Changing Payoff to Skills: What's Behind the Inequality Takeoff?

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The substantial and sustained wage inequality takeoff in the United States and other Western countries during the past three decades has motivated a growing body of economic and sociological research (Juhn et al. 1993, Lemieux 2006, Acemoglu 2002, Katz & Autor 1999). The ever-widening educational wage gap has led to a consensus that the evolution in skill demand has transformed the wage structure today. However, scholars have traditionally labored under a surprisingly uni-dimensional conception of skills, which may be inadequate in explaining the complexity of labor market developments. In this study I examine changes in wage rewards to a number of different skill types in the U.S. labor market during the 1977-2008. What types of skills have exhibited the steepest increase/decrease in relative incumbent size and wage return? How do occupational changes in skills' size and return contribute respectively to the growth in wage inequality? This study will provide some insights into these questions.

As my analytical framework, I develop a topology of skills (see table 1), all of which are measured at the detailed occupational level. Each skill type is a factor generated from a set of variables measuring the tasks, skills, and knowledge of each occupation. Grouped into three main categories, these skill types are associated with specific market developments that have potentially widened the wage distribution. The possible wage impact of changes in these skill types are discussed separately below. While my skill variables are measured at the occupational level, my wage data come from individual-level cross-sectional data, collected yearly from late 1970s to mid 2000s, including individual wage, human capital, and demographics. Using these data, I first examine how wage rewards to different types of skills have changes over the years. I will then identify to what extent the inequality takeoff is attributable to these changes, using yearly growth in wage variance during this period.

[TABLE 1 ABOUT HERE]

Hypotheses

A growing number of economic and sociological studies have addressed the prolonged wage inequality takeoff, and many of them call attention to the importance of labor market skill evolution in recent decades. The most prominent among them is Skill-biased technological change (SBTC), which argues that the diffusion of advanced technology (e.g. computerization) in the workplace is skill biased rather than skill neutral; that is, it disproportionately increases the demand for high-level skills. Moreover, the pace of change is so rapid that the supply of skilled workers – while also increasing as college attendance grows – is unable to meet the demand. As a result, compensation to highly-skilled workers increases, which in turn widens wage distribution in the labor market. The skill and wage implication of SBTC is two-fold. First, a major impact of SBTC on skills is an increased demand for technology-specific human capital, especially information technology (IT) knowledge (Kruger 1993, Cappelli and Carter 2000, Black and Lynch 2001). As technological advancement has been extraordinary in manufacturing and white-collar jobs alike, there will be an increased demand for technology know-how to apply, operate, and develop these new technologies (Hypothesis

1). Second, SBTC may also raise the bar for general cognitive skills in the labor market by increasing the demand for abstract, formal, and procedural reasoning skills that replace tacit and intuitive skills (Autor et al. 1998, 2003, Fernandez 2001). Moreover, because the overall quantity, variety, and complexity of information would rise in many jobs, greater general cognitive and conceptual skills, systems thinking, and intellectual flexibility are needed for broadened job responsibilities (Hypothesis 2).

Hypothesis 1: The wage return to technology-specific skills has increased steeply during the past three decades, especially IT-specific human capital.
Hypothesis 2: The wage return to general cognitive skills has increased steeply during the past three decades.

However powerful technological changes may be, they are conditioned by a larger political context. Institutional change, here broadly defined as shifts in public policy and corporate strategy, may have substantial effects on wage inequality (DiPrete 2007, Lindert 2000). Inequality generating institutional changes in the past three decades can be roughly organized into public-sector (Card and Krueger 1994, Card 2001, Acemoglue et al. 2001, Kalleberg et al. 2000) and private-sector mechanisms (Lazonick & O'Sullivan 2000, Piketty & Saez 2006). The present study will focus on the latter, which may have inflated the demand for and rewards to managerial skills. First, Corporate America's "low road" strategy to enhance global competitiveness has bulked up a burdensomely large management (Gordon 1996). Second, the entrenchment of "maximizing shareholder value" as a dominant corporate governance principle has fostered a surge in (top) management compensation (Lazonick & O'Sullivan 2000). According to this principle, managers prioritize stock price and short-term dividend growth, which is tied to their compensation. This new wage setting, therefore, is increasingly in favor of managerial positions – especially top managers – over everyone else. Third, other labor market and policy changes may have further contributed to the surge in management compensation. The demand for managerial skills in the U.S. has undergone a shift from firm-specific to general managerial skills; hence competition for best managers have escalated from within-firm markets to an economy-wide market (Murphy and Zabojnik 2007). In addition, labor market deregulation that began in the 1980s has also granted executives increased ability to set their own pay and extract rents at the expense of shareholders (Piketty and Saez 2006).

Hypothesis 3: The wage return to managerial skills has increased steeply during the past three decades.

Another dimension of skill that is largely overlooked is creative and innovative skill. Considered the most important resource in the new economy by post-industrialists, creative capital is widely employed in a variety of occupations and industries (Howkins 2001). Be it scientific invention, entrepreneurial innovation, or cultural or artistic creation, creativity departs from intelligence or cognitive knowledge as the capacity of synthesizing, experimenting, and problem-solving with new ideas out of existing knowledge. Post-industrialists find an ever-widening economic divide between the "creative class" and the rest of the labor force, which has further increased wage inequality (Florida 2002). The past few decades have seen an explosion of creative economy. New institutional settings have spurred a proliferation of creative industries and occupations (e.g. the remarkable increase in venture capital investment), and an economic infrastructure is being built around them (e.g. corporations' and government's systematic increase in research and development investment). A growing return to creative skills is therefore expected.

Hypothesis 4: The wage return to creative skills has increased steeply during the past three decades (wage effect).

Caring skills refer to skills used in face-to-face service that develops the human capabilities (e.g. health, skills, or functional proclivities) of the recipient (England et al. 2002). Caring skills are often used in parenting, teaching, nursing, childcare, therapy, etc, both paid and unpaid. A lot of care work is traditionally done by women in the family, such as taking care of children or sick family members. Women's increased labor force participation during the past three decades have substantially increased the demand for caring skills in the paid labor market, as paid care work replaces women's unpaid care work. However, care work comes with a wage penalty. Independent of incumbent, occupational, and industrial characteristics, jobs involving caring skills pay less than those don't (England et al. 2002), possibly due to the altruistic nature of care work, gender bias, and over-representation of women in care work. As the wage penalty persists during this period, and as women's growing labor force participation provides abundant supply, the increased demand for caring skills should not have lead to increased wage. Caring skills are concentrated at the lower middle of the wage spectrum (England et al. 2002). Therefore, a larger proportion of the working population in care work should increase the overall wage inequality.

Hypothesis 5: The wage return to caring skills has decreased steeply during the past three decades.

Data and Methods

Occupational-level data come from the Occupational Information Network (O*NET) databases 4.0 and 14.0. The primary source of occupational information for the U.S. labor market, this dataset is extremely rich in terms of job tasks, work activities, skills, and knowledge requirements. Databases 4.0 and 14.0 have the same variables, but differ significantly in their data collection processes. Database 4.0 is also known as the "analyst database", in which trained analysts extrapolated data from the *Dictionary of Occupational Titles* (DOT). As a result, database 4.0 largely represents job tasks and skill requirements when DOT was last updated, i.e. 1977 for most of the occupations and 1991 for a small subset of them. Database 14.0, on the other hand, is known as the "incumbent database". Job incumbents were surveyed with the same questions between 2003 and 2006, in an effort to update the analyst database with more up-to-date information. Therefore, the difference between the two databases may represent not only actual changes in within-job skill requirements over the years, but also measurement differences between analyst and incumbent data. In order to compromise their measurement differences, I did the following steps. First, to measure each skill type, I select the same variables from Analyst and Incumbent data to run a confirmatory factor analysis, as presented in table 1. In this analysis, I force the factor loadings to be the same for the two databases. The factors generated from this analysis are used as skill measures. Second, I use certain occupations that have presumably changed little in specific skills over the years as benchmarks to purge the data. In specific, I read the detailed job description (usually 3 to 6 sentences describing the major tasks and responsibilities of a job) of each occupation, and select a few for each social class and each skill type. Details of these occupations can be found in table 2. I then ran a regression that estimates analyst factor of each skill type using the selected occupations' incumbent factor of the same skill. The intercept and coefficient from this regression would be attributed as the measurement difference between the two databases, be it psychological or methodological. I then plug in the incumbent factor for all occupations for each skill type, and replace the actual analyst factors with the predicted analyst factors. Now that the data are purged, I merge them with the individual-level data, which are measured yearly from 1977-2008. Because the analyst and incumbent data are representative for 1977 and 2006 respectively, I interpolate the years in between assuming a linear change.

[TABLE 2 ABOUT HERE]

Individual-level data come Current Population Survey's monthly outgoing rotation group supplement (CPS-ORG), which provides detailed information on the hourly earnings of each member of the household from 1977 to 2008. I focus on non-military workers between 16 and 65, who are not self-employed. The dependent variable is natural log of hourly wage, adjusted for inflation using Personal Consumption Expenditures (PCE), and a multiplier of 1.4 will be applied to top-coded wages and salaries (Card and DiNardo 2002).

I examine changes in payoff to different types of skills in two steps. First, individual- and occupational-level independent variables will be used to predict individual wage in the following hierarchical linear model (Raudenbush and Bryk 2002).

$$\ln Wage_{ijt} = \beta_{0jt} + \sum_{p}^{P} \beta_{pjt} X_{pijt} + r_{ijt}$$

$$\beta_{0jt} = \gamma_{00t} + \sum_{q}^{Q}\sum_{p}^{P} \gamma_{pqt} O_{pqt} + \sum_{s}^{S}\sum_{p}^{P} \gamma_{pst} S_{pst} + \mu_{0jt}$$

$$\beta_{pjt} = \gamma_{p0t} + \sum_{q}^{Q}\sum_{p}^{P} \gamma_{pqt} O_{pqt} + \sum_{s}^{S}\sum_{p}^{P} \gamma_{pst} S_{pst} + \mu_{pjt}$$

Where $\ln Wage_{ijt}$ is the natural log of hourly wage of individual (*i*) in occupation (*j*) at time (*t*). X represents a vector of individual-level variables, including demographic characteristics (age, gender, race, marital status, region and type of residence, and immigrant status), and human capital (education, work experience, part-time work status, union membership, and industry) at time (*t*). β is a vector of individual-level coefficients, whose within- and between-occupation variance is controlled for by a vector of occupational characteristics O, which includes non-skill related compositional variables (average incumbent education, union representation, proportion of female and Blacks, and occupational entry restrictions). It is also controlled for by a vector S of the different skill types, including general cognitive skills, creative skill, technological skills, and managerial and caring skills. γ is a vector of occupational-level coefficients. This model also allows the error terms to occur at both individual and occupational levels.

The second step is a year-by-year comparison between the coefficients for each type of skills. I will regard these coefficients to be indicators of wage return to the respective skills, so this comparison will be helpful in identifying the general trend in returns to various types of skill.

Preliminary Findings[1]

A year-by-year comparison of skill coefficients from 2000 to 2008 is presented in figures 1.1 and 1.2. In these figures, I have omitted coefficients of individual-level variables, whose magnitudes and significance levels are consistent with the literature. It is noteworthy that O*NET offers two variables for each task, skill, or knowledge measured. For example, for "reading comprehension", it has one variable for "level" (i.e. how complicated reading comprehension is used in the job), and another one for "importance" (i.e. how often reading comprehension is used in the job). I did separate analysis using the two aspects of each skill type. Figure 1.1 presents coefficients of the factors on skill levels, and figure 1.2. presents coefficients of the factors on skill importance. Because the coefficients are reasonably similar for most skill types, I will discuss the results together.

[FIGURES 1.1 & 1.2 ABOUT HERE]

Hypothesis 1 on technological skills doesn't have much support, judging from results on this period. Between 2000 and 2008, the wage rewards for information technological skill has fluctuated. It has been declining at first, and suddenly reached its peak in 2004 and 2005, and declined again afterwards. While this fluctuation may be related to the development of the dot-com bubble, no clear upward trend is observed during period. On the other hand, non-it scientific and technological skills are rewarded fairly constantly overtime.

Hypothesis 2 on general cognitive skills receives some interesting supports over this period. Analytical skill is the most rewarded skill of all, and its magnitude is increasing overtime. This is consistent with SBTC's hypothesis that as the amount and quality of information has increased in all kinds of jobs, the requirement for incumbents to act on them has also risen. The other two aspects of general cognitive skills don't seem to be rewarded as good. There is a decline in the rewards to verbal skills, and the rewards to quantitative skills are negative, partly due to the fact that most of the variables used to generate the quantitative factors are primitive quantitative skills (e.g. number

[1] Due to time constraint, I was able to finish analysis on the recent years only. I will present the results here, and I will be able to finish the rest of the analysis in about four week's time.

facility), which are largely taken over by computers today. Payoff to these skills today is unlikely to be high or increasing.

Hypothesis 3 is inconsistent with the results. Creative skills having negative wage returns. This finding is compatible with the theories on differentials. Creativity can be a highly personally satisfying element of a job, and highly creative jobs may therefore pay less than otherwise similar jobs. This finding may cast some doubt on post-industrialists' claims for the creative capital.

Hypothesis 4 on managerial skills receives some limited support. While its wage reward is positive and has been increasing. The magnitude of the coefficients themselves and that of its increase are too small to make any reasonable conclusion. More data from previous decades may be more helpful.

Hypothesis 5 on caring skills also receives some surprisingly interesting results. It is well-documented that caring skills are associated with a wage penalty (England et al. 2002). It is interesting that this penalty is on the rise, and has probably increased wage inequality overtime.

The next step is to continue the same analysis for the remain years, 1977-1999. After that, I will carry out counterfactual estimations to quantify the contribution of skill changes to the inequality takeoff during the past three decades. Given that only results for the most recent decade are available at the moment, it is probably too early to draw any decisive conclusion. However, these results give us a glimpse of what has been going on during that period. More importantly, the differential rewards to different skills types highlight the fact that a uni-dimensional conception of skills is ill-suited for the labor market developments, and a multi-dimensional approach can better explain changes in wage structure today.

Table 1. O*NET Variables in Generating Skill Factors

Cognitive 1: Verbal	**Cognitive 2: Quantitative**	**Cognitive 3: Analytical**
oral comprehension	mathematical reasoning	fluency of ideas
written comprehension	number facility	problem sensitivity
oral expression	mathematics	deductive reasoning
written expression	science	inductive reasoning
reading comprehension	mathematics	information ordering
active listening		category flexibility
writing		critical thinking
speaking		active learning
		learning strategies
Creativity	**Information Technology**	**Non-IT Science and Tech**
originality	programming	Operations analysis
thinking creatively	Computers and electronics	Technology design
innovation	Interacting with computers	Engineering and technology
		Design
		Mechanical
		physics
		chemistry
		biology
Managerial	**Care Work**	
Management of financial resources	Service orientation	
Management of material resources	Assisting and caring for others	
Management of personnel resources		
Administration and management		
Coordinating the work and activities of others		
Developing and building teams		
Guiding, directing, and motivating subordinates		

Table 2. Relatively Unchanged Occupations
(Skill types unlisted in "Exceptions" are unchanged skills)

Class	Occupation	Exception1	Exception2	Exception3
Managerial	Funeral Directors			
	Construction Managers	Information Technology	Science and Technology	
	Farmers and Ranchers	Information Technology	Science and Technology	
	Food Service Managers	Creative	Care Work	
	Social and Community Service Managers	Creative	Care Work	
	Lodging Managers	Information Technology	Care Work	
	Purchasing Agents and Buyers, Farm Products	Analytical		
	Tax Preparers	Information Technology		
Professional	Occupation	Exception1	Exception2	Exception3
	Biological Technicians	Information Technology	Science and Technology	
	Counselors			
	Clergy			
	Paralegals and Legal Assistants	Analytical	Information Technology	
	Preschool and Kindergarten Teachers			
	Archivists, Curators, and Museum Technicians	Information Technology		
	Actors			
	Athletes, coaches, umpires, and related workers			
	Editors	Information Technology		

Table 2. Continued.

Service	Occupation	Exception1	Exception2	Exception3
	Fire fighters			
	Parking enforcement workers			
	Transit and railroad police			
	Cooks			
	Food preparation workers			
	Bartenders			
	Waiters and waitresses			
	Maids and housekeeping cleaners			
	Funeral service workers			
	Barbers			
	Child care workers			
Sales	**Occupation**	**Exception1**	**Exception2**	**Exception3**
	Insurance Sales Agents	Analytical	Information Technology	Managerial
	Door-to-door sales workers, news and street vendors, and related workers			
	Eligibility Interviewers, government programs			
	library assistants, clerical			
	Meter readers, utilities			
	postal service mail carriers			
	Office machine operators, except computer	Science & Technology		
	Proofreaders and copy markers	Information Technology		

Table 2. Continued.

Construction	Occupation	Exception1	Exception2	Exception3
	Logging Workers			
	Carpenters			
	Painters, construction and maintenance			
	Pipe layers, plumbers, pipe fitters, and steamfitters			
	Roofers			
	Fence erectors			
	Locksmiths and safe repairers	Science & Technology		
Production	**Occupation**	**Exception1**	**Exception2**	**Exception3**
	Bakers			
	Butchers and other meat, poultry, and fish processing workers			
	Tailors, dressmakers, and sewers			
	Cabinetmakers and bench carpenters			
	Furniture finishers			
	Cutting workers			
	Bus drivers			
	Driver/sales workers and truck drivers			
	Taxi drivers and chauffeurs			
	Sailors and marine oilers			

Figure 1.1. Coefficient of Skill Factors Predicting Individual Wage
(Skill Level: how complicated the skill is used in the job)

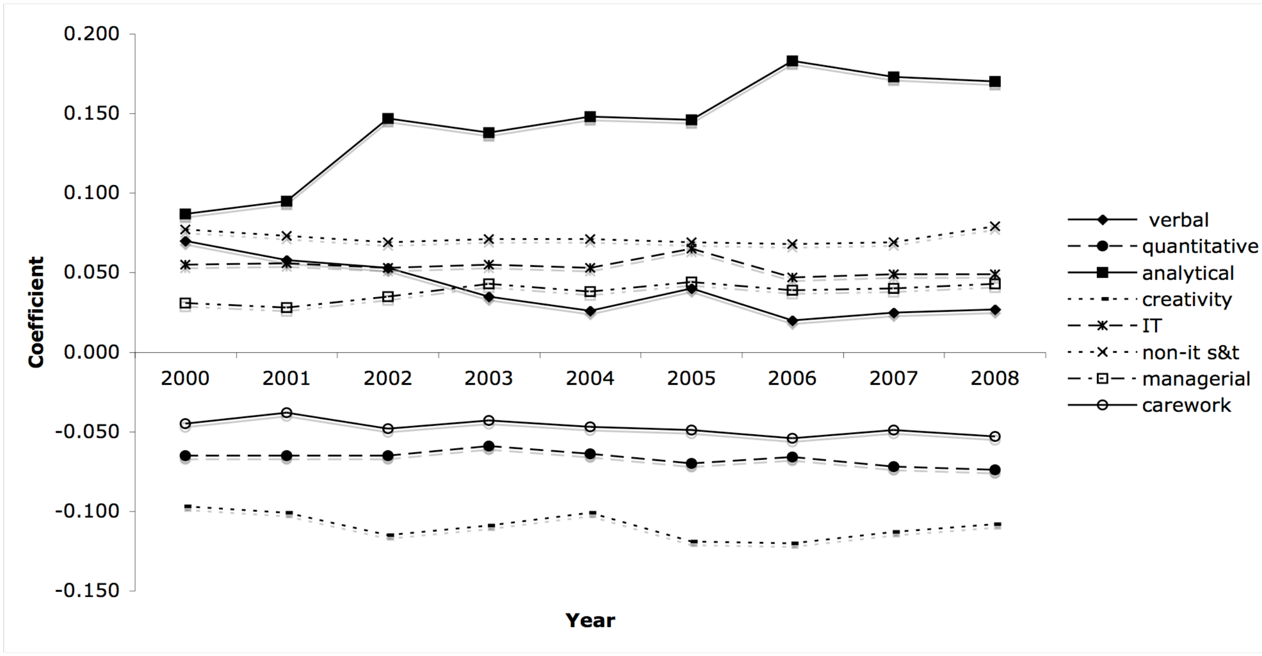

Figure 1.2. Coefficient of Skill Factors Predicting Individual Wage
(Skill Importance: how often the skill is used in the job)