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Skills and the evolution of wage inequality☆

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HIGHLIGHTS

- Mean employed cognitive skills have changed little in education-gender groups.
- Mean employed cognitive skills increased due to labour force composition changes.
- Returns to cognitive skills increased much more rapidly for higher skill levels.
- Skill price changes account for 60% of the growth in the college wage premium.
- Skills account for a small but growing fraction of residual wage inequality.

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ABSTRACT

This paper studies wage inequality in the United States between 1980 and 2010 in a framework that accounts for changes in the employment of physical and cognitive skills and their returns. I find that the secular rise in the employment of cognitive skills is largely accounted for by labour force composition changes in shares of gender–education groups rather than changes that occur within these groups. Average employed skills differ greatly across groups, but over time their average employed cognitive skills have remained approximately constant. Returns to cognitive skills increased very sharply for high skill levels, more gradually around mean levels, and decreased at low levels. Returns to physical skills generally declined. These trends account for approximately 63% of the increase in the college wage premium, with changes in returns to cognitive skills playing a dominant role.

1. Introduction

The college wage premium and residual wage inequality in the United States have increased dramatically between 1980 and 2010.[1] This paper examines the role of employed cognitive and physical skills in explaining these trends. I first document new patterns in the employment of these skills within education and gender groups, and estimate the returns to these skills over time. I then evaluate the extent to which changes in quantities and prices of skills can account for the observed evolution of wage inequality.

Earnings vary greatly with occupations and changes in the returns to different occupations explain a very large fraction of the increase in the returns to college. A main finding of this paper is that these changes are directly related to occupational cognitive skill requirements and changes in their returns.

I show that the well established result that the employment of cognitive skills has increased over time is largely accounted for by the rising fraction of college educated women in the workforce, followed by the decline in high school men dropouts. Within gender–education groups, average employed cognitive skills have remained approximately constant over the entire period, so labour force composition changes account for almost the entire change in employed skills observed at the aggregate level. Changes in quantities of employed skills account for only a very small fraction of the rising college wage premium.

I find that non-linearities in skill returns are very important in understanding the evolution of inequality since returns to different levels of cognitive skills have evolved very differently over time: they increase

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[1] See for example Katz and Murphy (1992), Card and DiNardo (2002), Autor et al. (2005b), and Lemieux (2008).

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very sharply toward the top of the cognitive skill distribution, more gradually around mean levels, and decrease at the bottom of the distribution. These patterns in skill prices alone account for approximately 60% of the increase in the return to college.

This paper adds to a growing recent literature that attempts to better define and measure workers' skills and explain trends in inequality. There is a very large literature studying the rising skill premium and changes in the supply and demand for skills, mainly focusing on how skill-biased technical change and international trade have led to shifts in the demand for various skills (e.g., Bound and Johnson (1992), Katz and Murphy (1992), Juhn et al. (1993), Krusell et al. (2000), and Acemoglu (2003)). One difficulty in this literature has been in defining and measuring workers' skills. Education and experience are the two most commonly used measures, but these may not be adequate since the underlying skills affected by technical change or international trade may vary significantly within education and experience categories. More recent literature has re-examined wage inequality using models that account for more precise skill measures constructed using observed occupational characteristics available in the Dictionary of Occupational Titles (DOT) (e.g., Autor et al. (2003), Wolff (2003), Ingram and Neumann (2006), Bacolod and Blum (2010), Acemoglu and Autor (2011) and Firpo et al., 2011).

Building on this literature, I study trends in employed skills and their returns over time using CPS data matched with occupational characteristics from the DOT. This paper focuses on employed cognitive and physical skills and finds that these two skill measures result in a ranking of occupations that is as informative in explaining trends in inequality as more detailed and specific skill categories. The skill content of occupations is fixed at the levels captured by the DOT 1991 Revised Fourth Edition, so the analysis is focused entirely on extensive margin changes, i.e., changes in the relative frequency of occupations with different skill requirements as observed in the 1991 DOT. The analysis deals entirely with the skill content of workers' occupations rather than individual workers' skills which are not observed.

Disaggregating the analysis by gender–education groups provides new insights into wage inequality patterns. Labour force composition changes explain most of the total increase in average employed cognitive skills over time, while average employed cognitive skills within groups have remained approximately constant. This implies that changes in occupational structure have not led to systematic changes in average skills across groups, at odds with some existing literature suggesting that the composition of employment across occupations is related to the rising college premium (e.g., Acemoglu and Autor (2011)).

Skills contribute to the rising college premium mainly through price effects. Returns to very low levels of cognitive skills have decreased, predicting a compression in the wages of workers in different occupations at the bottom end of the cognitive skill distribution. However, moving higher along the distribution of cognitive skills, I find that skill returns increase, and these increases become very steep as we approach the top end of the distribution. For example, the wage premium associated with a one standard deviation point increase in cognitive skills above the 1995 mean increases from 6% in 1980 to 22% in 2010 and the premium associated with an additional standard deviation point at the top of the distribution increases from 1% to 29% (moving from 1 to 2 s.d. points above the mean).

Changes in skill prices alone explain 60% of the increase in the male college premium, with non-linearities in returns to skills accounting for 8.5%. Thus, a college degree is increasingly valuable not because the average occupation of a college graduate changes in terms of skill requirements, but because employment in this average occupation itself has become more valuable as the returns to the required cognitive skills have increased dramatically. Similarly, low educated individuals are not pushed into less cognitive skill intensive occupations over time. Rather, the returns to skills employed by these occupations have mostly decreased.

2. Data description

2.1. The Dictionary of Occupational Titles

The main analysis is conducted using data from the Dictionary of Occupational Titles (DOT) 1991 Revised Fourth Edition and the Current Population Survey (CPS). In the Data Appendix A I conduct several robustness checks using the DOT 1977 Fourth Edition, discuss the differences between the 1977 and 1991 editions, and present additional analysis that uses information from both.

The 1991 DOT contains information on 12,741 detailed occupations. Each occupation is described in terms of several dimensions that summarize the job requirements and conditions: the degree of interaction with Data, People and Things, General Educational Development level, Specific Vocational Preparation, Physical Demands, Environmental Conditions, Aptitudes, Temperaments, and the Materials, Products, Subject Matter and Services related to the job. Each of these characteristics is recorded in one of three ways: either as a number on a scale (e.g., General Learning Aptitude can range from 1 to 5, where 1 represents a level of ability present in the top 10% of the distribution and 5 is associated with the lowest 10%); a letter indicating the level of an activity (e.g., "S" for "Sedentary" and "V" for "Very Heavy" in the description of Strength); or an indicator that appears when the characteristic applies to the job (e.g., the Temperament "Dealing with People" is indicated by the letter D when this characteristic is present).

The DOT has some important limitations studied in detail in Miller et al. (1980) and Spenner (1983). In all cases, there is some degree of subjectivity in assessing occupational requirements. Also, we can only infer ordinal rankings of requirements, not cardinal measures. In addition, the DOT only contains information on the minimum requirements of each occupation. In reality, expectations may be much higher, and the difference between actual expectations and minimum requirements may systematically vary with the type of occupation.

2.2. Construction of physical and cognitive skill measures

I match the DOT 1991 occupational characteristics to occupations held by respondents in the CPS using available crosswalks and correspondences, described in the Data Appendix A. Each Census occupation is usually associated with many detailed DOT occupations since in any given year there are only between 441 and 526 Census occupation codes, so I take the average of the DOT characteristics over each Census occupation. In the Data Appendix A, I show that the results are not sensitive to the weighting of DOT occupations when constructing mean skill requirements for Census occupations.

Many occupational characteristics in the DOT measure the same broad skills. Existing literature has explored various skill measures constructed using data reduction methods combining similar characteristics into broader skill categories.[2] In this paper, I focus on two skills, physical and cognitive, constructed using factor analysis on selected DOT occupational characteristics that are likely to be highly correlated with these skill measures, listed in Table 1. I focus on these two more general skills rather than the more detailed skill categories studied in previous literature to keep the analysis as simple as possible. I find that these two skills in fact result in a ranking of occupations that is as informative in explaining trends in inequality as the more detailed

[2] For example, Ingram and Neumann (2006) use factor analysis to obtain four skill dimensions: intelligence, fine motor skills, coordination and strength. Bacolod and Blum (2010) also use factor analysis to construct measures of cognitive skills, fine motor skills, people skills, and physical strength. Autor et al. (2003) focus on routine and non-routine tasks by averaging over a few chosen characteristics embodying these.