

RESEARCH ARTICLE

WILEY -APPLIED ECONOMETRICS

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 contributings factors to the large gender imbalance in doubtroal materials and the schooling to the schooling of the groups. First, we find that differences between males and females in nearest and groups. First, we find that differences between males and females in nearest and schooling of the Second, we show that black makes have the largest response to improvements in family background characteristics for black and white youths reduces the gender and in college confirmed among black such by 50%.

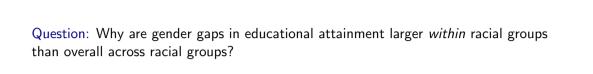
1 | INTRODUCTION

The dispatrities in educational outcomes between black and while Americans have received substantial attention in social science research for decades. While the reacile gap in educational attainment is large, gender dispatrities in educational attainment within race are even starker, yet have received far less attention. For example, overall, while youths are 35% more likely to emoil in college than their mades youths. However, among black youths, females are 55% more likely to enroll in college than their made counterparts, making the gender gap within black youth significantly larger than the scales—white racial gap. These gender installances have condicted be implications from a public policy standardoris, affecting a ranger of issues from made the mylogenest and base or market conscenses. (Accomplie A Actua, 2011), to family formation to the proper of issues from made the mylogenest and base or market conscenses. (2) 1, and ending a brothe, 2014, the high formation (2) 1, and 1, and

Research studying the aggregate gender gap in educational attainment (Buchmann & DiPrete, 2006; Chetky, Hendren, Lin, Majerovitz, & Scuderi, 2016;DiPrete & Jennings, 2012; Fortin, Oreopoulos, & Phipps, 2015; Goldin, Katz, & Mondrey, 2006; Jacob, 2020) has highlighted two important mechanisms: first, the role of underlying ground differences in character-

*Accurage and Amer (2011) show that sestings and employment prospects of loss educated workers have decident deathey show the earny forms, that access colorate is an eschaed in a periodart behavior have fore opportunities to the last hear reader to the interaction of the interaction of the interaction of the interproduces contained and the form to the last produces contained to the second of the last produces contained to the last

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 racid 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 sender gap of brake woult was 16.5pp.

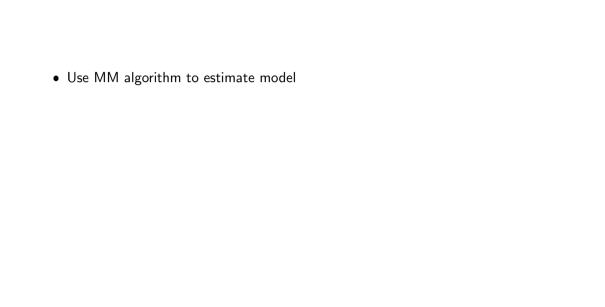


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- \bullet Allow differential factor responses by race \times gender \times grade level



Use MM algorithm to estimate model
• Use estimates to simulate effectiveness of policies that would narrow factor gaps

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Use estimates to simulate effectiveness of policies that would narrow factor gaps

- 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)

Arnaud Maurel, Duke University, NBER, and IZA

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 pain 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 high light the mediance of the properties of the prop

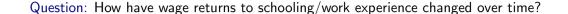
We thank Christian Belzil, Michael Böhm, Richard Blundell, Flavio Conha, Attila Lindner, Charles Manski, Matt Masten, Michela Tincani, and participants at various seminars and conferences for useful comments and discussions at various stages of this research. We especially wish to thank Vladislav Slanchev for providing us with a version of his statistical software for estimating discrete choice models with a latent

Submitted June 4, 2018; Accepted September 25, 2020; Electronically published July 23, 2021.

Journal of Labor Economics, volume 39, number 4, October 2021.

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Question: How have wage returns to schooling/work experience changed over time?	



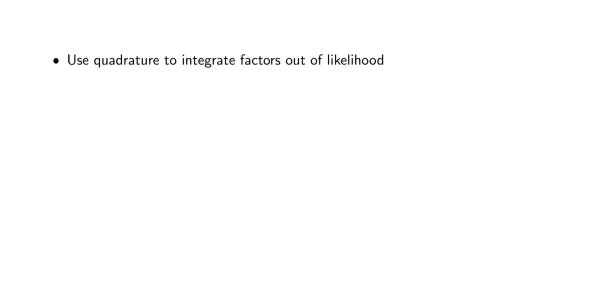
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- Noncognitive factor identified from panel data serial correlation



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Ignoring actual work experience ⇒ overstates education returns

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

Esteban Aucejo

Arizona State University

Jonathan James

 $California\ Polytechnic\ State\ University$

This paper studies the formation of muth and verbal skills during compulsory education and their impact on educational statisment. Using longitudinal data that follow students in England from elementary and the state of the state of the state of the state of the state 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 explaning university enrollment than math skills. This finding, combined with the large female sharting in verbal skills, has key in

I. Introduction

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

We thus! Peer Arcidiacono, Ghazda Arma; Caroline Hoshy, Monica Langella, Alan Maning, Gan Michael, Swee Bothle, Tyler Ramonn, Marco Sand, Zaduny Tohio, Geegony Veramendi, and seminar participants at transerous conferences and universities for highly retreated to the conference and transportation of the conference and universities for the conference of the conference and universities for the conference or conclusions devoted from the National Psych Darab Psychological States are possibled a supplementary material colline. On the plant particle Alexan provided a supplementary material colline.

Electronically published August 28, 2021 [Jurnal of Polifical Economy, 2021, vol. 129, no. 10] © 2021 by The University of Chicago, All rights reserved, 0022-3808/2021/12910-0005\$10.60

Question: How do math vs. verbal skills shape educational attainment in UK?

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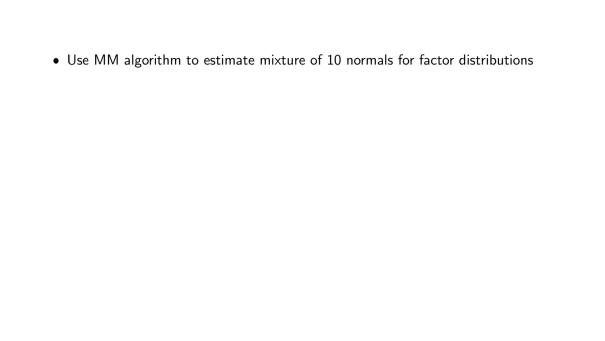
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- Account for selection into (elective) KS4 subjects via conditional logit



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- ullet U.S. validation (NLSY97): similar verbal > math pattern for enrollment

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 sustems 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, dunamic 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., Criliches and Ringstad 1970; Amemiya

*Brown University. This work is supported by the US National Science Foundation under grants SES-1659334 and SES-1950969. The author would like to thank Vincent 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

Starck, four anonymous referees, and the editor for helpful

[†] Go to https://doi.org/10.1257/jel.20211355 to visit the article page and view author disclosure statement(s).

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