 2012; Kang et al. 2016), job allocation, promotion, and compensation (Penner 2008; Cotter et al. 2001). Differences in occupational niches and related labor market characteristics further contribute to persistent advantages (Witteveen and Attewell 2017; Manzoni and Streib 2019). Rivera (2015) shows that elites tend to recruit elites, reducing the chances for applicants from less affluent backgrounds to secure high-level white-collar jobs. Similarly, Laurison and Friedman (2016) identify a working-class penalty in these occupations. In addition, Birkelund (2024) demonstrates that individuals entering occupations held by family members often receive a wage premium compared to those without a family history in the field.

Previous Attempts to Adjust for Selectivity

A few studies have attempted to correct for selectivity into college completion based on various sets of observed personal characteristics (Karlson 2019; Zhou 2019; Yu and Elwert 2025; Yu and Zhao 2025), all using the same NLSY data employed in our analysis. These studies agree that college graduates and nongraduates differ in skills, aspirations, and other background characteristics. However, they diverge on the extent to which these differences influence intergenerational mobility. Using reweighting techniques to account for selectivity, Zhou (2019) finds that obtaining a college degree has no effect on income mobility—average intergenerational income mobility is similar for those with and without a college degree. After adjusting for a slightly different set of observable control variables, Yu and Elwert (2025) and Yu and Zhao (2025) reach similar conclusions. In contrast, employing similar reweighting methods to Zhou’s, Karlson (2019) concludes that selectivity does not explain higher levels of intergenerational occupational mobility among college graduates. These inconsistent findings likely reflect differences in the outcomes examined and the specific choice of control variables from a multiverse of possible combinations (Young 2018; Engzell and Mood 2023).

All of these studies account for selectivity into college graduation using only observed variables and therefore must assume that any remaining selection is “as good as random.” Although Zhou’s (2019, P. 477) sensitivity analysis suggests that unobserved factors are unlikely to have affected results, his estimates do not explicitly account for them.[1] Observed differences between graduates and nongraduates can be directly included in a model if adequately measured. In practice, however, we are rarely aware of all potential sources of bias. Even if we have perfect knowledge of all sources of bias, suitable data on every relevant predictor seldom—if ever—exists. Ignoring unobserved selectivity in college graduation may therefore lead to an incomplete understanding of the relationship between college education and social mobility. The challenge is further complicated by the difficulty of determining *a priori* whether omitting unobserved characteristics attenuates or amplifies the estimates of the effects of college and family background on adult SES. We formally demonstrate this problem below.

How Selectivity in College Completion Might Bias Estimates of Social Mobility

Before discussing our approach, it is helpful to consider how unobserved selectivity can bias mobility estimates for both college graduates and nongraduates. To illustrate this, we represent the effect of college attainment on intergenerational SES associations using an endogenous switching regression model (Mare and Winship 1987; Winship and Mare 1992). This model evaluates the causal relationship between college graduation and SES outcomes using a potential outcomes framework (Morgan and Winship 2015). Let Y denote the potential SES outcome (e.g., income or occupational status) of a child and x denote the observed SES outcome for the child’s parent. Irrespective of whether they completed college, each child has two potential SES outcomes: the outcome *if* they had completed college (Y_1) and the outcome *if* they had not completed college (Y_0). The potential SES outcome if the child has not completed college is given by

$$Y_0 = a_0 + b_0 x + e_0, \tag{1}$$

and if the child completed college is given by

$$Y_1 = a_1 + b_1 x + e_1, \tag{2}$$

where b_0 and b_1 represent the average effects of parental SES on the potential SES outcomes, and a_0 and a_1 are constants. The influence of unobserved variables is captured by the random error terms e_0 and e_1, which are assumed to be normally distributed and correlated. We assume normality only for illustrative purposes: it enables us to easily obtain analytical results. Later, when we estimate selection models, we relax the normality assumption. Finally, b_1 and b_0 are assumed to be fixed, meaning that they represent averages in the population independent of individual responses to parental outcomes (Heckman and Vytlacil 1999).

Given that the potential outcomes Y_0 and Y_1 are not independently observed, the observed SES outcome is expressed as a mixture model of the potential outcomes:

$$Y = Y_1 D + (1 - D) Y_0, \tag{3}$$

where D represents a dummy regressor coded 1 for college completion and 0 for no college completion. D is obtained from the selection equation:

$$D = 1\left(\alpha + \beta x + u > 0\right), \tag{4}$$

where α is a constant and β is the coefficient representing the effect of parental SES (x) on college completion, D. Equations (1), (2), and (4) constitute the endogenous switching model, assuming u, the error term in the selection equation, is correlated with the error terms, e_0 and e_1, in Equations (1) and (2).

The selectivity of college graduates and non-college graduates is represented by the correlations (ρ) between u and e_0 and e_1 (Mare and Winship 1987). When $\rho_{e_{1,u}} > 0$, there is positive selection into the college graduation state—that is, net of parental SES, the potential SES outcome is higher for college graduates than it would be for the average person in the population. When $\rho_{e_{0,u}} < 0$, there is positive selection into the nongraduate state—that is, nongraduates have a higher probability of the potential outcome than the average person in the population. If $\rho_{e_{0,u}} > 0$, there is negative selection among nongraduates. In this case, nongraduates have lower potential SES outcomes than the population average. If selection into college graduation is positive but selection into the nongraduate state is negative, the sorting into college is suboptimal and potentially inequality-enhancing in the sense that in the absence of college, outcomes would have been more similar.[2]

Critical for our study, the direction and magnitude of the correlations in the errors can bias the estimated intergenerational SES associations among both those with and without a college degree. We now formally show why this is so (for detailed proofs, see the online supplement B). We start with the impact for those with a degree, $D = 1$:

$$\begin{aligned}
\hat{b}_1 &= \frac{cov\left(Y, x \mid D=1\right)}{var\left(x \mid D=1\right)} = \frac{cov\left(Y|D=1, x|\,D=1\right)}{var\left(x \mid D=1\right)} = \frac{E\left(Y|D=1 \cdot \left((x|\,D=1) - \mu_{x|D=1}\right)\right)}{var\left(x \mid D=1\right)} \\
&= \frac{E\left(\left(\overbrace{a_1 + b_1\left(x \,\middle|\, D=1-\mu_{x|D=1}\right) + e_1|D=1}^{Y|D=1}\right) \cdot \left(\left(x \,\middle|\, D=1\right) - \mu_{x|D=1}\right)\right)}{\sigma^2_{x|D=1}} \\
&= \frac{E\left(a_1 \cdot \left((x|D=1) - \mu_{x|D=1}\right)\right) + E(b_1((x|D=1) - \mu_{x|D=1}) \cdot ((x|D=1) - \mu_{x|D=1}))}{\sigma^2_{x|D=1}} \\
&+ \frac{E(e_1|D=1 \cdot ((x|D=1) - \mu_{x|D=1}))}{\sigma^2_{x|D=1}} = \frac{b_1\sigma^2_{x|D=1} + \rho_{e_{1,u}}\sigma_{e_1} cov\left(\frac{\varphi(\alpha+\beta x)}{\Phi(\alpha+\beta x)}, x|D=1\right)}{\sigma^2_{x|D=1}},
\end{aligned} \tag{5}$$

where $\mu_{x|D=1} = E(x|D=1)$ and where the third equality uses

$$cov\,(y, x) = cov(y, x - E\,(X)) = E(y \cdot (x - E\,(X))).$$

We have that $s_1 = -\frac{cov\left(\frac{\varphi(\alpha+\beta x)}{\Phi(\alpha+\beta x)}, x|D=1\right)}{\sigma^2_{x|D=1}}$. Because $s_1 > 0$ when $\beta > 0$ (i.e., parental SES is positively correlated with offspring college attainment), the estimated effect of parental SES for those with a college degree, $D = 1$, is

$$\hat{b}_1 = b_1 - \rho_{e_{1,u}} \sigma_{e_1} s_1. \tag{6}$$

Similarly, the estimated effect of parental SES for those without a degree, $D = 0$, is

$$\hat{b}_0 = b_0 - \rho_{e_{0,u}} \sigma_{e_0} s_0, \tag{7}$$

where

$$s_0 = -\frac{cov\left(-\frac{\varphi(\alpha+\beta x)}{1-\Phi(\alpha+\beta x)},\, x \mid D=0\right)}{\sigma^2_{x|D=0}}. \tag{8}$$

The nature and magnitude of omitted variable bias in Equations (6) and (7) depend on the correlations among the error terms. If there is positive selection into both states—that is, $\rho_{e_{1,u}} > 0$ and $\rho_{e_{0,u}} < 0$—the intergenerational SES association will be understated for college graduates and overstated for nongraduates. In this case, the “true” effect of a college degree on mobility is smaller than conventional estimates of the intergenerational SES associations by college attainment ($\hat{b}_1$ and $\hat{b}_0$) suggest. Conversely, if there is positive selection into the college graduation but negative selection into the nongraduate state—that is, $\rho_{e_{1,u}} > 0$ and $\rho_{e_{0,u}} > 0$—both associations will be understated. Because the bias also depends on the magnitude of the error correlations, it is difficult to determine *a priori* whether it would weaken, have no effect on, or reinforce the conclusion that college functions as an equalizer.

The nature of the bias is further complicated by the fact that s_1 and s_0 also influence its magnitude. Intuitively, these terms act as scaling factors that translate unobserved selection into bias in the estimated intergenerational association for graduates and nongraduates. They are determined by how the variance in parental SES is divided between the two groups: if one group is drawn from a narrower segment of the parental SES distribution, a given amount of unobserved selection has a larger impact on the estimated slope for that group. Because the composition of the graduate and nongraduate groups depends on the share of the population that completes college, the percentage graduating directly affects the relative size of s_1 and s_0 and thus the magnitude of the resulting bias.

The two terms, s_1 and s_0, depend on the variances of x (parental SES) conditional on the two values of D. The direction and size of the bias associated with s_1 or s_0 are affected by the percentage of the population completing a college degree. If fewer than half the population obtains a degree ($E(D) < 0.5$), then $s_1 > s_0$, implying that $\hat{b}_1 < \hat{b}_0$ even if $b_1 = b_0$, all else equal. In other words, even when the “true” effect of parental SES is identical for graduates and nongraduates, the estimated effect will incorrectly appear weaker for graduates.

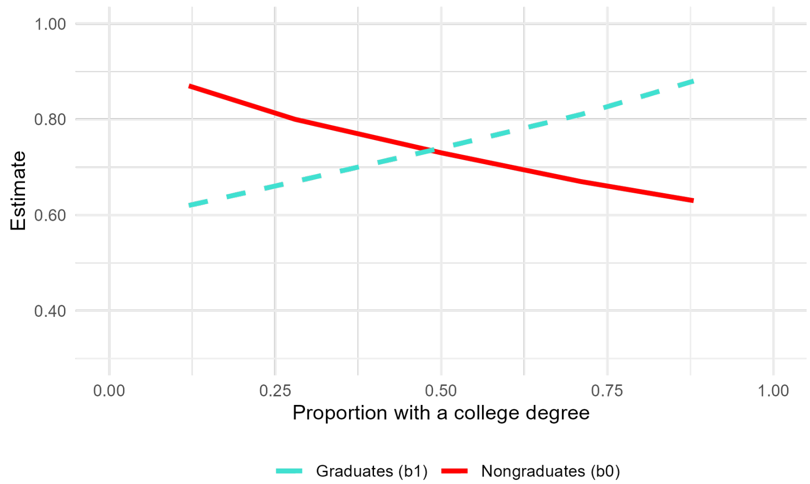

Figure 1: Estimated intergenerational SES association for college graduates ($\hat{b}_1$) and non-graduates ($\hat{b}_0$) when the true effects are identical ($b_1 = b_0 = 1$), by proportion of the cohort with a college degree. Note: Simulated data.

As shown in Figure 1, if the true effects are identical ($b_1 = b_0 = 1$), the discrepancy in estimated intergenerational associations declines as the proportion of a cohort with a college degree approaches 50 percent. The two curves converge and intersect when half the cohort completes college. Consequently, because the share of the population with a college degree rose from about 25 percent for those born around 1950 to about 40 percent for those born around 1980 (Horowitz 2018), we would expect the estimated associations to have converged over time, all else being equal. This analytical prediction aligns with empirical findings indicating that the effect of family background on college graduation has strengthened as college attainment has increased (see Torche 2011). In theory, this convergence could have been offset by changes in the correlations of the error terms over time. For example, as college enrollments expand, admissions may become less selective, and the composition of graduates in terms of unobserved characteristics may shift, potentially altering the strength of these correlations.

To summarize, failing to account for selectivity into college graduation in research on intergenerational mobility could create three key problems: (1) the estimated impact of college on SES outcomes may be overstated, (2) intergenerational SES associations for both college graduates and nongraduates may be biased, and (3) these associations could appear to differ for graduates and nongraduates even if the true effects are identical. These potential problems underscore the importance of correcting for college selectivity when assessing intergenerational social mobility, with particular attention to unobserved heterogeneity. Building on Carneiro et al. (2011) analysis of the heterogeneous returns to schooling, our approach is the first to directly examine the potential influence of unobserved factors on whether college functions as an equalizer.

Data and Methods

We use public-use and restricted geographic data from the NLSY (NLSY79). Directed by the U.S. Bureau of Labor Statistics, these data were collected annually and later biennially between 1979 and 2022. The NLSY79 is a panel survey of a national probability sample of 12,686 Americans born between 1957 and 1964 (aged 14–22 during the first interview in 1979). We restrict our analysis to white men for three reasons. First, it enables direct comparison with Carneiro et al.'s (2011) influential study on the returns to college, which used the same data and from whose replication package we obtained our IVs. Second, credible IVs are available only for white males, as their replication package contains IVs solely for counties in which white men were sampled. Third, including women and black respondents would complicate our assessment of heterogeneity in the returns to a college degree because these groups face distinct educational and labor market opportunities (Carneiro et al. 2011).[3]

Although Carneiro et al. (2011) examined heterogeneous returns to schooling, they did not assess its role in social mobility. We necessarily augment their original data with information on parents' and respondents' occupational status and permanent family income. Some respondents were missing data on these variables—particularly parental information—resulting in different effective sample sizes for our three mobility outcomes: $N = 1{,}259$ for log income, $N = 1{,}312$ for rank income, and $N = 1{,}544$ for occupation SES. As a robustness check, we also fitted the models using imputed values for missing information on parental income, derived from other parental characteristics such as education, occupational status, and marital status (for a similar approach, see Jácome, Kuziemko, and Naidu 2024). Table 1 presents descriptive statistics for the three analytical samples.

Occupational Mobility

Occupational mobility is measured using Duncan's (1961) socioeconomic index (SEI). The NLSY79 provides SEI scores based on 1970 census occupation codes, with later censuses harmonized through appropriate crosswalks. *Respondent's SEI* is calculated as the average SEI score reported from ages 34 to 42, reflecting occupational maturity. *Parental SEI* was collected only in the initial 1979 wave of the NLSY. We use the highest SEI score of the child's two parents; if only one parent's information is available, we use that parent's score.

Income Mobility

We measure income mobility using total family income, expressed in constant 2017 U.S. dollars. For *parental income*, we follow Davis and Mazumder (2024), calculating the average of up to three reports on total family income from 1979 to 1981. *Respondent's income* is calculated as the average of five measurements taken between ages 36 and 45. We examine two widely studied measures of income mobility: the intergenerational elasticity based on log income and the income rank–rank association (Torche 2015; Deutscher and Mazumder 2023). Because elasticities are sensitive to outliers, we restrict the log-income values to the first to

Table 1: Descriptive statistics and means (standard deviations).

	Nongraduates	Graduates	Total
Mobility variables			
Parental income ranks	0.64 (0.24)	0.75 (0.21)	0.67 (0.24)
Adult income ranks	0.55 (0.25)	0.79 (0.19)	0.62 (0.26)
Sample size	986 (75.1%)	326 (24.9%)	1,312 (100%)
Parental log income	11.22 (0.52)	11.43 (0.48)	11.27 (0.52)
Adult log income	11.15 (0.63)	11.71 (0.62)	11.30 (0.68)
Sample size	952 (75.6%)	307 (24.4%)	1,259 (100%)
Parental occupational status (Duncan SEI)	40.90 (21.79)	59.54 (20.51)	46.33 (23.03)
Adult occupational status (Duncan SEI)	36.63 (19.30)	63.79 (16.46)	44.21 (22.16)
Sample size	1,098 (71.1%)	446 (28.9%)	1,544 (100%)
IVs			
Presence of public four-year college at 14	48.6%	62.4%	52.5%
Local log earnings at 17	10.28 (0.18)	10.26 (0.20)	10.28 (0.19)
Local unemployment at 17 (in %)	7.11 (1.78)	7.02 (1.90)	7.08 (1.81)
Tuition in public four-year colleges in county of residence at 17 (in $100)	21.68 (7.93)	21.27 (8.10)	21.51 (7.98)
Control variables			
Years of experience as of 1991	9.51 (3.35)	5.89 (2.76)	8.49 (3.58)
Adjusted AFQT score	0.15 (0.99)	1.21 (0.95)	0.50 (1.05)
Mother's years of education	11.58 (2.15)	13.43 (2.26)	12.12 (2.33)
Number of siblings	3.11 (2.00)	2.47 (1.56)	2.93 (1.91)
Urban residence at 14	72.0%	80.7%	74.4%
Permanent local log earnings at 17	10.27 (0.16)	10.28 (0.19)	10.28 (0.16)
Permanent state unemployment rate at 17	6.30 (0.99)	6.12 (0.95)	6.25 (0.99)
Log local earnings in 1991	10.27 (0.16)	10.35 (0.17)	10.29 (0.17)
Local unemployment rate in 1991 (in %)	6.84 (1.31)	6.74 (1.16)	6.78 (1.27)
Born in 1957	11.5%	11.4%	11.5%
Born in 1958	10.4%	13.3%	11.2%
Born in 1959	13.3%	8.9%	12.0%
Born in 1960	15.3%	14.5%	15.1%
Born in 1961	15.0%	14.7%	14.9%
Born in 1962	19.4%	18.9%	19.3%
Born in 1963	15.0%	18.2%	15.9%
Full sample size	1,255 (71.8%)	492 (28.2%)	1,747 (100%)

99th percentiles (Jäntti and Jenkins 2015). Supplementary analyses show that our main findings hold regardless of whether this restriction is applied (see the online supplement Table A1).

College Attainment

Although the NLSY79 records education in years, its documentation indicates that 16 years of formal schooling is equivalent to completion of a four-year college degree (Bureau of Labor Statistics 2019). Accordingly, respondents with 16 years or more years of education are coded as college graduates (coded 1), whereas those with less than 16 years are coded as nongraduates (coded 0). Education is measured at age 30, or, if data at that age are missing, at the closest available age (from ages 26 to 34).

Control Variables

Following Carneiro et al. (2011), we control for a range of observed characteristics known to influence educational and labor market outcomes. Including these controls reduces the burden on the exclusion restrictions, thus strengthening the credibility of the IVs we later describe (Card 2001).

At the individual level, we account for mother’s years of schooling, number of siblings, whether the respondent lived in an urban area at age 14, cognitive ability, years of labor market experience, and year of birth. Cognitive ability is measured using the armed forces qualification test (AFQT), adjusted for years of schooling at the time of testing because AFQT scores partly reflect learned skills and educational attainment rather than pure ability (see Hansen, Heckman, and Mullen 2004). Years of experience, a key determinant of earnings in the human capital framework, reflects the total number of years the respondent had spent in the workforce by 1991. Year of birth is included as a factor to control for cohort effects that may influence both educational attainment and labor market outcomes.

We also include four contextual variables capturing stable local labor market conditions: logged average earnings in the respondent’s county of residence in 1991, the state-level unemployment rate in 1991, and two retrospective measures from age 17—permanent local log earnings and permanent state unemployment. These variables help isolate random variation in college enrollment decisions from persistent features of local labor markets, which is essential for interpreting the effects of the IVs.

Instrumental Variables

We leverage the four IVs developed by Carneiro et al. (2011) to correct for heterogeneous selection into college graduation. For a variable to serve as a valid IV, it must influence college enrollment (relevance) and affect socioeconomic attainment only through college completion (the exclusion restriction).

Presence of a four-year college in the county of residence at age 14. This variable captures proximity to college, a commonly used IV in labor economics (Card 2001). It assumes that living near a college increases the likelihood of attending by reducing financial and logistical barriers (relevance). At the same time, it should not directly influence labor market outcomes decades later (exclusion restriction); that is, it is unlikely that employers consider the presence of a college near an applicant’s teenage residence when making hiring decisions. Still, local economic conditions correlated with the presence of a college could indirectly influence adult outcomes. To mitigate this concern, we control for a wide array of factors to isolate the exogenous effect of college proximity. At the county level, we include long-term average wages (1973–2000 average), 1991 average wages, and 1991 unemployment rates. At the individual level, we control for cognitive ability (AFQT), mother’s education, family size, urban residence, and birth cohort.

Average tuition in public four-year colleges in the county of residence at age 17. This IV, also common in labor economics (Card 1999), assumes that higher tuition increases the financial cost of attending college, thereby reducing college attendance (relevance). Although tuition indirectly affects labor market outcomes by influencing educational attainment, it is unlikely that the tuition paid by earlier cohorts directly impacts individuals' labor market outcomes years later (exclusion restriction). As with the first IV, our extensive controls help remove any potential direct influence, ensuring that average tuition during adolescence affects adult outcomes only through its effect on college attendance.

Local earnings fluctuations in the county of residence at age 17. This IV, first used in Cameron and Heckman's (1998) influential study of educational transitions, assumes that temporarily higher local wages during adolescence increase the immediate incentive to enter the workforce after high school, thereby reducing the likelihood of college enrollment (relevance). Admittedly, local labor market conditions during adolescence could also directly affect adult outcomes if they reflect persistent economic advantages or disadvantages, thus potentially violating the exclusion restriction. However, by controlling for permanent local labor market conditions and explicitly including county wages in 1991, the remaining variation captures wage fluctuations rather than stable local economic conditions. We argue that these short-term wage fluctuations influence adult labor market outcomes only indirectly, through their effect on college attendance (exclusion restriction).

Local unemployment rate fluctuations in the state of residence at age 17. Also employed by Cameron and Heckman (1998), this IV suggests that temporarily high unemployment rates at adolescence lower the immediate opportunity cost of attending college, thus increasing college enrollment (relevance). As with local wages, unemployment conditions during adolescence could potentially influence adult labor market outcomes directly, independently of education, which would threaten the exclusion restriction. To address this, we control for stable labor market conditions—including the long-term average state unemployment rate (1973–2000) and the state unemployment rate in 1991—cognitive skills (AFQT), and a rich set of family-background characteristics. These controls help ensure that temporary unemployment fluctuations in adolescence affect adult outcomes only indirectly, through their influence on college completion (exclusion restriction).

Because our identification strategy relies on the validity of four IVs—which cannot be directly tested—we conducted sensitivity analyses that sequentially omitted IVs from the model. The results demonstrate strong robustness: across 15 alternative specifications—including those that exclude the two local labor market IVs—our core findings remain unchanged (see the online supplement Tables A10–A12). We also probed possible exclusion violations through migration or social capital channels, by regressing migration across county or state from ages 17 to 30, religious attendance in 2000, volunteering in 2006, and job-finding through social networks on the first-stage predictors (online supplement Table A13). These tests were overall insignificant; the few borderline unadjusted p values do not survive corrections for multiple testing, providing no systematic evidence that the instruments operate through these channels. Our strategy also depends on instrument relevance: all four IVs significantly predict college attainment, though the local labor market IVs are somewhat weaker than the distance and tuition IVs (online supplement Tables A6–A8). In short, our results are not driven by any single IV whose exclusion restriction might be questionable. Further discussion of IV validity is provided in the Discussion section.

Analytical Approach

Our goal is to assess the extent to which intergenerational mobility in income and occupation differs between college graduates and nongraduates, correcting for selectivity bias. Our analytical approach builds on the Heckman sample selection model (Heckman 1979; Winship and Mare 1992) and parallels the general specification of Carneiro et al. (2011). Although the method can be applied to any labor market outcome, we focus on family income and occupational SEI. Returning to Equations (1) and (2), we are particularly interested in $b_1 - b_0$, which represents the difference in the estimated effects of parental SES (x) on children's potential SES outcomes (Y) for nongraduates ($D = 0$) and college graduates ($D = 1$).

As our analytical results demonstrate, standard OLS estimates may be biased and inconsistent if there is unobserved selectivity in college completion. Fortunately, unbiased estimates for D, x, and the differences between the coefficients $(b_1 - b_0)$ can be obtained using an endogenous switching regression model with IVs (Winship and Mare 1992). We begin by modeling college attendance as a function of the IVs:

$$D = 1(\alpha + \beta x + \gamma z + u), \tag{9}$$

where z is a vector of variables that, while possibly correlated with x, are independent of the potential outcomes and of U_0 and U_1. In other words, z satisfies the criteria for a valid IV (Heckman and Vytlacil 1999). We then have

$$E\left(Y \mid X = x, Z = z\right) = E\left(Y \mid X = x, P\left(Z\right) = p\right), \tag{10}$$

where $P\left(Z\right) = F_V\left(\gamma z\right) = P\left(D = 1 \mid X = x, Z = z\right)$. The conditional expectation of Y given $X = x$ and $P(Z) = p$ is

$$\begin{aligned} &E\left(Y \mid X = x, P\left(z\right) = p\right) \\ &\quad = E\left(Y_0 \mid X = x, P\left(z\right) = p\right) + E\left(Y_1 - Y_0 \mid X = x, D = 1, P\left(z\right) = p\right) p. \end{aligned} \tag{11}$$

Using Equation (9) to estimate p, this can be written as

$$\begin{aligned} &a_0 + b_0 x + \left(a_1 - a_0 + \left(b_1 - b_0\right) x\right) p + \int_{-\infty}^{\infty} \int_0^p \left(e_1 - e_0\right) f\left(e_1 - e_0 | X = x, V = v\right) \\ &\quad dvd\left(e_1 - e_0\right) = a_0 + b_0 x + \left(a_1 - a_0 + \left(b_1 - b_0\right) x\right) p + K\left(p\right), \end{aligned} \tag{12}$$

where $V = F_U\left(U\right)$ and $K\left(p\right) = \int_0^p E\left(e_1 - e_0 | X = x, V = v\right) dv$.

A note on the role of the instruments, z, is warranted. Returning to Equation (12), if z were omitted, identification of $b_1 - b_0$ would depend on correctly specifying p, which is a nonlinear function of x. When included, γz (assuming a continuous distribution) captures the independent variation in p across all values of x, meaning that p is nonparametrically identified independently from the effect of x. Because

z is independent of the potential outcomes (even if conditional on x), including it in the college completion model (Eq. [9]) is equivalent to randomly assigning a value of z to each respondent. This random variation in college completion, net of x, allows estimation of the causal effect of college across many values of x, provided that z varies at all values of x. This requirement, known as the issue of common support (Heckman and Vytlacil 1999), ensures that each college graduate ($D = 1$) can be compared to a similar nongraduate ($D = 0$) with comparable p. If this condition is not satisfied, it is impossible to estimate the full potential distribution of outcomes of both college graduates and nongraduates.[4]

Our models differ from the general specifications of Carneiro et al. (2011) in several necessary ways. First, while they examined college enrollment, we focus on college completion, so our college indicator reflects education attainment by age 30.[5] Second, we use more comprehensive measures of respondents' permanent income and SEI. Third, we re-specify the model to enable direct assessment of the intergenerational associations in occupation and income for both college graduates and nongraduates.

Returning to the model, let D denote college attainment, Y_0 and Y_1 denote the SES of those without and with a college degree, x denote parents' SES, m denote the control variables, and z denote the IVs. The selection equation is then given by

$$D = 1\left(a + \theta x + \gamma m + \delta z + u_D\right), \tag{13}$$

and the outcome equations are given by

$$Y_0 = \kappa_0 + \beta_0 x + \mu_0 m + e_0, \tag{14}$$

$$Y_1 = \kappa_1 + \beta_1 x + \mu_1 m + e_1, \tag{15}$$

where θ represents the effect of parental SES, γ is the effects of the observed control variables, δ is the effect of the instruments, all on college completion, and β_0 and β_1 capture the intergenerational associations in SES corrected for selectivity net of the control variables, m.

We focus on the difference in the intergenerational association in SES for college graduates and nongraduates under the assumption that sorting into college is as "good as random" (Karlson 2019). Our interest lies in the marginal associations, rather than the partial associations controlling for m. To achieve this, we orthogonalize the relationships between the control variables, m, and parental SES, x, using the residuals from the linear model:

$$m_k = n + \tau x + \tilde{m}_k. \tag{16}$$

We then replace m with $\tilde{m}$ in the selection and outcome equations:

$$D = 1\left(a+\theta x+\gamma \widetilde{\boldsymbol{m}}+\delta z+u_D\right), \tag{17}$$

$$Y_0 = l_0 + \beta_0^* x + \mu_0 \widetilde{\boldsymbol{m}} + e_0, \tag{18}$$

$$Y_1 = l_1 + \beta_1^* x + \mu_1 \widetilde{\boldsymbol{m}} + e_1, \tag{19}$$

where $\widetilde{\boldsymbol{m}}$ is a vector of the control variables, $k = 1, \ldots, K$. Importantly, residualizing the control variables does not alter their coefficients; it only affects the coefficients for parental SES, giving them a marginal association interpretation.

We are interested in the total effect of x on Y, regardless of whether the variables in $\widetilde{\boldsymbol{m}}$ act as confounders or mediators. For example, the controls include cognitive ability (a confounder) and parenting styles (a mediator). The total effect of x absorbs the influence of both innate ability and parenting styles. The coefficients β_0^* and β_1^*, our key parameters of interest, thus represent the intergenerational associations in SES while correcting for selectivity into college graduation. By including both IVs to account for unobserved heterogeneity and residualized control variables, we ensure that β_0^* and β_1^* are not affected by confounding factors beyond sample selection.

Assuming suitable instruments are used, Equation (12) produces consistent estimates. These estimates can be obtained in at least three ways (Brave and Walstrum 2014; Andresen 2018). First, assuming joint normality of e_1, e_0, and u_D allows for the standard endogenous switching model (Winship and Mare 1992). Second, $K(p)$ can be approximated with a polynomial in p. Following the Stone–Weierstrass approximation theorem (Rudin 1973), $K(p)$ can be closely approximated by a suitable polynomial in p. That is, an estimate of p is obtained from Equation (9), and then a sufficiently high-order polynomial is added as a control function to the estimating equation. This approach is relatively straightforward, computationally undemanding, and makes no distributional assumptions about e_1, e_0, and u_D. The appropriate polynomial order is determined by adding higher order terms until model fit no longer improves. Third, $K(p)$ can be estimated semi-parametrically using local IVs (Heckman and Vytlacil 1999). We employ all three estimation approaches in our empirical analyses.

We fit a set of four competing models to predict each of the three outcomes: log income, rank income, and occupation-based SES. These models differ in their assumptions about the distribution of the error terms. Model 0 is a standard linear regression model that completely ignores selection bias related to college completion, making no correction for selectivity. This model aligns with the conventional approach to test the "college as equalizer" hypothesis. Model 1 is a standard endogenous switching model that assumes all unobserved variables (i.e., the error terms in the two potential outcomes and the college completion equation) are jointly normally distributed. This implies that $K(p)$ is equal to the inverse Mills ratio multiplied by a regression coefficient capturing the correlation between e_j, $j = 0, 1$ and u for each value of $D = 0, 1$. By assuming joint normality, model 1 imposes the strictest assumptions on the errors. Models 2 and 3 relax the assumption of normality by approximating the functional form of the effects of unobserved variables using polynomials for the IVs in Equation (12) (model 2 is linear and model 3 is quadratic). Model 4, the least restrictive of the models, estimates the polynomial semi-parametrically using the local IVs in Equation (12).

A lack of common support in the IVs for college graduates and nongraduates can lead to biased and inefficient estimates (Carneiro et al. 2011; Andresen 2018). Figures A1 and A2 in the online supplement illustrate the level of common support in our analyses. Consistent with Carneiro et al. (2011), we do not observe full support. For the parametric switching models, this issue is addressed through extrapolation using the assumed functional form (e.g., multivariate normality). Similarly, for the polynomial approach, values of p in unsupported intervals are replaced via polynomial extrapolation. For the semiparametric models, estimation was limited to the sample with overlapping support. To assess the potential impact of limited support, we also fitted supplementary models trimming 5 percent and 10 percent of the sample. Estimates from these models, reported in the online supplement Tables A3–A5, are consistent with our main results.[6] In short, we are confident that our findings are not driven by a lack of common support.

Unlike conventional IVs methods such as two-stage least squares, which identify average effects for a specific subpopulation of "compliers" (i.e., individuals whose treatment status is affected by the instrument), our approach builds on the more general estimator developed within the marginal treatment effect framework (Heckman and Vytlacil 1999, 2005). Specifically, we employ the local IVs method, which identifies causal effects across the full distribution of the unobserved propensity to complete college. This approach allows us to recover treatment effect estimates that are not limited to individuals influenced by a particular instrument. Instead, we trace how the effects of college vary across individuals with different latent propensities, providing a richer understanding of unobserved selection. Consequently, our estimates are not local in the LATE (local average treatment effect) or CACE (complier average causal effect) sense. Rather, they reflect broader variation in returns to college across our study population. Our conclusions are thus less dependent on a narrow complier subgroup and more informative about population-level patterns of selection and mobility—at least within the population of white men that we analyze.

Results

Table 2 reports the results from the four model specifications for all three intergenerational SES mobility outcomes: logged income, ranked income, and occupational SES. For each outcome, the first column contains the estimated intergenerational association for non-college graduates (b_0), the second column contains the estimated association for college graduates (b_1), and the third column displays the *difference* between the intergenerational association for college graduates and non-college graduates ($b_1 - b_0$). This difference is equivalent to a college completion $\times$ parental SES interaction term.

We start with the results for mobility in log income. Given that both parental income and respondents' income are logged, the effects represent elasticities. Model 0, which does not correct for selectivity, produces estimates that are consistent with the standard "college-as-equalizer" finding reported in the literature. For college graduates, the elasticity is only 16 percent; it is 32 percent for nongraduates. The difference between the two elasticities ($b_1 - b_0 = -0.17$) is negative and statistically significant. Consistent with previous studies, the general conclusion from model 0 is clear: obtaining a college degree is a central driver of intergenerational mobility.

We now turn to the results from models 1 to 4, which correct for selectivity. Although they have different specifications to account for unobserved heterogeneity,

Table 2: Estimated from models estimating the intergenerational association in logged family income, ranked income, and occupational SES for those without and with a college degree.

	Income (Log)			Income (Rank)			Occupation SES		
Model	Nongraduates (b_0)	Graduates (b_1)	Δ ($b_1 - b_0$)	Nongraduates (b_0)	Graduates (b_1)	Δ ($b_1 - b_0$)	Nongraduates (b_0)	Graduates (b_1)	Δ ($b_1 - b_0$)
Model 0 No correction	0.32^{*}	0.16^{*}	-0.17^{*}	0.30^{*}	0.16^{*}	-0.14^{*}	0.23^{*}	$0.08^{\dagger}$	-0.16^{*}
	(0.04)	(0.07)	(0.08)	(0.03)	(0.06)	(0.07)	(0.03)	(0.04)	(0.05)
Model 1 Standard ES model	0.27^{*}	0.44^{*}	0.17	0.26^{*}	$0.34^{\dagger}$	0.08	0.18^{*}	0.23	0.05
	(0.05)	(0.21)	(0.21)	(0.04)	(0.19)	(0.19)	(0.04)	(0.15)	(0.16)
Model 2 First-order polynomial	0.28^{*}	0.45^{*}	0.17	0.27^{*}	$0.34^{\dagger}$	0.08	0.18^{*}	$0.24^{\dagger}$	0.05
	(0.05)	(0.20)	(0.21)	(0.04)	(0.18)	(0.19)	(0.04)	(0.14)	(0.15)
Model 3 Second-order polynomial	0.28^{*}	0.45^{*}	0.17	0.26^{*}	$0.34^{\dagger}$	0.08	0.18^{*}	$0.24^{\dagger}$	0.05
	(0.05)	(0.20)	(0.21)	(0.04)	(0.18)	(0.19)	(0.04)	(0.14)	(0.15)
Model 4 Semiparametric ES model	0.28^{*}	$0.40^{\dagger}$	0.12	0.27^{*}	$0.35^{\dagger}$	0.08	0.19^{*}	0.18	-0.01
	(0.05)	(0.21)	(0.22)	(0.04)	(0.18)	(0.18)	(0.05)	(0.15)	(0.15)
N			1,259			1,312			1,544

Note: $^{\dagger}p < 0.10$; $^{*}p < 0.05$. Standard errors in parentheses. Standard errors for model 4 (semiparametric model) were derived from bootstrapping (200 replications). Estimates based on samples without dropping outliers and with imputation are shown in the online supplement Tables A1–A2.

they produce similar results. Compared to the uncorrected models, however, these models produce a quite different conclusion. In contrast to model 0, they provide no evidence that college is an equalizer. Relative to the uncorrected model, the elasticity differs only slightly for nongraduates (falling from 0.32 to 0.28 in model 4) but the estimates for college graduates are significantly higher (rising from 0.16 to 0.45 in models 2 and 3). In contrast to model 0, which demonstrates a significantly stronger elasticity for nongraduates ($b_1 - b_0 = -0.17$), the differences are positive, although not statistically significant, in all four models.

After correcting for selectivity, intergenerational social mobility for college graduates is similar, and perhaps even lower, than for nongraduates. In other words, obtaining a college degree does not equalize the effect of parental income. The selectivity correction also affects the elasticity estimates for graduates and nongraduates differently (cf. Eqs. [6] and [7]), revealing a strong positive selection into college graduation but little selection among those who do not obtain a college degree. That is, individuals who complete college tend to possess unobserved characteristics associated with higher SES outcomes, whereas those who do not complete college do not systematically differ from the population average in these unobserved traits.

As shown in Table 2, the rank–rank income mobility models convey the same substantive story. As with log income, the non-selectivity corrected estimates (model 0) reveal college as an equalizer; the selectivity-corrected models (models 1–4) do not. After correcting for selectivity, the effect of parental income reduces slightly for nongraduates but it is substantially larger for college graduates ($b_1 = 0.16$ in model 0; it is never lower than 0.34 in the selectivity-corrected models). Finally, like log income, all the selectivity-corrected differences in the rank–rank income association between college graduates and nongraduates are positive but statistically insignificant.

The pattern for intergenerational mobility in occupational SES is similar, even if mobility rates are generally higher than for income (i.e., the coefficients are smaller).[7] The smaller coefficients, especially for college graduates, most likely reflect that the average education of occupations is included in the calculation of occupational SES (Duncan 1961). Similar to the results for income, the standard model (model 0) suggests that college is an equalizer. The intergenerational association in occupational SES is nearly three times larger for nongraduates ($b_0 = 0.23$) compared to college graduates ($b_1 = 0.08$). This difference ($b_1 - b_0 = -0.15$) is statistically significant and identical to the differences for income mobility. Yet again, this result disappears after correcting for selectivity. In models 1–4, all estimates of the difference in mobility for college graduates and nongraduates are nearly zero and statistically insignificant.

The impact of correcting for selectivity is also illustrated in Figure 2. Each panel plots the effect of parental SES for college graduates and nongraduates. The rows of the three panels show the pattern for the three mobility outcomes. The panels on the left represent model 0 (i.e., the model not correcting for unobserved heterogeneity); the slopes from model 1 (the standard endogenous switching model that corrects for selectivity) are on the right. The slope for college graduates is steeper than the slope for nongraduates after correcting for unobserved heterogeneity. The significantly

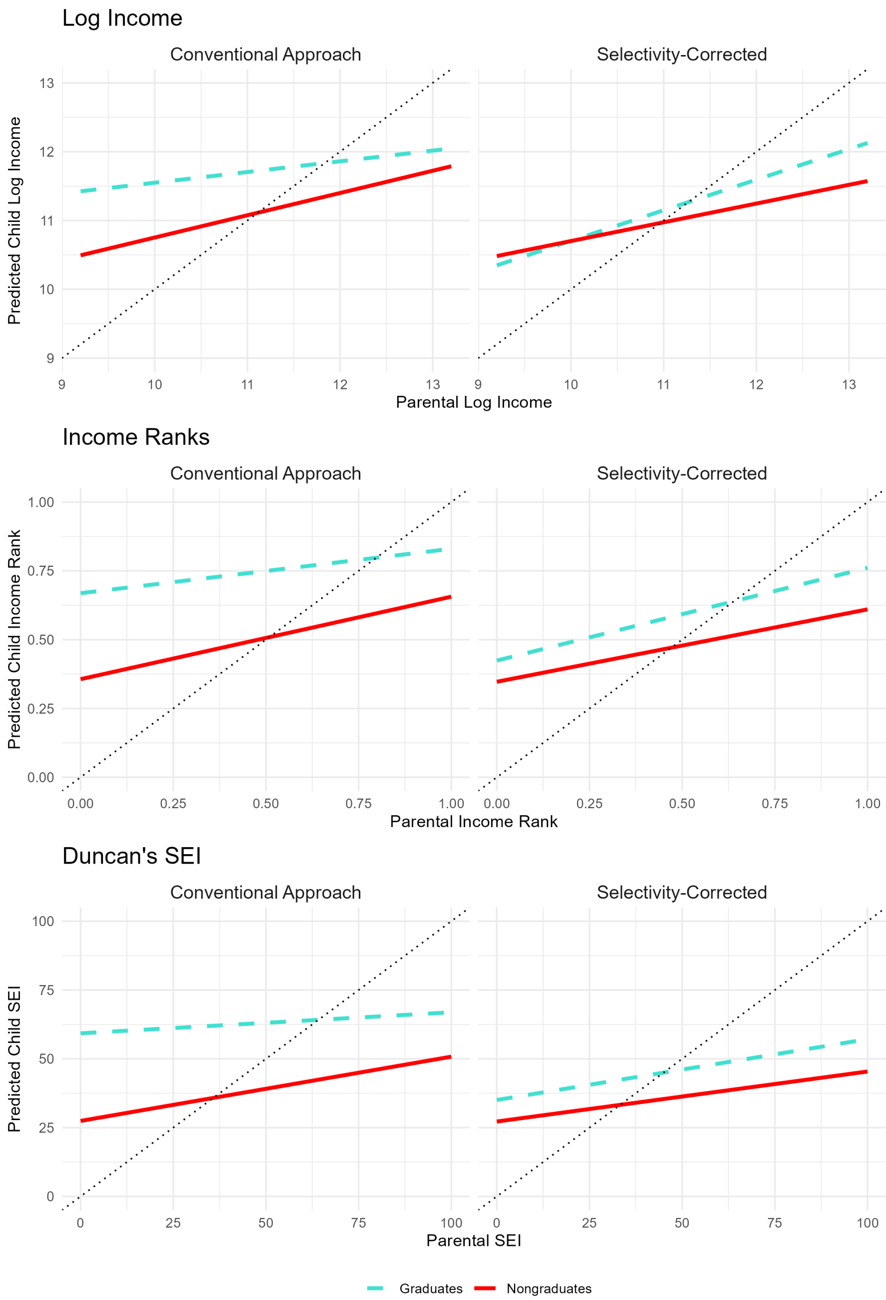

Figure 2: Predicted slopes for college graduates and nongraduates in log income, income ranks, and Duncan's SEI with and without correction for selection on unobserved variables. Note: Selectivity-corrected estimates are based on the standard switching model (model 1). Gray diagonal line represents the identity line.

smaller estimated average return to a college degree (i.e., the distance between the two slopes) in model 1 is also clear. These findings clearly suggest that the conventional approach severely overstates the causal returns to a college degree.

Table 3 reports the derived causal effects of a college degree for college graduates and nongraduates. Following the econometric literature, we refer to these effects as

Table 3: Average causal effects of college by labor market outcome for college graduates and nongraduates.

Treatment Effect	Income (Log)	Income (Ranks)	Occupation SES
ATT (graduates)	1.009* (0.225)	0.338* (0.081)	31.02* (5.47)
ATU (nongraduates)	−0.030 (0.747)	0.057 (0.275)	1.091 (14.61)

Note: $^{\dagger}p < 0.10$; $^{*}p < 0.05$. Estimates based on standard endogenous selection model (Model 1). ATT refers to the average treatment effect on the treated (i.e., college-degree holders); ATU refers to the average treatment effect on the untreated (i.e., those without a degree).

treatment effects, where completion of a college degree is the treatment. Echoing Carneiro et al. (2011) results for white men, the causal effect of a college degree is large and statistically significant for graduates but negligible for those without a degree. Completing a college degree appears to confer about a 100 percent premium on family income for those who graduate; for nongraduates, the family income premium is almost zero. The same pattern is observed for income ranks and occupation. These patterns are consistent with differential selectivity in college attainment: under current conditions, white men who complete college benefit substantially from doing so, whereas those who do not complete college are, on average, selected on traits that make their returns to a degree relatively modest. This finding contrasts with some prior evidence suggesting that those least likely to attend college stand to benefit the most (Brand and Xie 2010). Instead, our results align with Breen, Choi, and Holm (2015), who similarly found that individuals who did not earn a college degree would have experienced limited gains had they done so. Taken together, our findings indicate that, given the current pattern of selection into college graduation, expanding enrollment to those who currently do not enroll would not dramatically increase average returns among that group.

We conducted several robustness analyses, all of which corroborate our main finding that college is not an equalizer. First, to ensure that missing information on parents’ income and SEI did not impact our results, we imputed missing values. As shown in the online supplement Table A2, the results are virtually identical to our main findings, suggesting that differences in samples are not driving our results. Second, in the online supplement Table A1, we report estimates for log income without truncating log income at the first and 99th percentiles. Our main finding persists: college is not an equalizer. In fact, this analysis produces an even stronger effect of SES for those with a college degree. We interpret this more extreme pattern as resulting from the sensitivity of the elasticity to outliers. Third, as we described earlier, we tested the robustness of our results to lacking support in the propensity to obtain a college degree. Trimming the propensity by either five or 10 percent at the tails had little effect on any of the results we report (see the online supplement Tables A3–A5). Fourth, given prior findings on the un-equalizing effects of advanced degrees (Torche 2011), we re-estimated the models restricting the college sample to individuals without a graduate or professional degree. The overall pattern of results remains similar (see the online supplement Table A9).[8]

Discussion

Whether college serves as a “great equalizer” is a central concern in stratification research. Seminal studies found weaker intergenerational associations in occupational status and earnings for college graduates than for nongraduates (Hout 1984, 1988; Torche 2011). More recent work, however, suggests that this pattern may largely reflect selection into college based on characteristics that differ systematically between graduates and nongraduates (Karlson 2019; Zhou 2019; Yu and Elwert 2025; Yu and Zhao 2025). These studies primarily adjust for observed characteristics; none directly account for the influence of unobserved traits. Our study is the first to correct for selection on both observed and unobserved characteristics. Using an established instrumental-variable approach, we find no difference in intergenerational SES associations between graduates and nongraduates. This conclusion holds whether SES is measured by income rank, log income, or occupational status.

Our study contributes to a growing body of work addressing the selection challenge in estimating college’s role in intergenerational social mobility—an unresolved debate in sociology. Our findings broadly align with Witteveen and Attewell (2017), Zhou (2019), Yu and Elwert (2025), and Yu and Zhao (2025), most of which use the same data and correct for selectivity on a rich set of observed variables.[9] In fact, our results for the intergenerational association in income ranks are nearly identical to those reported for men by Zhou (2019). On the other hand, Karlson’s (2019) study—which relies on inverse probability weighting with a comprehensive list of observed variables also using the same data—suggests that education has an equalizing effect. These discrepancies underscore the merit of our approach: rarely, if ever, is the full universe of relevant control variables known or adequately measured, and the strategies for adjusting for them are numerous. By explicitly accounting for unobserved sources of selectivity, our approach offers an important new path in a multiverse of the “garden of forking paths,” with the hope to move the literature toward a more definitive answer over time (Young 2018; Engzell and Mood 2023).

It is important to distinguish the question of whether college is valuable from whether it functions as an equalizer. We show that, on average, a degree yields substantial returns and individuals from disadvantaged backgrounds benefit from these returns about as much as their more advantaged peers. This finding aligns with previous research demonstrating that college is central to accessing stable employment, high incomes, and prestigious occupations in the United States (Hout 2012; Autor 2014; Bloome et al. 2018) and internationally (see, e.g., Psacharopoulos and Patrinos 2004).

At the same time, our results suggest that—at least among white men in the NLSY79 cohort—college disproportionately attracts students who already possess traits highly rewarded in the labor market, especially among those from low SES families. These traits—often not easily observable or measurable in surveys—include cognitive ability (Deary et al. 2007; Allensworth and Clark 2020; O’Connell and Marks 2021), aspirations (Sewell et al. 1969; Morgan 2004), and personality attributes (Tross et al. 2000; Furnham et al. 2003; Cucina and Vasilopoulos 2005;

Komarraju et al. 2009; Poropat 2009; Trapmann et al. 2007; Corazzini et al. 2021; Mammadov 2021).

As with any analysis using IVs, our approach relies on the strong assumption that the instruments influence long-term socioeconomic outcomes only through their effect on college attainment. From a sociological perspective, the exclusion restriction may seem particularly vulnerable when instruments reflect local labor market conditions during adolescence. For example, fluctuations in the state-level youth unemployment rate at age 17—a commonly used IV—could affect later-life outcomes not only through college graduation but also via other channels such as social capital or migration. Although these concerns cannot be entirely dismissed, our sensitivity analyses show robust results: sequentially omitting instruments leaves the results unchanged, and indirect exclusion checks on migration and adult social capital show no systematic evidence that the instruments operate through these pathways. Together, these findings indicate that our results are not driven by any single instrument—including those for which the exclusion restriction may be most debatable. The generalizability of our conclusions is somewhat limited because valid instruments could be reliably constructed only for a sample of white men born between 1957 and 1964. Nevertheless, using the same data, we closely replicate prior uncorrected estimates for this group that portray college as an equalizer. This consistency highlights the importance of understanding how unobserved selectivity drives mobility outcomes within this subpopulation. Limitations in sample size also prevented us from examining whether the effects of college vary by type of institution, degree length, or field of study—factors that may influence intergenerational mobility (Davies and Guppy 1997; Goyette and Mullen 2006; Dillon and Smith 2016; Chetty et al. 2020; Ciocca Eller 2023; Leukhina 2023). As more comprehensive data become available, future research could build on our findings by testing whether the patterns we observe differ by gender, race and ethnicity, across birth cohorts, and over time. Such work could also extend our analysis to other countries to investigate how cultural, institutional, and policy contexts shape the impact of college education on intergenerational mobility (van de Werfhorst 2024).

In short, our results do not call into question the value of college for those who complete a degree; rather, they show that under current patterns of selection, the next individuals induced into college graduation would be unlikely to experience large returns. At the same time, for higher education to fulfill its promise as a true equalizer, successful college completion—and the traits that make completion likely—must become less dependent on family background. Only under such conditions would expanding college attainment meaningfully reduce intergenerational inequality.

As a primary gateway to socioeconomic opportunity, college education plays a central role in social stratification, yet mounting evidence shows that class-based inequalities constrain its meritocratic potential (Laurison and Friedman 2016; Rivera and Tilcsik 2016; Friedman and Laurison 2019). Our analysis leads to a clear, sobering conclusion: among white men of the late Baby Boomer generation, education does not function as the great equalizer it is often assumed to be. We found no meaningful difference in intergenerational mobility between college graduates and nongraduates. From a policy perspective, this underscores that without targeted support to help low-SES students access and persist in college, higher education is unlikely to overcome the entrenched advantages of family background.

Notes

1 Zhou's (2019, P. 477) sensitivity analysis examines the hypothetical scenario in which selection on an unobserved confounder is as strong as the selection on the covariates included in his model, including cognitive ability. The results suggest that obtaining a college degree could have a disequalizing effect, rather than an equalizing effect—that is, parental background might exert a stronger influence on those with a college degree than those without one. In sum, the analysis assumes that the impact of unobservables is as strong, but not stronger, than the observables. It is important to note that the explanatory power of the observed covariates accounts for only 5–10 percent of the variance in the outcome variables.

2 For completeness, we can also consider negative selection among college graduates, $\rho_{e_{1,u}} < 0$; however, this would imply a perverse scenario in which the SES outcomes of college graduates would be lower than those of the average person in the population (see Mare and Winship 1987).

3 Expanding the sample to these groups was not feasible because the replication file provides instrumental variables only for counties where only white men were sampled. Although this limitation constrains the generalizability of our findings, the same sample has been widely used in prior research on the relationship between a college degree and intergenerational mobility. As we demonstrate later, our uncorrected estimates closely replicate the equalizing pattern documented in earlier studies. Moreover, most recent mobility studies divide samples by race and gender (e.g., Torche 2011; Zhou 2019) and find that gender differences are relatively modest (Torche 2011; Karlson 2019).

4 This specification is robust to heterogeneous first-stage effects (Heckman and Vytlacil 2005; Carneiro, Heckman, and Vytlacil 2011). That is, the model remains valid even if the instruments affect the two groups differently. For example, tuition might influence college completion primarily for children from low-SES families, low-SES groups may be less sensitive to college proximity, or different SES groups might respond differently to unskilled wage shocks. In such cases, the model's estimates would be unaffected.

5 There is near-perfect agreement between our college variable and that of Carneiro, Heckman, and Vytlacil (2011), with only about 2.5 percent of cases classified differently. Goodman and Kruskal's gamma coefficient is 0.99.

6 For occupational mobility (online supplement Table A5), the standard endogenous switching model shows a pattern consistent with college as an equalizer, even if it is not statistically significant. However, this pattern does not appear in the polynomial specifications or in the semi-parametric model, suggesting that our main findings are robust despite potential issues with limited support.

7 For each mobility outcome, parental SES and child's SES are on the same scale, meaning that the theoretical range for the coefficient capturing their relationship is [-1,1]. This allows the magnitude of the SES effect to be directly compared across the three outcomes.

8 The only exception is the occupational SEI model, where excluding those with advanced degrees leaves the intergenerational association for college graduates essentially unchanged at zero. We note this for completeness but do not pursue it further here.

9 All of these studies but one (Witteveen and Attewell 2017) have results from the NLSY79 data.

References

Alderotti, Giammarco, Rapallini, Chiara, and Traverso, Silvio. 2023. “The Big Five Personality Traits and Earnings: A Meta-Analysis.” *Journal of Economic Psychology* 94:102570. https://doi.org/10.1016/j.joep.2022.102570

Allensworth, Elaine M. and Kallie Clark. 2020. “High School GPAS and ACT Scores as Predictors of College Completion: Examining Assumptions About Consistency Across High Schools.” *Educational Researcher* 49(3):198–211. https://doi.org/10.3102/0013189X20902110

Andresen, Martin A. 2018. “MTEFE: A Flexible Stata Command for Marginal Treatment Effects.” *The Stata Journal* 18(1):118–58. https://doi.org/10.1177/1536867X1801800108

Arcidiacono, Peter, Patrick Bayer, and Aurel Hizmo. 2010. “American Economic Journal: Applied Economics.” *American Economic Journal: Applied Economics* 2(4):76–104. https://doi.org/10.1257/app.2.4.76

Autor, David H. 2014. “Skills, Education, and the Rise of Earnings Inequality Among the ’Other 99 Percent’.” *Science* 344(6186):843–51. https://doi.org/10.1126/science.1251868

Birkelund, Jesper Fels. 2024. “Economic Returns to Reproducing Parents’ Field of Study.” *British Journal of Sociology. Online First.* https://doi.org/10.1111/1468-4446.13090.

Blau, Peter and Otis Dudley Duncan. 1967. *The American Occupational Structure*. New York: Free Press.

Bloome, Deirdre, Shauna Dyer, and Xiang Zhou. 2018. “Educational Inequality, Educational Expansion, and Intergenerational Income Persistence in the United States.” *American Sociological Review* 83(6):1215–53. https://doi.org/10.1177/0003122418809374

Bourdieu, Pierre. 1977. “Cultural Reproduction and Social Reproduction.” Pp. 487–510 in *Power and Ideology in Education*, edited by Jerome Karabel and A. H. Halsey. New York: Oxford University Press.

Brand, Jennie E. and Yu Xie. 2010. “Who Benefits Most from College? Evidence for Negative Selection in Heterogeneous Economic Returns to Higher Education.” *American Sociological Review* 75(2):273–302. https://doi.org/10.1177/0003122410363567

Brand, Jennie E. 2023. *Overcoming the Odds: The Benefits of Completing College for Unlikely Graduates*. New York: Russell Sage Foundation. https://doi.org/10.1353/book.112674

Brave, Scott A. and Thomas Walstrum. 2014. “Marginal Treatment Effects Using Parametric and Semiparametric Methods.” *The Stata Journal* 14(1):191–217. https://doi.org/10.1177/1536867X1401400113

Breen, Richard, ed. 2004. *Social Mobility in Europe*. Oxford, UK: Oxford University Press. https://doi.org/10.1093/0199258457.001.0001

Breen, Richard. 2010. “Educational Expansion and Social Mobility in the 20th Century.” *Social Forces* 89(2):365–88. https://doi.org/10.1353/sof.2010.0076

Breen, Richard and Jan O. Jonsson. 2005. “Inequality of Opportunity in Comparative Perspective: Recent Research on Educational Attainment and Social Mobility.” *Annual Review of Sociology* 31(1):223–43. https://doi.org/10.1146/annurev.soc.31.041304.122232

Breen, Richard and Jan O. Jonsson. 2007. "Explaining Change in Social Fluidity: Educational Equalization and Educational Expansion in Twentieth-Century Sweden." *American Journal of Sociology* 112(6):1775–810. https://doi.org/10.1086/508790

Breen, Richard, Seongsoo Choi, and Anders Holm. 2015. "Heterogeneous Causal Effects and Sample Selection Bias." *Sociological Science* 2(1):351–69. https://doi.org/10.15195/v2.a17

Breen, Richard and Walter Müller, eds. 2020. *Education and Intergenerational Social Mobility in Europe and the United States*. Stanford, CA: Stanford University Press. https://doi.org/10.11126/stanford/9781503610163.001.0001

Bureau of Labor Statistics, U.S. Department of Labor. 2019. *National Longitudinal Survey of Youth 1979 Cohort, 1979–2016 (Rounds 1–27)*. Produced and distributed by the Center for Human Resource Research (CHRR), Columbus, OH: The Ohio State University.

Cameron, Stephen V. and James J. Heckman. 1998. "Life Cycle Schooling and Dynamic Selection Bias: Models and Evidence for Five Cohorts of American Males." *Journal of Political Economy* 106(2):262–333. https://doi.org/10.1086/250010

Campbell, Karen E., Peter V. Marsden, and Jeanne S. Hurlbert. 1986. "Social Resources and Socioeconomic Status." *Social Networks* 8(1):97–117. https://doi.org/10.1016/S0378-8733(86)80017-X

Card, David. 1999. "The Causal Effect of Education on Earnings." Pp. 1801–63 in Handbook of Labor Economics, edited by O. Ashenfelter and D. Card. Amsterdam: North-Holland. https://doi.org/10.1016/S1573-4463(99)03011-4

Card, David. 2001. "Estimating the Return to Schooling: Progress on Some Persistent Econometric Problems." *Econometrica* 69(5):1127–60. https://doi.org/10.1111/1468-0262.00237

Carneiro, Pedro, James J. Heckman, and Edward J. Vytlacil. 2011. "Estimating Marginal Returns to Education." *American Economic Review* 101(6):2754–781. https://doi.org/10.1257/aer.101.6.2754

Castilla, Emilio J. and Ezra J. Poskanzer. 2022. "Through the Front Door: Why Do Organizations (Still) Prefer Legacy Applicants?" *American Sociological Review* 87(5):782–826. https://doi.org/10.1177/00031224221122889

Chetty, Raj, John N. Friedman, Emmanuel Saez, Nicholas Turner, and Danny Yagan. 2017. "Mobility Report Cards: The Role of Colleges in Intergenerational Mobility." *Working Paper 23618*. National Bureau of Economic Research. https://doi.org/10.3386/w23618

Chetty, Raj, John N. Friedman, Emmanuel Saez, Nicholas Turner, and Danny Yagan. 2020. "Income Segregation and Intergenerational Mobility Across Colleges in the United States." *Quarterly Journal of Economics* 135(3):1567–633. https://doi.org/10.1093/qje/qjaa005

Ciocca Eller, Christina. 2023. "What Makes a Quality College? Reexamining the Equalizing Potential of Higher Education in the United States." *American Journal of Sociology* 129(3):637–714. https://doi.org/10.1086/727891

Clark, Damon and Paco Martorell. 2014. "The Signaling Value of a High School Diploma." *Journal of Political Economy* 122(2):282–318. https://doi.org/10.1086/675238

Collins, Randall. 1971. "Functional and Conflict Theories of Educational Stratification." *American Sociological Review* 36(6):1002–19. https://doi.org/10.2307/2093761

Corazzini, Luca, Salvatore D'Arrigo, Elisabetta Millemaci, and Pietro Navarra. 2021. "The Influence of Personality Traits on University Performance: Evidence from Italian Freshmen Students." *PLOS ONE* 16(11) https://doi.org/10.1371/journal.pone.0258586

Cotter, David A., Joan M. Hermsen, Seth Ovadia, and Reeve Vanneman. 2001. “The Glass Ceiling Effect.” *Social Forces* 80(2):655–81. https://doi.org/10.1353/sof.2001.0091

Cucina, Jeffrey M. and Nicholas L. Vasilopoulos. 2005. “Nonlinear Personality-Performance Relationships and the Spurious Moderating Effects of Traitedness.” *Journal of Personality* 73(1):227–60. https://doi.org/10.1111/j.1467-6494.2004.00309.x

Davies, Scott and Neil Guppy. 1997. “Fields of Study, College Selectivity, and Student Inequalities in Higher Education.” *Social Forces* 75(4):1417–38. https://doi.org/10.2307/2580677

Davis, Jonathan M. V. and Bhashkar Mazumder. 2024. “The Decline in Intergenerational Mobility after 1980.” *The Review of Economics and Statistics. Online First.* https://doi.org/10.1162/rest_a_01413

Deary, Ian J., Steve Strand, Pauline Smith, and Cres Fernandes. 2007. “Intelligence and Educational Achievement.” *Intelligence* 35(1):13–21. https://doi.org/10.1016/j.intell.2006.02.001

Deutscher, Nathan and Bhashkar Mazumder. 2023. “Measuring Intergenerational Income Mobility: A Synthesis of Approaches.” *Journal of Economic Literature* 61(3): 988–1036. https://doi.org/10.1257/jel.20211413

Dillon, Eleanor Wiske and Jeffrey Andrew Smith. 2016. “Determinants of the Match Between Student Ability and College Quality.” *Journal of Labor Economics* 35(1). https://doi.org/10.1086/687523

DiMaggio, Paul and Filiz Garip. 2012. “Network Effects and Social Inequality.” *Annual Review of Sociology* 38:93–118. https://doi.org/10.1146/annurev.soc.012809.102545

Duncan, Otis Dudley. 1961. “A Socioeconomic Index for All Occupations.” Pp. 109–38 in *Occupations and Social Status*, edited by Albert J. Reiss Jr. New York: Free Press.

Duncan, Otis Dudley, David L. Featherman, and Beverly Duncan. 1972. *Socioeconomic Background and Achievement*. New York: Seminar Press.

Engzell, Per and Carina Mood. 2023. “Understanding Patterns and Trends in Income Mobility Through Multiverse Analysis.” *American Sociological Review* 88(4):600–26. https://doi.org/10.1177/00031224231180607

Erickson, Bonnie H. 1996. “Culture, Class, and Connections.” *American Journal of Sociology* 102(1):217–51. https://doi.org/10.1086/230912

Erickson, Bonnie H. 2001. “Good Networks and Good Jobs: The Value of Social Capital to Employers and Employees.” Pp. 127–58 in *Social Capital: Theory and Research*, edited by Nan Lin, Karen S. Cook, and Ronald S. Burt. New York: Aldine de Gruyter. https://doi.org/10.4324/9781315129457-6

Erikson, Robert and Jonsson, Jan O.. 1998. “Social Origin as an Interest-Bearing Asset: Family Background and Labour-Market Rewards among Employees in Sweden.” *Acta Sociologica* 41(1):19–36. https://doi.org/10.1177/000169939804100102

Fernandez, Roberto M. and Isabel Fernandez-Mateo. 2006. “Networks, Race, and Hiring.” *American Sociological Review* 71(1):42–71. https://doi.org/10.1177/000312240607100103

Fiel, Jeremy E. 2020. “Great Equalizer or Great Selector? Reconsidering Education as a Moderator of Intergenerational Transmissions.” *Sociology of Education* 93(4):353–71. https://doi.org/10.1177/0038040720927886

Friedman, Sam, and Daniel Laurison. 2019. *The Class Ceiling: Why It Pays to Be Privileged*. Bristol, UK: Policy Press. https://doi.org/10.46692/9781447336075

Furnham, Adrian, Tomas Chamorro-Premuzic, and Fiona McDougall. 2003. “Personality, Cognitive Ability, and Beliefs About Intelligence as Predictors of Academic Performance.” *Learning and Individual Differences* 14(1):47–64. https://doi.org/10.1016/j.lindif.2003.08.002

Goyette, Kimberly A., and Ann L. Mullen. 2006. “Who Studies the Arts and Sciences? Social Background and the Choice and Consequences of Undergraduate Field of Study.” *The Journal of Higher Education* 77(3):497–538. https://doi.org/10.1080/00221546.2006.11778936

Granovetter, Mark S. 1973. “The Strength of Weak Ties.” *American Journal of Sociology* 78(6):1360–80. https://doi.org/10.1086/225469

Hansen, Karsten T., James J. Heckman, and Kathleen J. Mullen. 2004. “The Effect of Schooling and Ability on Achievement Test Scores.” *Journal of Econometrics* 121(1–2):39–98. https://doi.org/10.1016/j.jeconom.2003.10.011

Heckman, James J. 1979. “Sample Selection Bias as a Specification Error.” *Econometrica* 47(1):153–61. https://doi.org/10.2307/1912352

Heckman, James J. and Edward J. Vytlacil. 1999. “Local Instrumental Variables and Latent Variable Models for Identifying and Bounding Treatment Effects.” *Proceedings of the National Academy of Sciences* 96:4703–34. https://doi.org/10.1073/pnas.96.8.4730

Heckman, James J. and Edward J. Vytlacil. 2005. “Structural Equations, Treatment Effects, and Econometric Policy Evaluation.” *Econometrica* 73(3):669–738. https://doi.org/10.1111/j.1468-0262.2005.00594.x

Horowitz, Jonathan. 2018. “Relative Education and the Advantage of a College Degree.” *American Sociological Review* 83(4):771–801. https://doi.org/10.1177/0003122418785371

Hout, Michael. 1984. “Status, Autonomy, and Training in Occupational Mobility.” *American Journal of Sociology* 89(6):1379–409. https://doi.org/10.1086/228020

Hout, Michael. 1988. “More Universalism, Less Structural Mobility: The American Occupational Structure in the 1980s.” *American Journal of Sociology* 93(6):1358–400. https://doi.org/10.1086/228904

Hout, Michael. 2012. “Social and Economic Returns to College Education in the United States.” *Annual Review of Sociology* 38:379–400. https://doi.org/10.1146/annurev.soc.012809.102503

Hout, Michael and Thomas A. DiPrete. 2006. “What We Have Learned: RC28’s Contributions to Knowledge About Social Stratification.” *Research in Social Stratification and Mobility* 24(1):1–20. https://doi.org/10.1016/j.rssm.2005.10.001

Huang, Xianbi and Mark Western. 2011. “Social Networks and Occupational Attainment in Australia.” *Sociology* 45(2):269–86. https://doi.org/10.1177/0038038510394029

Jácome, Elisa, Ilyana Kuziemko, and Suresh Naidu. 2024. “Mobility for All: Representative Intergenerational Mobility Estimates over the 20th Century.” *Journal of Political Economy. Online First.* https://doi.org/10.1086/732527

Jäntti, Markus and Stephen P. Jenkins. 2015. “Income Mobility.” The Oxford Handbook of Economic Inequality, edited by W. Salverda, B. Nolan, and T. Smeeding. Oxford: Oxford University Press.

Jencks, Christopher, Marshall Smith, Henry Acland, Mary Jo Bane, David Cohen, Herbert Gintis, Barbara Heyns, and Stephan Michelson. 1972. *Inequality: A Reassessment of Family and Schooling in America*. New York: Basic Books.

Kang, Sonia K., Katherine A. DeCelles, András Tilcsik, and Sora Jun. 2016. "Whitened Résumés: Race and Self-Presentation in the Labor Market." *Administrative Science Quarterly* 61(3):469–502. https://doi.org/10.1177/0001839216639577

Karlson, Kristian Bernt. 2019. "College as Equalizer? Testing the Selectivity Hypothesis." Social Science Research 80:216–229. https://doi.org/10.1016/j.ssresearch.2018.12.001

Komarraju, Meera, Steven J. Karau, and Ronald R. Schmeck. 2009. "Role of the Big Five Personality Traits in Predicting College Students' Academic Motivation and Achievement." *Learning and Individual Differences* 19(1):47–52. https://doi.org/10.1016/j.lindif.2008.07.001

Lareau, Annette. 2015. "Cultural Knowledge and Social Inequality." *American Sociological Review* 80(1):1–27. https://doi.org/10.1177/0003122414565814

Laurison, Daniel and Friedman, Sam. 2016. "The Class Pay Gap in Higher Professional and Managerial Occupations." *American Sociological Review* 81(4):668–695. https://doi.org/10.1177/0003122416653602

Lin, Nan, Walter M. Ensel, and John C. Vaughn. 1981. "Social Resources and Strength of Ties: Structural Factors in Occupational Status Attainment." *American Sociological Review* 46(4):393–405. https://doi.org/10.2307/2095260

Leukhina, Oksana. 2023. "The Changing Role of Family Income in College Selection and Beyond." *Federal Reserve Bank of St. Louis Review* 105(3):198–222. https://doi.org/10.20955/r.105.198-222

Lin, Nan. 1999. "Social Networks and Status Attainment." *Annual Review of Sociology* 25:467–87. https://doi.org/10.1146/annurev.soc.25.1.467

Mammadov, S. 2021. "Big Five Personality Traits and Academic Performance: A Meta-Analysis." *Journal of Personality* 90(2):222–55. https://doi.org/10.1111/jopy.12663

Manzoni, Anna and Jessi Streib. 2019. "The Equalizing Power of a College Degree for First-Generation College Students: Disparities Across Institutions, Majors, and Achievement Levels." *Research in Higher Education* 60:577–605. https://doi.org/10.1007/s11162-018-9523-1

Mare, Robert D. 1981. "Change and Stability in Educational Stratification." *American Sociological Review* 46(1):72–87. https://doi.org/10.2307/2095027

Mare, Robert D. 1993. "Educational Stratification on Observed and Unobserved Components of Family Background." Pp. 351–76 in *Persistent Inequality: Changing Educational Attainment in Thirteen Countries*, edited by Y. Shavit and H.-P. Blossfeld. Boulder, CO: Westview Press.

Mare, Robert D. and Christopher Winship. 1987. "Endogenous Switching Regression Models for the Causes and Effects of Discrete Variables." Working Paper no. 1987-32. Center for Demography and Ecology, University of Wisconsin-Madison. Retrieved November 18, 2024 (https://cde.wisc.edu/wp-1987-32/).

McDonald, Steve. 2011. "What's in the 'Old Boys' Network? Accessing Social Capital in Gendered and Racialized Networks." *Social Networks* 33(4):317–30. https://doi.org/10.1016/j.socnet.2011.10.002

McPherson, Miller, Lynn Smith-Lovin, and James M. Cook. 2001. "Birds of a Feather: Homophily in Social Networks." *Annual Review of Sociology* 27:415–44. https://doi.org/10.1146/annurev.soc.27.1.415

Morgan, Stephen L. 2004. "Methodologist as Arbitrator: Five Models for Black-White Differences in the Causal Effect of Expectations on Attainment." *Sociological Methods & Research* 33(1):3–53. https://doi.org/10.1177/0049124104263657

Morgan, Stephen L. and Christopher Winship. 2015. *Counterfactuals and Causal Inference*. 2nd ed. Cambridge: Cambridge University Press.

Naumann, William C., Deborah Bandalos, and Terry B. Gutkin. 2003. “Identifying Variables That Predict College Success for First-Generation College Students.” *Journal of College Admission* 181:4–9.

O’Connell, Michael and Gary N. Marks. 2021. “Are the Effects of Intelligence on Student Achievement and Well-Being Largely Functions of Family Income and Social Class? Evidence from a Longitudinal Study of Irish Adolescents.” *Intelligence* 84:101511. https://doi.org/10.1016/j.intell.2020.101511

Ortiz, Susan Y. and Vincent J. Roscigno. 2009. “Discrimination, Women, and Work: Processes and Variations by Race and Class.” *The Sociological Quarterly* 50(2):336–59. https://doi.org/10.1111/j.1533-8525.2009.01143.x

Pager, Devah, Bruce Western, and Bart Bonikowski. 2009. “Discrimination in a Low-Wage Labor Market: A Field Experiment.” *American Sociological Review* 74(5):777–99. https://doi.org/10.1177/000312240907400505

Penner, Andrew M. 2008. “Race and Gender Differences in Wages: The Role of Occupational Sorting at the Point of Hire.” *The Sociological Quarterly* 49(3):597–614. https://doi.org/10.1111/j.1533-8525.2008.00129.x

Poropat, Arthur E. 2009. “A Meta-Analysis of the Five-Factor Model of Personality and Academic Performance.” *Psychological Bulletin* 135(2):322–38. https://doi.org/10.1037/a0014996

Pfeffer, Fabian T. and Florian R. Hertel. 2015. “How Has Educational Expansion Shaped Social Mobility Trends in the United States?” *Social Forces* 94(1):143–80. https://doi.org/10.1093/sf/sov045

Psacharopoulos, George and Harry Anthony Patrinos. 2004. “Returns to Investment in Education: A Further Update.” *Education Economics* 12(2): 111–34. https://doi.org/10.1080/0964529042000239140

Rivera, Lauren A. 2012. “Hiring as Cultural Matching: The Case of Elite Professional Service Firms.” *American Sociological Review* 77(6):999–1022. https://doi.org/10.1177/0003122412463213

Rivera, Lauren A. 2015. *Pedigree: How Elite Students Get Elite Jobs*. Princeton, NJ: Princeton University Press. https://doi.org/10.1515/9781400865895

Rivera, Lauren A. and András Tilcsik. 2016. “Class Advantage, Commitment Penalty: The Gendered Effect of Social Class Signals in an Elite Labor Market.” *American Sociological Review* 81(6):1097–1131. https://doi.org/10.1177/0003122416668154

Rudin, Walter. 1973. *Functional Analysis*. New York: McGraw-Hill.

Sewell, William Hamilton, Archibald O. Haller, and Alejandro Portes. 1969. “The Educational and Early Occupational Attainment Process.” *American Sociological Review* 34(1):82–92. https://doi.org/10.2307/2092789

Streib, Jessi. 2023. *The Accidental Equalizer: How Luck Determines Pay after College*. Chicago: University of Chicago Press. https://doi.org/10.7208/chicago/9780226829685.001.0001

Torche, Florencia. 2011. “Is a College Degree Still the Great Equalizer? Intergenerational Mobility Across Levels of Schooling in the United States.” *American Journal of Sociology* 117(3):763–807. https://doi.org/10.1086/661904

Torche, Florencia. 2015. “Analyses of Intergenerational Mobility: An Interdisciplinary Review.” *The ANNALS of the American Academy of Political and Social Science* 657(1):37–62. https://doi.org/10.1177/0002716214547476

Trapmann, Sabine, Bettina Hell, Jörg-Oliver W. Hirn, and Heinz Schuler. 2007. “Meta-Analysis of the Relationship Between the Big Five and Academic Success at University.” *Zeitschrift Für Psychologie/Journal of Psychology* 215(2):132–51. https://doi.org/10.1027/0044-3409.215.2.132

Tross, Sharon A., Jane P. Harper, Lynn W. Osher, and Lisa M. Kneidinger. 2000. “Not Just the Usual Cast of Characteristics: Using Personality to Predict College Performance and Retention.” *Journal of College Student Development* 41(3):323–34.

Vallet, Louis-André. 2004. “Social Mobility and Educational Inequalities in France: The Recent Trends.” Pp. 115–147 in *Social Mobility in Europe*, edited by Richard Breen. Oxford, UK: Oxford University Press.

Vallet, Louis-André. 2020. “Intergenerational Mobility and Social Fluidity in France over Birth Cohorts and Across Age: The Role of Education.” Pp. 91–121 in *Education and Intergenerational Social Mobility in Europe and the United States*, edited by Richard Breen and Walter Müller. Stanford, CA: Stanford University Press. https://doi.org/10.11126/stanford/9781503610163.003.0005

van de Werfhorst, Herman G. 2024. “Is Meritocracy Not So Bad After All? Educational Expansion and Intergenerational Mobility in 40 Countries.” *American Sociological Review*, online first: https://doi.org/10.1177/00031224241292352.

Wilkins, Amy C. 2014. “Race, Age, and Identity Transformations in the Transition from High School to College for Black and First-Generation White Men.” *Sociology of Education* 87(3):171–87. https://doi.org/10.1177/0038040714537901

Winship, Christopher and Robert D. Mare. 1992. “Models for Sample Selection Bias.” *Annual Review of Sociology* 18:327–50. https://doi.org/10.1146/annurev.so.18.080192.001551

Witteveen, Dirk and Paul Attewell. 2017. “Family Background and Earnings Inequality Among College Graduates.” *Social Forces* 95(4):1539–76. https://doi.org/10.1093/sf/sow109

Young, Cristobal. 2018. “Model Uncertainty and the Crisis in Science.” *Socius: Sociological Research for a Dynamic World* 4:1–9. https://doi.org/10.1177/2378023117737206

Yu, Ang and Felix Elwert. 2025. “Nonparametric causal decomposition of group disparities.” *The Annals of Applied Statistics* 19(1):821–45. https://doi.org/10.1214/24-AOAS1990

Yu, Ang and Jiwei Zhao. 2025. “Counterfactual Slope and Its Applications to Social Stratification.” *Sociological Methodology 55*(2):329–55. https://doi.org/10.1177/00811750251340392

Zhou, Xiang. 2019. “Equalization or Selection? Reassessing the ‘Meritocratic Power’ of a College Degree in Intergenerational Income Mobility.” American Sociological Review 84(3):459–485. https://doi.org/10.1177/0003122419844992

Acknowledgments: The authors thank Richard Breen, Wenhao Jiang, Robert Manduca, Kim Weeden, Ang Yu, and participants at PAA 2025, the Sociological Science 2025 Conference, and ASA 2025 for their helpful comments and support. This research was conducted with restricted access to Bureau of Labor Statistics (BLS) data. We thank the staff at BLS and NORC at the University of Chicago for their assistance with accessing restricted data. The views expressed here do not necessarily reflect the views of the BLS.

Funding statement: For Kristian Bernt Karlson, the research leading to the results presented in this article has received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (grant agreement no. 851293).

Haowen Zheng: Stone Center for Inequality Dynamics, University of Michigan. E-mail: zhenghw@umich.edu.
Robert Andersen: Ivey Business School, Western University. E-mail: bob.andersen@ivey.ca.
Anders Holm: Department of Sociology, Western University. E-mail: aholm@uwo.ca.
Kristian Bernt Karlson: Department of Sociology, University of Copenhagen.
E-mail: kbk@soc.ku.dk.