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RESEARCH ARTICLE

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Catching up to girls: Understanding the gender imbalance in educational attainment within race

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Summary

We estimate a sequential model of schooling to assess the major contributing factors to the large gender imbalance in educational attainment within racial groups. First, we find that differences between males and females in measures of early behavior account for the majority of the gender gap for each racial group. Second, we show that black males have the largest response to improvements in family background characteristics, such that equalizing the distribution of family background characteristics for black and white youths reduces the gender gap in college enrollment among black youth by 50%.

1 | INTRODUCTION

The disparities in educational outcomes between black and white Americans have received substantial attention in social science research for decades. While the racial gap in educational attainment is large, gender disparities in educational attainment within race are even starker, yet have received far less attention. For example, overall, white youths are 35% more likely to enroll in college than black youths. However, among black youths, females are 50% more likely to enroll in college than their male counterparts, making the gender gap within black youth significantly larger than the black–white racial gap.[1] These gender imbalances have considerable implications from a public policy standpoint, affecting a range of issues from male employment and labor market outcomes (Acemoglu & Autor, 2011), to family formation and the economic mobility of future generations (Autor & Wasserman, 2013; Lundberg & Pollak, 2014; McDaniel, DiPrete, Buchmann, & Shwed, 2011), as well as diversity on college campuses.[2]

Research studying the aggregate gender gap in educational attainment (Buchmann & DiPrete, 2006; Chetty, Hendren, Lin, Majerovitz, & Scuderi, 2016;DiPrete & Jennings, 2012; Fortin, Oreopoulos, & Phipps, 2015; Goldin, Katz, & Kuziemko, 2006; Jacob, 2002) has highlighted two important mechanisms: first, the role of underlying group differences in character-

[1]In the National Longitudinal Survey of Youth 1997, among black youth, females are 17pp more likely to attend college than males, while the black–white racial gap in college enrollment is 14.7pp. Similar gaps can be found in the American Community Survey (ACS). In the 2009 ACS, the racial gap in college enrollment was 14.1pp and the gender gap for black youth was 16.5pp.

[2]Acemoglu and Autor (2011) show that earnings and employment prospects of less-educated workers have declined sharply since the early 1980s, such that recent cohorts of less-educated males, and in particular black males, have fewer opportunities in the labor market than their predecessors. Autor and Wasserman (2013) document that less-educated males have lower marriage rates but father children at rates equal to more-educated males. Consequently, the children of less-educated men are more likely to to come from broken families. As discussed in McDaniel et al. (2011), Autor and Wasserman (2013), Lundberg and Pollak (2014); Heckman (2011), these children receive fewer parental investments, facing larger risks of academic achievement deficits that may perpetuate current inequalities. Finally, the shortage of black males in postsecondary education may also weaken efforts to increase college campus diversity, which is "a compelling state interest," as Justice Sandra O'Connor wrote for the majority in Grutter v. Bollinger, 539 U.S. 306 (2003).

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- Model grade-by-grade decisions (10th grade $\rightarrow$ college)
- Allow differential factor responses by race $\times$ gender $\times$ grade level

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- Find that Black men are uniquely responsive to family background:
  - equalizing family factor for Blacks and Whites would reduce gender gap by 50%

Changes across Cohorts in Wage Returns to Schooling and Early Work Experiences

Jared Ashworth, *Pepperdine University*

V. Joseph Hotz, *Duke University, National Bureau of Economic Research (NBER), and Institute of Labor Economics (IZA)*

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Tyler Ransom, *University of Oklahoma and IZA*

This paper investigates the wage returns to schooling and actual early work experiences and how these returns have changed over the past 20 years. Using the NLSY surveys, we develop and estimate a dynamic model of the joint schooling and work decisions that young men make in early adulthood and quantify how they affect wages using a generalized Mincerian specification. Our results highlight the need to account for dynamic selection and changes in composition when analyzing changes in wage returns. In particular, we find that ignoring the selectivity of accumulated work experiences results in overstatement of the returns to education.

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- Ignoring actual work experience $\Rightarrow$ overstates education returns

The Path to College Education: The Role of Math and Verbal Skills

Esteban Aucejo

Arizona State University

Jonathan James

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This paper studies the formation of math and verbal skills during compulsory education and their impact on educational attainment. Using longitudinal data that follow students in England from elementary school to university, we find that the production functions of math and verbal skills are inherently different, where cross effects are present only in the production of math skills. Results on long-term educational outcomes indicate that verbal skills play a substantially greater role in explaining university enrollment than math skills. This finding, combined with the large female advantage in verbal skills, has key implications for gender gaps in college enrollment.

I. Introduction

The employment prospects of less-educated workers have worsened significantly since the early 1980s (Autor and Wasserman 2013). As formal

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Measurement Systems†

Susanne Schennach*

Economic models often depend on quantities that are unobservable, either for privacy reasons or because they are difficult to measure. Examples of such variables include human capital (or ability), personal income, unobserved heterogeneity (such as consumer "types"), et cetera. This situation has historically been handled either by simply using observable imperfect proxies for each of the unobservables, or by assuming that such unobservables satisfy convenient conditional mean or independence assumptions that enable their elimination from the estimation problem. However, thanks to tremendous increases in both the amount of data available and computing power, it has become possible to take full advantage of recent formal methods to infer the statistical properties of unobservable variables from multiple imperfect measurements of them. The general framework used is the concept of measurement systems in which a vector of observed variables is expressed as a (possibly nonlinear or nonparametric) function of a vector of all unobserved variables (including unobserved error terms or "disturbances" that may have nonadditively separable affects). The framework emphasizes important connections with related fields, such as nonlinear panel data, limited dependent variables, game theoretic models, dynamic models, and set identification. This review reports the progress made toward the central question of whether there exist plausible assumptions under which one can identify the joint distribution of the unobservables from the knowledge of the joint distribution of the observables. It also overviews empirical efforts aimed at exploiting such identification results to deliver novel findings that formally account for the unavoidable presence of unobservables. (*JEL* C30, C55, C57, D12, E21, E23, J24)

1. *Introduction*

Economists have long understood that economic behavior is largely determined by quantities that are difficult to measure accurately or are entirely unobserved (e.g., Griliches and Ringstad 1970; Amemiya 1985; Bound, Brown, and Mathiowetz 2001; Hausman 2001; Aigner et al. 1984). Fortunately, techniques to handle such situations have been under constant development for a long time and, in fact, have experienced a recent surge in interest in

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- Rich data + computing power $\Rightarrow$ formally account for unobservables