The Economic Return to Education Revisited:
The Role of Cognitive Skills and Socioemotional Traits in Wage Inequality

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ABSTRACT

While the economic return to education remains a parsimonious explanation for rising wage inequality and its current high level, this account tends to be limited to the demand for cognitive skills and between-education group wage inequality. Using data from the National Longitudinal Survey of Youth 1979, this paper examines the role of socioemotional traits as well as cognitive skills in between- and within-education group wage inequality. I hypothesize that socioemotional traits (e.g., locus of control and self-esteem) as a form of cultural capital affect wage inequality due to their contribution to resolving information asymmetry in the employer-employee relationship. Quantile regression analysis shows that differences in cognitive skills and socioemotional traits account for a significant portion of the college wage premium and wage dispersion within college graduates; socioemotional traits play a more pronounced role in wage inequality among college graduates; and the wage effect of these skills and traits strengthens as workers reach their prime ages in the labor market. I discuss implications of these findings with emphasis on the role of the family as an important institutional actor responsible for wage inequality.

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INTRODUCTION

Rising wage inequality in the U.S. labor market since the 1980s and increases in the economic return to education have attracted much attention in the social sciences (Autor, Katz, and Kearney 2005; Juhn, Murphy, and Pierce 1993; Morris and Western 1999). A well-established body of economic literature holds that these changes are due to an increase in the demand for skills and a supply side response to such demand (Katz and Murphy 1992; Murphy and Welch 1992). The "college wage premium" epitomizes the tightened nexus between education and labor market outcomes.

While informative, this line of research tends to overlook several key aspects of the process underlying overall wage inequality. First, there has been a lack of attention to the role of multidimensionality of skills, with most research focusing on cognitive skills alone (Card 1995a; Juhn, Murphy, and Pearce 1993; Murnane, Willett, and Levy 1995; Taber 2001). Second, this literature has yet to address the polarized pattern of the current U.S. wage structure which shows a larger wage inequality in the upper portion of the wage distribution than in other parts of the distribution (Autor, Katz, and Kearney 2006; Lemieux 2006). Third, due to a narrow focus on between-education group wage inequality (e.g., wage differentials between high school and college graduates), the sources of within-education group wage inequality (e.g., wage dispersion within college-educated workers) are surprisingly understudied in previous literature, despite its significance for overall wage inequality (Bernhardt et al. 2001; Buchinsky 1998; McCall 2000). And finally, there has been little research that examines why the college wage premium increases as workers reach their prime ages, which exhibits a dynamic feature of the U.S. labor market (Card 1995b, 1999).

To fill these gaps in the literature, this paper investigates the role of socioemotional traits as well as cognitive skills in producing high levels of wage inequality. Drawing on the work on forms of capital, I conceptualize socioemotional traits as attitudinal and behavioral traits and habits that represent a form of cultural capital (Bourdieu 1984; Lareau 2002; Swidler 1986). Given the prevalence of asymmetric information in the employer-employee relationship, socioemotional traits (e.g., locus of control and self-esteem) in conjunction with cognitive skills may be a critical factor of labor market inequality (Bowles, Gintis, and Osborne 2001). A growing body of literature has documented their positive effects on labor market outcomes (Bowles and Gintis 2002; Heckman, Stixrud, and Urzua 2006; Moss and Tilly 1996). And yet, methodological complexities have kept researchers from assessing *differential* effect of such skills and traits across the wage distribution. As the dominant method in the literature on wage inequality, ordinary least squares (OLS) estimates the conditional mean effect of wage determinants to detect the sources of between-group wage inequality but makes it difficult to evaluate their effect on within-group wage inequality. Using a quantile regression method, I seek to overcome this drawback of traditional regression analysis (Hao and Naiman 2007; Koenker and Bassett 1978). The quantile regression method allows me to simultaneously examine both types of wage inequality by gauging the relative contribution of cognitive skills and socioemotional traits at various locations of the wage distribution (e.g., at the lower and upper tails and the median).

Specifically, this paper analyzes data from the National Longitudinal Survey of Youth 1979 (NLSY79) to address four interrelated questions: (1) What role do cognitive skills and socioemotional traits play in generating wage inequality? How does their effect vary across the wage distribution?; (2) How much of the college wage premium and wage dispersion within college graduates are explained by differences in these skills and traits?; (3) What is the relative importance of cognitive skills and socioemotional traits in accounting for education-group wage inequality?; and (4) Does the wage effect of these skills and traits increase as workers age and accumulate labor market experience?

Addressing these questions is crucial for gaining insight into the relationship between socioeconomic inequality and intergenerational mobility. Research shows that while socioemotional traits are less innate and more malleable than cognitive skills, the formation of such skills and traits are heavily influenced by family background and parenting behaviors (Carneiro and Heckman 2003; Farkas 2003). To the extent that differences in cognitive skills and socioemotional traits account for wage inequality in general and between- and within-education group wage inequality in particular, this would suggest that researchers need to pay more attention to the role of the family and early child education in the skill formation process rather than simply looking at families' ability to provide their children with a college education.

WAGE INEQUALITY AND THE EDUCATION-LABOR MARKET NEXUS

In the United States, overall wage inequality rapidly increased in the 1980s and though relatively stabilized in the 1990s, remains at a historically high level (Autor, Katz, and Kearney 2005). Among a variety of explanations in social scientific research (see Morris and Western (1999) for a summary), the economic return to education has been proposed as a comprehensive, but parsimonious account for changes in and levels of wage inequality. The major strength of this thesis lies in its capacity to incorporate the demand for skills and the supply side response to such demand. On the labor demand side, factors including industrial restructuring, globalization, immigration, and technological changes have increased a demand for high-skilled jobs, stemming from deindustrialization, an increased demand for high-ranking managerial jobs, and computerization in the workplace. On the labor supply side, there have been increasing variations in workers' educational attainment due to changes in the education composition among workers, school quality, and human capital investment. As Card (1995b:23) put it, therefore, "one of the most important 'facts' about the labor market is that individuals with more education earn higher wages." The college wage premium is evidence for the positive correspondence between the demand for and supply of skilled labor in the labor market.

Despite its theoretical elegance and empirical support, the thesis about the economic return to education has yet to address several important features of the dynamics of overall wage inequality.[1] First, this account does not fully explore the role of the multidimensionality of skills in generating wage inequality. Although most discussions in this line of research implicitly acknowledge that skills are not unidimensional, the main interest in unobserved skill bias is focused on cognitive skills. It posits that as individuals who possess a higher level of cognitive skills are more likely to achieve higher education, the wage effect of education may simply reflect unmeasured abilities of the more educated. What one's educational attainment signals to the labor market is his or her level of productivity-enhancing skills formed before schooling rather than education itself (Belzil and Hansen 2002; Murnane, Willett, and Levy 1995; Taber 2001). However, numerous economic and sociological studies provide evidence for the causal effect of education on wages (see Card (1995b, 1999) and Cawley et al. (2000) for a review). This finding holds true even as more rigorous analytical approaches are used to control for unobserved heterogeneity.[2] These conflicting results point to the need to examine what role other types of unobserved skills—what I call "socioemotional traits"—than cognitive skills play in producing wage inequality in light of the increasing economic return to education.

As a related concern, this thesis offers little account for the so-called polarization of wage growth, a unique phenomenon in the current U.S. labor market. A close look at the trend in wage inequality shows that the upper-half overall wage inequality steadily rose while the lower-half overall wage inequality ceased to rise since the late 1980s (Autor, Katz, and Kearney 2006; Lemieux 2006). Wage growth occurred most rapidly at the top quartile of the wage distribution and more slowly at the middle two quartiles than at the bottom quartile. This polarized pattern of

[1] This paper treats macro-level factors as given to address the sources of wage inequality. The focus here is on the potential sources of the economic return to education at the individual level—workers' characteristics and responses to shifts in the labor demand for skills and changes in the labor supply.
[2] Whether employing instrumental variables method (Angrist and Krueger 1991; Card 1995a) or exploiting sibling or twin data (Ashenfelter and Rouse 1998), both approaches produce a larger effect of education on wage differentials than do conventional OLS methods.

the U.S. wage structure clearly indicates that the determinants of wages may not be uniform across the wage distribution. In this vein, whether and how cognitive skills and socioemotional traits have differential effect at various locations of the wage distribution would be a critical piece of the puzzle concerning U.S. wage inequality.

Second, most accounts of the economic return to education concentrate on explanations for between-education group wage inequality, even though within-education group wage inequality occupies a larger portion of overall wage inequality (Autor, Katz, and Kearney 2005). The increasing economic return to education accounts for only about one third of the total increase in wage inequality (Bernhardt et al. 2001).[3] Indeed, wage dispersion has become largest among college graduates, with the smallest wage dispersions observed among high school dropouts (Buchinsky 1998; McCall 2000). And yet, how much of wage variation among workers with a similar education are due to cognitive skills and socioemotional traits remains to be addressed.

Third, previous literature tends to presume that unobserved skills impact the economic return to education in the same fashion, whether they are cognitive or socioemotional (Juhn, Murphy, and Pierce 1993; Taber 2001). By this logic, taking account of socioemotional traits alongside cognitive skills would simply help identify total effects of skills as a whole. However, whether that is the case is an empirical question (Heckman, Stixrud, and Urzua 2006). If cognitive skills and socioemotional traits play distinctive roles in between- and within-education group wage inequality, accounting for the multidimensionality of skills may be a promising venue for addressing education group wage inequality.

Finally, a prevailing notion in the labor market literature is that educational attainment has a stronger impact on wage differentials among older workers (Card 1995b, 1999). Levels of wage

[3] One possible explanation for within-education group wage inequality concerns a composition effect, which is an increase of college graduates in the labor market. However, Autor, Katz, and Kearney (2005) show that within-education group wage inequality has remained prevalent during the 1990s after taking the composition effect into account. Rather, the composition effect played a role in the stagnation of lower tail wage inequality since the late 1980s, offsetting the impact of the economic return to education in the lower tail of the wage distribution.

inequality in terms of educational attainment are relatively low among younger workers because college-educated workers likely have less labor market experience. As they age and accumulate labor market experience, the economic return to education would increase. However, we know strikingly little about why this process happens. Examining how the wage effect of cognitive skills and socioemotional traits evolves as college graduates reach their prime ages in the labor market would give a reliable clue to explain the larger wage effect of college education among older age groups.

In summary, prior research on the economic return to education, though fruitful, should incorporate the multidimensionality of skills and within-education group wage inequality into its framework in order to better understand the tightened education-labor market nexus. In the following section, I provide theoretical considerations and empirical findings of the role of socioemotional traits in addition to cognitive skills in the labor market.

COGNITIVE SKILLS AND SOCIOEMOTIONAL TRAITS AS A SOURCE OF EDUCATION-GROUP WAGE INEQUALITY

The Concept of Socioemotional Traits

Socioemotional traits refer to individuals' attitudinal and behavioral traits and habits. Whereas cognitive skills denote a general intelligence (or the "*g*" factor), usually measured by standardized test scores, socioemotionl traits pertain to enduring dispositions that are not captured by cognitive skills but relevant to socioeconomic success, such as perseverance, self-confidence, motivation, sociability, emotional stability, interpersonal skills, and a future orientation (Carneiro and Heckman 2003; Farkas 2003).[4] From a developmental perspective, socioemotional traits can be improved until late teenage years, while cognitive skills are fairly

[4] In the literature, socioemotional traits also refer to soft skills or noncognitive skills and are measured by locus of control, self-esteem, externalizing/internalizing problem behaviors, and executive functioning among others (Farkas 2003; Kuhn and Weinberger 2005).

stable after age 8 (Bowles and Gintis 2000; Carneiro and Heckman 2003; Heckman and Rubinstein 2001).

The idea of socioemotional traits can be better understood as a form of cultural capital. In an effort to extend Bourdieu's (1977) concept of *habitus*, Swidler (1986:275) considers cultural capital as a 'tool kit' that constructs 'strategies of action': "One can hardly pursue success in a world where the accepted skills, styles, and informal know-how are unfamiliar. One does better to look for a line of action for which one already has the cultural equipment."[5] In this vein, the conceptualization of socioemotional traits as a form of cultural capital reflects the shaping role of family background. Research shows that these traits are unevenly distributed across children whose families differ by levels of socioeconomic resources and parenting practice (Condron 2007; Lareau 2002). In an ethnographic study of middle and working class families, Lareau (2002) observes that middle class children take a cumulative advantage of "concerted cultivation" in developing their socioemotional traits. They gain a sense of entitlement through wide-ranging family resources, organized leisure activities, and extensive reasoning by their parents. Meanwhile, working class and poor children display a sense of constraint and powerlessness as a result of lack of family resources, their parents' belief in an "accomplishment of natural growth," and their frequent use of directives.

Another aspect of cultural capital is its convertibility into economic and social capital and *vice versa* (Bourdieu 1984; Bourdieu and Wacquant 1992). As education takes a leading role in the social stratification system, cultural capital can be utilized in accumulation of human capital in ways that are rewarded and reinforced in schools and workplaces (Bowles and Gintis 2002; Farkas et al. 1990; Rosenbaum 2001). Therefore, these aspects of socioemotional traits as a form of cultural capital have important implications for explaining wage inequality in light of

[5] DiMaggio (1982) defines cultural capital more formally as interest in and experience with prestigious cultural resources. While highlighting an important dimension of cultural capital, this definition is not as directly concerned with personal traits and habits as is Swidler's.

intergenerational mobility, because they highlight that individuals' socialization for work takes place well before their entry into the labor market.

The Relevance of Socioemotional Traits to Wage Determination

Why do socioemotional traits, which are not usually thought of as "skills," matter to wage inequality? Bowles, Gintis, and Osborne's (2001) labor market models provide a theoretical framework for ways in which socioemotional traits function as a critical factor of wage determination.[6] In a neoclassical model ("Walrasian"), labor markets are assumed to rapidly reach equilibrium, which means that there is sufficient information that circulates on both the labor demand and supply sides. Employees' labor efforts are rewarded according to their level of productivity that is determined by their pre-market attributes. Hence, wage differentials result entirely from cognitive skill differences, i.e., productivity-enhancing skills, between individual workers.

However, given that the assumption of labor market equilibrium is not realistic, one should consider "disequilibrium rents" as a determinant of wage differentials along with cognitive skills ("Schumpeterian"). Labor market disequilibria often provide a wage premium for workers with higher levels of self-directedness, internality as opposed to fatalism, and a future orientation, because of their competence to deal with technological and organizational changes and other market shocks. Although such socioemotional traits might not be considered productivity-enhancing skills, they likely have a positive impact on wage inequality.

Furthermore, when incomplete and asymmetric information exists in the employer-employee relationship, a situation known as the "principal-agent" problem ("Coasean"), employees' socioemotional traits are treated as a substantial element in the wage determination processes.

[6] Bowles, Gintis, and Osborne (2001) call each labor market model "Walrasian," "Schumpeterian," and "Coasean," respectively, following these economists' specification of earnings determination: Leon Walras offered a neoclassical model of labor market; Joseph Schumpeter introduced the concept of disequilibrium rents; and Ronald Coase identified the "principal-agent" problem in the labor market.

The principal-agent problem means that employers cannot directly discern employees' effort level as assumed in the neoclassical model, even if knowing employees' educational attainment and to a lesser degree cognitive ability. So employers tend to set the incentive structure within the workplace in which to value employees' socioemotional traits that lead to productivity gains in an indirect manner. This sort of socioemotional traits is referred to as "incentive-enhancing preferences," which include an orientation toward the future, personal efficacy, and internalized locus of control. Because employees with socially desirable traits are more likely to respond positively to the employer-setting incentive structure, employers are more likely to confer a wage premium on them. In this sense, socioemotional traits in conjunction with cognitive skills may function as a crucial determinant of not only between- but also within-education group wage inequality.

Empirical Findings

In support of these theoretical perspectives, recent literature has documented empirical findings on the role of socioemotional traits in labor market outcomes. One line of research directly examines what employers want from job applicants and employees; and another line focuses on the direct impact of cognitive skills and socioemotional traits in wage determination. First, unlike most of the research that is based on the labor supply side, Holzer's (1996) study utilizes an employer survey supplement to the Multi-City Study of Urban Inequality in order to address employers' hiring decisions for low-educated workers. He finds that both cognitive skills and socioemotional traits are a substantial part of what employers require of workers for task performance, as shifts in industries and occupations are more oriented toward "information-processing" jobs. According to Holzer's estimates, employers interviewed nearly 90 percent of job applicants to make their personal hiring judgment in addition to available objective measures, with politeness and motivation the most highly stressed factors for hiring, followed by verbal skill and physical appearance.[7]

More importantly, employers' demand for socioemotional traits is not merely limited to the low-educated. A recent report of employers who hired new college graduates indicates that communication, motivation, teamwork, and leadership skills all exert more influence on hiring decisions than do academic achievement or grade point average (National Association of Colleges and Employers 2000). In addition, in the Employers' Manpower and Skills Practices Survey, which is more general but conducted in the UK, personnel managers presented poor attitude, motivation, and personality as a major recruitment problem, compared to lack of technical skills (Green, Machin, and Wilkenson 1998). Taken together, employer surveys collected in the 1990s suggest that socioemotional traits are as much valued as cognitive skills in the employers' hiring decision processes.

Second, a significant body of literature has provided evidence for the effect of such skills and traits on wage differentials. Jencks et al. (1979) and Rosenbaum (2001) find that socioemotional traits such as perseverance, industriousness, and leadership had a positive effect on wages even after controlling for a number of human capital variables and cognitive skills, with socioemotional traits having the larger effect than cognitive skills.[8] In an analysis of the General Educational Development (GED) certificate, Heckman and Rubinstein (2001) demonstrate that GED recipients have higher cognitive skills than high school dropouts but earn lower wages than high school graduates, because they have lowest noncognitive skills among education groups. Their study suggests that the GED is a "mixed" signal in which the economic return to education

[7] These findings are consistent with those of Moss and Tilly's (1996) qualitative study of employers' hiring practices among entry-level jobs. Also, another employer survey reveals that for employers seeking non-supervisory or production workers, the rank on the importance of workers' characteristics is attitude, communication skills, industry-based skill credentials, years of schooling, and academic performance in order (Bureau of the Census 1998).
[8] Interestingly, Kuhn and Weinberger (2005) report a larger effect of leadership skills on wages when estimated in the 1990s than in the 1970s. They also stress that leadership skills operate within managerial occupation, which implies the role of socioemotional traits in within-group wage inequality.

is not simply reduced to cognitive skills and educational credentials. Heckman, Stixrud, and Urzua (2006) confirm that socioemotional traits constructed as a latent factor is as important as cognitive skills in explaining differentials in wages, employment status, and occupational attainment.

Dunifon and Duncan (1998) show that an orientation toward challenge and a sense of personal control have a stronger effect on earnings at later ages, implying that it takes a substantial amount of time for employers to assess workers' socioemotional traits. Dunifon, Duncan, and Brooks-Gunn (2001) further present that "home cleanliness" is a significant factor predicting earnings outcomes 25 years later when controlling for socioeconomic background, own education and cognitive ability, and time spent in housework. They conjecture that home cleanliness reflects an overall ability to maintain a sense of order, which in turn carries over the ability to keep a degree of organization and efficiency that may be a skill valued in the labor market. These findings suggest that the long-run wage effect of cognitive and socioemotional abilities may be a key source that drives the increase in the college wage premium among older aged workers.

HYPOTHESES

My analysis concerns what role socioemotional traits as well as cognitive skills play in the process that generates wage inequality in general and between- and within-education group wage inequality in particular. Building on the theoretical discussions and empirical findings described above, I test four hypotheses. First, while prior research documents the significant effect of these skills and traits in wage determination, it is limited in that their wage effect is assumed to be constant across the wage distribution. However, should the demand for skills be more substantial among high wage jobs, it is likely that the wage effect of cognitive skills and socioemotional traits is more pronounced in the upper portion of the distribution than its lower portion, suggesting their role in the polarization of the U.S. wage structure.

Hypothesis 1: Workers with higher levels of cognitive skills and socioemotional traits are more likely to earn higher wages and this relationship is stronger in the upper portion of the wage distribution.

Second, according to the labor market models depicted above, between- and within-education group wage inequality is due in part to differences in cognitive skills and socioemotional traits. It is because cognitive skills function as productivity-enhancing skills and socioemotional traits are responsive to disequilibrium rents and employer-setting incentive structure. Along with cognitive skills, socioemotional traits do not merely affect wage differentials between education groups by influencing individuals' educational attainment; they also impact wage dispersion among workers with a similar education, given that employers' demand for skills requires employees to internalize the norms of attitudes and behaviors set in the organization of workplace.

Hypothesis 2: Cognitive skills and socioemotional traits are important predictors of the college wage premium and wage dispersion within college educated workers.

Third, the principal-agent problem further suggests that while employers could infer workers' cognitive skills from their educational credentials or course grades, there is little formal information that can be utilized to directly assess workers' socioemotional traits. I expect distinctive roles to obtain for cognitive skills and socioemotional traits in producing wage inequality. Cognitive skills may play a more salient role with respect to between-education group wage inequality, whereas socioemotional traits may do so with respect to within-education group wage inequality.

Hypothesis 3: The effect of cognitive skills is more influential in reducing the college wage premium, whereas that of socioemotional traits is more salient in diminishing wage dispersion among college graduates.

The last hypothesis is concerned with the shapes of the effect of the college premium across the wage distribution according to the aging and accumulation of labor market experience of college-educated workers. Less labor market experience among young college graduates compared to high school graduates implies a relatively low level of education group wage inequality, leaving not much room for the role of cognitive skills and socioemotional traits. Meanwhile, their role is likely to increase as levels of the college wage premium and wage dispersion within college graduates become relatively high among older and more experienced workers.

Hypothesis 4: The contribution of cognitive skills and socioemotional traits in accounting for education group wage inequality becomes stronger as workers reach their prime ages in the labor market.

DATA, MEASURES, AND METHOD

Data

This paper uses data from the National Longitudinal Survey of Youth 1979 (NLSY79). The NLSY79 is a nationally representative sample of 12,686 young men and women who were 14 to 22 years old when they were first surveyed in 1979 (Center for Human Resource Research (CHRR) 2004). These individuals were interviewed annually through 1994 and since then, have been interviewed on a biannual basis. Despite its long term coverage, retention rates are high. Since their first interview, many of the respondents have made transitions from school to work. These data make it possible to study a large sample that represents American men and women born in the late 1950s and early 1960s, who have witnessed rising wage inequality over the last 30 years throughout their labor market experiences. A key feature of this survey is that it gathers information in a work history format, in which dates are collected for the beginning and ending of work-related experiences. Educational attainment and labor market performance are detailed in this manner. The NLSY79 provides rich sets of variables for earnings, respondents' cognitive skills and socioemotional traits, educational attainment and work experience, family background, and other key demographic characteristics.

The analytic sample is restricted to individuals who worked at least one week in the year prior to the survey year; did not attend school when information on their wages was gathered; and were among noninstitutional civilian population. The sample is further restricted to individuals who were 15-18 years old in 1980, because measures of cognitive skills and socioemotional traits are constructed as pre-college and pre-labor market factors to minimize reverse causality (see the measures section).[9] For Hypotheses 1 through 3, the analysis is conducted with the 2002 sample because respondents in this sample were at their prime working age. After constructing all measures, the final analytic sample size is 2,527. For Hypothesis 4, the analysis utilizes multiple biannual samples. Since college education tends to delay labor market entry, it is likely that less-educated workers are overrepresented in earlier waves of the NLSY79. Therefore, I use the samples from 1990 to 2002. These multiple samples allow me to address whether and how the wage effect of skills and traits varies by workers' aging and time spent in the labor market (Duncan and Dunifon 1998). The 1990 sample consists of respondents in the late 20s with the average labor market experience of about 8 years and the 2002 sample consists of those in the late 30s and early 40s with the average labor market experience of about 18 years.

Measures

HOURLY WAGES The dependent variable is log hourly wages averaged over 3 or 5 years.[10] It has been shown that wages are more reliable if averaged over multiple years than if measured only at one year. Wage data include respondents who had wage information for at least two of the 3 or 5

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[9] This study cautions against the generalizability of results reported here, given limitations of the analytic samples such as age range and an underrepresentation of the white population (see Table 1). Current Population Survey (CPS) has been widely used in the wage inequality literature, but it does not contain information on cognitive skills and socioemotional traits. A preliminary analysis (not shown) suggests that there are some discrepancies in demographic compositions between the CPS and the NLSY79, but the basic patterns of the economic return to education are very similar in both data sets. Also, there is little difference between the analytic samples and the samples before listwise deletion.

[10] For the samples from 1994 onward, only three observations per individual are available because the NLSY79 has collected data biannually since then.

year span. Nominal data are inflated to 2000 price levels by the implicit deflator of personal consumption expenditures for gross national product. Before log-transformed, wage rates in 2000 dollars below $1 were set equal to $1 and wage rates above $100 were set to $100.

COGNITIVE SKILLS AND SOCIOEMOTIONAL TRAITS The variables of most interest are levels of cognitive skills and socioemotional traits individuals possess during adolescence.[11] For a measure of cognitive skills, the NLSY79 provides an aptitude indicator, the full Armed Services Vocational Aptitude Battery (ASVAB) consisting of a series of tests measuring knowledge and skill in areas such as mathematics and language. It was administered to 94 percent of the sample respondents in 1980. A composite score derived from the ASVAB is used to construct an Armed Forces Qualifications Test (AFQT) score, which has been extensively used to measure cognitive skills (Cawley et al. 2000).

For a measure of socioemotional traits, the NLSY79 includes a 4-item abbreviated version of the Rotter's locus of control scale and the 10-item Rosenberg's self-esteem scale, administered in 1979 and 1980, respectively (see Appendix for the lists of both scale items). Locus of control measures the degree of control individuals feel. According to Rotter (1966), individuals who believe that outcomes are due to luck have an external locus of control while individuals who believe that outcomes are due to their own efforts have an internal locus of control. Each item consists of a pair of statements, from which I generate a 4-point Likert scale ranging from 1 (external) to 4 (internal) and sum the scores. The self-esteem scale measures perceptions of self worth (Rosenberg 1965). Each 4-point Likert scale item is coded as 1 (low) to 4 (high) and summed to calculate a summary score. Then I create a composite index of both scales with a minimum value of 28 and a maximum value of 56 (Cronbach's $\alpha = .72$), which has been

[11] As suggested in the literature, cognitive skills and socioemotional traits correlate with each other but represent distinct dimensions of abilities (Bowles and Gintis 2002; Heckman, Stixrud, and Urzua 2006). The correlation between these two is .28 in the 2002 sample.

commonly employed in past research on the effects of socioemotional traits on socioeconomic outcomes (Carneiro and Heckman 2003).[12]

This study constructs age- and schooling-adjusted scores of cognitive skills and socioemotional traits on the ground that when unadjusted scores are used, their wage effect is likely to be confounded by the influences of unexpected academic and labor market success (or failure) on such skills and traits. The adjusted measures are constructed by (1) restricting the analytic sample to respondents who were adolescents in 1980 (15 to 18 years old) and (2) calculating standardized residual values from a regression model where the composite index of cognitive skills or socioemotional traits is regressed on age dummies and years of schooling in 1980.[13] We need to be cautious in using these relative measures, as an issue of measurement error indicates uncertainty about how perfectly both measures represent an individual's cognitive skills and socioemotional traits. But these measures resonate well with the theoretical views described earlier, and the measure of socioemotional traits is likely to underestimate their wage effect given that it captures only part of one's socioemotional traits. I introduce both measures simultaneously in the full model in order to cancel out some of the measurement error problem, because motivated individuals are more likely to obtain higher test scores (or *vice versa*).

EDUCATIONAL ATTAINMENT As another key variable, educational attainment is measured by highest level of education completed at the time hourly wages were measured. This consists of a set of mutually exclusive and exhaustive dummy variables, which are high school dropouts, high school graduates (reference group), some college attendees, and 4-year college graduates. This study treats GED holders as high school dropouts, following Cameron and Heckman (1993) and Heckman and Rubinstein (2001) that show GED holders are more similar to high school dropouts than high school graduates in various adult outcomes. In the analysis, I focus on the

[12] While the internal consistency of the locus of control scale is quite low, it correlates well with the self-esteem scale (CHRR 2004).

[13] A preliminary analysis (available upon request from the author) shows that using the raw composite scores does not alter the findings reported here.

coefficients of being college graduates to address the relationship between the college wage premium and cognitive and socioemotional abilities.

FAMILY BACKGROUND Family background covers family structure and parental education at age 14, and parental occupational status, the number of siblings, and family income in 1979. Family structure is categorized as two biological-parent families (reference group), two-parent step families, single-mother families, and other families (e.g., single father families or foster families). Parental education is measured with the highest level of education either of the parents obtained and has the same classification scheme as respondents' level of education. Parental occupational status is measured by whether or not either of the parents was in professional or management occupations, based on the 3-digit occupational classification.

CONTROL VARIABLES I include other demographic variables such as sex (male/female), race/ethnicity, residence in the South and urban residence at age 14. Race/ethnicity is classified as non-Hispanic whites (reference group), non-Hispanic blacks, Hispanics, and other race (e.g., Asians, Native Americans, etc.). Other relevant labor market characteristics consist of actual work experience, actual work experience squared, residence in the South, urban residence, full-/part-time work status, and local unemployment rate (more than or equal to 6% or not) at the time hourly wages were measured. Actual work experience is calculated using the work history data from the NLSY79.[14]

Method

A conventional approach to examining the economic return to education is to employ ordinary least squares (OLS) models, which regress individual wages on educational attainment and observable individual attributes. With the conditional means as a measure of central tendency,

[14] The analysis is based on an extended version of the Mincer equation, where log wages are modeled as the sum of a linear function of years of education and a quadratic function of years of potential labor market experience. I do not include detailed occupation groups as a control, because some occupation groups have too few observations at either the lower or the upper tail of the wage distribution in the analytic sample, which prevents me from estimating quantile regression models.

OLS provides a parsimonious description of the association between the explanatory and dependent variables. It facilitates accounting for between-education group variations in different dimensions, and then interprets the distribution of the wage residuals as capturing within-education group wage inequality.

However, OLS has at least two drawbacks inherent to the conditional mean models (Hao and Naiman 2007). First, they are not readily extended to detecting the relationship between the explanatory and dependent variables in non-central locations of the whole wage distribution. Given that the natural interest of economic inequality and mobility lies in the poor (lower tail) and the rich (upper tail), an important question is whether and how the college premium and other explanatory variables—e.g., skills and traits—have differential effects at various locations of the wage distribution. In this vein, the conditional mean models may be an inefficient way to delineate a comprehensive picture of between-education group wage inequality. Second, the emphasis on central location in OLS models tends to pay less attention to the shape of the wage distribution. Assuming that the conditional effects of the explanatory variables on wages are constant across the whole distribution, they do not allow for gauging changes in the college wage premium due to varying effects of other explanatory variables along the wage distribution. Taken together, these weaknesses of traditional regression analysis seem to do disservice to directly linking between- and within-education group wage inequality.

As an alternative analytic approach, quantile regression models estimate the potential differential effects of the explanatory variables on various quantiles in the conditional wage distribution (Buchinsky 1998; Hao and Naiman 2007; Koenker and Bassett 1978; Koenker and Hallock 2001). *Quantile* refers to a generalized case of quartile, quintile, decile, and percentile, so it can be specified at any point in a distribution. For example, the 10^{th} quantile indicates 10% of a population lies below that quantile. Because of its distribution-based approach, quantile regression is capable of simultaneously describing both between- and within-education group wage inequality (Buchinsky 1994). One can evaluate between-education group wage inequality by examining changes in the college wage premiums at each conditional quantile before and after controlling for other wage determinants. This in turn enables one to address within-education group wage inequality by comparing the college wage premiums between the lower and upper tails of the wage distribution (e.g., the 10^{th} vs. 90^{th} quantiles).

Let $i=1, \ldots, n$ be a sample of individuals, y_i be the log transformed wages for individual i, and x_i be a $K \times 1$ vector of covariates. Quantile regression can be written as

$$y_i = x_i \beta_\theta + u_{\theta i}, \quad \text{Quant}_\theta(y_i | x_i) = x_i \beta_\theta, \quad \text{where } 0 < \theta < 1. \tag{1}$$

In Equation 1, θ points to the cumulative proportion of the sample, $\text{Quant}_\theta(y_i|x_i)$ denotes the θ^{th} quantile of y_i, conditional on the vector of the explanatory variables x_i, and $u_{\theta i}$ is the error term at the θ^{th} quantile that has zero expectation. The quantile regression estimator is analogous to that of OLS but has one different feature. While the least-squares estimator is obtained by taking the values of the parameters of the explanatory variables that minimize the sum of squared residuals, the quantile regression estimator solves for the parameters by minimizing a weighted sum of absolute residuals.[15] This can be written as

$$\min_{\beta \in R^k} \left\{ \sum_{i: y_i \geq x_i \beta_\theta} \theta \,|\, y_i - x_i \beta_\theta \,| + \sum_{i: y_i < x_i \beta_\theta} (1-\theta) \,|\, y_i - x_i \beta_\theta \,| \right\} = \min_{\beta \in R^k} \left\{ \sum_i \rho_\theta (y_i - x_i \beta_\theta) \right\}, \tag{2}$$

where $\rho_\theta(\lambda) = \theta\lambda$ if $\lambda \geq 0$ or $\rho_\theta(\lambda) = (1 - \theta)\lambda$ if $\lambda < 0$. From Equation 2, we can see that different weights are assigned to positive and negative residuals. For example, when estimating the parameters of the explanatory variables for the 90^{th} quantile regression, 10% of observations with positive residuals are given a weight of .9 and the rest with negative residuals are given a weight of .1.

It should be noted that quantile regression should not be understood as segmenting the outcome variable into subsets and running the OLS regressions fitting on these subsets, which gives rise to distortion due to sample selection (Koenker and Hallock 2001). Since the quantile

[15] Minimizing the sum of absolute residuals is equivalent to solving a linear programming problem and in the analysis, parameter estimates are generated using the STATA *sqreg* command. It calculates standard errors for the explanatory variables using the bootstrap method recommended by Buchinsky (1998).

regression function is the weighted sum of absolute residuals, estimation for each location is based on the whole sample, not the subsets of the sample. Quantile regression estimates can be interpreted in the same fashion as in OLS estimates. In the following analyses, OLS regression results are also presented for the purpose of comparison.

RESULTS

Descriptive Results

Table 1 presents the descriptive statistics of hourly wages and covariates by highest education completed in the NLSY79 2002 sample. Since the college wage premium is of main interest in this study, I focus on high school and college graduates. Consistent with the wage inequality literature, college graduates earn higher wages and possess higher levels of cognitive skills and socioemotional traits, compared to high school graduates. Also, they are more likely than high school graduates to be white, come from two biological-parent families, and have parents with college education. During adolescence, college graduates were more likely than high school graduates to have parents who were in professional or management occupations, have higher family income, have fewer siblings, not live in the South and live in urban areas. At the time the information on hourly wages was collected, college graduates had more labor market experience, were less likely to live in the South, more likely to live in urban areas, and worked in local areas with lower unemployment rates, compared to high school graduates.

<< Table 1 about here >>

With respect to the relationship between the economic return to education and cognitive and socioemotional abilities, the descriptive results in Table 1 reveal several patterns that warrant further investigation. First, as shown in the variance of hourly wages within each education group, wage inequality among college graduates is larger than that among high school graduates. Second, the gap in cognitive skills between high school and college graduates is wider than that in socioemotional traits. Third, the variance of socioemotional traits is larger among college graduates than among high school graduates, which is opposite to that of cognitive skills. These patterns suggest that although cognitive skills and socioemotional traits may impact both the college wage premium and wage inequality within college graduates, the ways in which each of these skills and traits operates may differ. While cognitive skills appear more concerned with wage inequality between high school and college graduates, socioemotional traits appear more related to wage inequality within college graduates. I scrutinize these descriptive findings in the following multivariate results section.

The Differential Effect of Cognitive Skills and Socioemotional Traits across the Wage Distribution

As a first step, I examine the direct effect of cognitive skills and socioemotional traits on wages, using quantile regression models estimated with all control variables but without educational attainment variables. Table 2 shows that in Models A and B, the wage effect of these skills and traits is highly significant across the whole wage distribution and larger in the upper portion of the wage distribution. While the OLS estimates in the last column indicate that on average, one standard deviation increase in cognitive skills and socioemotional traits is associated with a 13 percent ($=e^{.124}$) and a 7 percent ($=e^{.069}$) increase in hourly wages, respectively, the quantile regression estimates show that each set of these skills and traits is associated with a 9 percent and a 3 percent increase at the 10th percentile and with a 19 percent and a 13 percent increase at the 90th percentile. Model C suggests that these findings hold true even when both skills and traits are introduced at the same time. Although the wage effect of cognitive skills remains larger than that of socioemotional traits, both have a significantly strong effect on wage inequality especially in the upper portion of the wage distribution.[16] This implies that the polarization of the recent

[16] In a supplemental analysis, I added respondents' log wages at the time of labor market entry to the quantile regression models. These wage change models provide a stricter test of the wage effect of cognitive skills and socioemotional traits, controlling for unobserved skill differences that are not

U.S. wage structure driven by the upper half wage inequality is due in part to the demand for both cognitive skills and socioemotional traits among high wage jobs.

<< Table 2 about here >>

The Role of Cognitive Skills and Socioemotional Traits in the College Wage Premium and Wage Dispersion within College Graduates

Table 3 reports quantile regression estimates of the wage premium for college education and cognitive and socioemotional abilities using the 2002 sample. Note that each model includes other educational attainment and all control variables. Model A shows that with no control for skills and traits, the college premium is highly significant across the whole wage distribution and larger in the upper portion of the wage distribution. The OLS estimate shows that on average, college graduates earn approximately 53 percent ($=e^{.423}$) more hourly wages than high school graduates; meanwhile, the quantile regression estimates show that the college premium is associated with a 33 percent increase in hourly wages at the 10^{th} percentile and with a 63 percent increase at the 90^{th} percentile. This differential effect of the college premium results in a significant wage inequality within college graduates. The second row of Model A indicates that the magnitudes of the college wage premium coefficients statistically differ between the lower and upper tails in the wage distribution.

<< Table 3 about here >>

In Models B and C, cognitive skills and socioemotional traits are introduced respectively. Both models show that as in Table 2, each type of skills and traits has positive impacts on wages in almost all locations of the distribution and generally a larger effect in the upper portion of the wage distribution. Although the college premium coefficients remain significant, taking cognitive skills and socioemotional traits into account reduces their magnitudes by about 8 to 21

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captured in the models in Table 2. The results do not alter the findings reported here (available upon request from the author).

percent and 0.4 to 17 percent across the wage distribution, respectively. In addition, while the 95th vs. 5th percentile difference in the college premium coefficients is statistically significant in both models (a 12 percent and a 17 percent reduction), the 90th vs. 10th percentile difference is barely significant when controlling for cognitive skills (a 24 percent reduction) and becomes insignificant when controlling for socioemotional traits (a 40 percent reduction). Therefore, Models B and C indicate that the difference in the college premium coefficients between the lower and upper tails in the wage distribution is due in part to differences in skills and traits.

Model D presents the results from the full model that includes both types of skills and traits. Some coefficients of socioemotional traits become insignificant but the results are generally consistent with those in Models B and C. In Model D, the college premium coefficients are still significant but their magnitudes are further reduced by about 14 to 31 percent across the wage distribution. The college premium is associated with a 28 percent increase in hourly wages at the 10th percentile and with a 40 percent increase at the 90th percentile. What is striking from these results is that compared to Model A, the 90th vs. 10th percentile difference in the college premium coefficients becomes insignificant after controlling for cognitive skills and socioemotional traits (a 53 percent reduction). In summary, these findings lend strong support to the premise of the economic return to education, captured by the college wage premium. It holds up even after controlling for skills and traits and regardless of where in the wage distribution the college premium is estimated. However, Table 3 also suggests that differences in cognitive skills and socioemotional traits contribute significantly to reducing both the college wage premium and wage inequality within college graduates. This result comes mostly from the more pronounced effect of such skills and traits in the upper portion of the wage distribution.

<< Table 4 about here >>

Obviously, these findings do not mean that cognitive skills and socioemotional traits fully account for wage inequality within college graduates, because by definition, levels of hourly wages are much higher in the upper tail of the wage distribution. So using the quantile regression models in Table 3, I calculate the predicted hourly wages (in 2000 dollars) of college graduates at the 10th and 90th percentiles in the wage distribution, in order to gauge the extent to which these skills and traits explain wage inequality among college graduates. Results appear in Table 4. Model A shows that the college premium difference between the lower and upper tails of the wage distribution is about 42 dollars when including only educational attainment and all control variables. Models B and C indicate that introduction of each set of skills and traits explains 10 percent and 7 percent of wage inequality among college graduates, respectively. Finally, Model D reports that the combined effect of cognitive skills and socioemotional traits accounts for 13 percent of wage inequality within college graduates. This effect size seems significant but modest. Recall, however, that both measures of skills and traits are constructed as an early predictor of workers' earnings and in general terms rather than in job-specific terms. It is possible that the effect size is likely to increase if we have more comprehensive and timely approximate measures of individual skills and traits. While what other factors could explain the rest of wage dispersion among college graduates is beyond the scope of this paper, I conjecture that macro-level demand- and supply-side factors, such as deindustrialization, organizational reconfiguration, skill-based technological change (SBTC), and the composition effect of educational expansion, should exert a substantial influence on wage inequality within college graduates (Autor, Katz, and Kearney 2006; Lemieux 2006; Morris and Western 1999). In the conclusion section, I discuss other potential factors of wage inequality within college graduates.

The Distinctive Role of Cognitive Skills and Socioemotional Traits in Education Group Wage Inequality

To examine whether the wage effect of cognitive skills and socioemotional traits operates differently with respect to between- and within-education group wage inequality, Table 5 presents quantile regression estimates of the interaction effects on wages between each set of skills and traits and the college premium. As seen in Model A, when cognitive skills interact with the college premium, both their main and interaction effects are mostly concentrated at the locations above the median in the wage distribution with some exceptions at the 90th percentile for the main effect and at the 95th percentile for the interaction effect. Model B shows that while socioemotional traits have a main effect at the middle portion of the wage distribution, they have a strong interaction effect at the upper tail. These results suggest that cognitive skills come into play for both between-education group wage inequality and wage inequality among college graduates, whereas socioemotional traits play a more important role in wage inequality among college graduates than in between-education group wage inequality.

<< Table 5 about here >>

Model C estimates the effect of both types of skills and traits conditional on the college wage premium. In general, cognitive skills appear to have a main effect on wages in a similar way as in Model A but their effect is not dependent on the college premium. Unlike the OLS estimate, there is no statistically significant interaction effect of cognitive skills along the wage distribution. In contrast, socioemotional traits do not have the strong main effect but their effect is highly contingent on the college premium at the upper tail of the wage distribution. The OLS estimate may be misleading in this regard, because of its failure to detect this interaction effect of socioemotional traits in specific segments of the wage distribution. The quantile regression interaction models, therefore, provide a more nuanced picture relative to the OLS interaction models. As shown in Model C, the OLS result indicates that although both cognitive skills and socioemotional traits contribute to a reduction in between-education group wage inequality, it is only cognitive skills that matter in wage inequality among college graduates. However, the quantile regression result shows that the wage effect of cognitive skills runs more noticeably between high school and college graduates and that of socioemotional traits does so within college graduates.[17] These findings suggest a distinctive role of socioemotional traits in patterns

[17] It should be noted that this result does not mean the effect of cognitive skills (socioemotional traits) is irrelevant to explaining within- (between-) education group wage inequality. As discussed in the previous section, both contribute to reductions in the college wage premium and wage dispersions within college

of the economic return to education. This may be unexpected in the unobserved ability bias story, which tends to assume that unobserved skills, whether cognitive or socioemotional, operate in a similar fashion in explaining between- and within-education group wage inequality.

The Role of Cognitive Skills and Socioemotional Traits in Accounting for the Long-Run Effect of the College Wage Premium

Finally, I address whether the contribution of cognitive skills and socioemotional traits in accounting for between- and within-education group wage inequality changes due to workers' aging and accumulation of labor market experiences.[18] The quantile regression models in Tables 3 and 4 are re-estimated for a series of biannual samples. Figure 1 plots a growth in the college wage premium at the lower, the median, and the upper tails of the wage distribution as the sample cohort gets old, before and after controlling for these skills and traits. At the 10th percentile, the effect of cognitive skills and socioemotional traits reduces the college wage premium by 7 percent when the mean age of the sample cohort is 27 and by 19 percent when the mean age is 39. Changes in the college wage premium at the median indicate that these skills and traits explain 16 percent of the wage difference between high school and college graduates, whether the mean age is 27 or 39. In the meantime, cognitive skills and socioemotional traits play a more important role in the growth in the college wage premium at the 90th percentile as it increases steadily. Controlling for such skills and traits yields a 13 percent reduction in the college premium when the mean age of the sample cohort is 27 and a 29 percent reduction when the mean age is 39. The effect of cognitive skills and socioemotional traits on between-education

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graduates. The result from the quantile regression interaction model simply confirms that the wage effect of each set of skills and traits operates quite differently in explicating between- and within-education group wage inequality.

[18] The analysis for this section is agnostic about whether and how much the results presented here are confounded by period effect. Note, however, that the related literature shows a stable increase in wage inequality during the 1990s, though to a lesser degree than during the 1980s (Autor, Katz, and Kearney 2006; Lemieux 2006). Random- or fixed-effects models could be used for taking potential period effects into consideration, but they are yet to be implemented in the quantile regression framework. In the analysis, all available workers are included in each of the biannual samples.

group wage inequality tends to amplify as workers age and spend more time in the labor market and at the same time, their effect becomes stronger at the upper tail of the wage distribution.

<< Figure 1 about here >>

Figure 2 depicts the effect of these skills and traits on wage inequality within college graduates in their course of approaching prime ages in the labor market. As wage dispersion among college-educated workers increases, differences in such skills and traits explain 5 percent of wage difference between the 10^{th} and 90^{th} percentiles of the distribution when the mean age is 27 and 13 percent when the mean age is 39. As college graduates accumulate more labor market experience, individual skills and traits play the more salient role in wage dispersion among them. The finding in Figure 1 has an important consequence for this result. It suggests that the impact of skills and traits on wage inequality within college graduates is derived from their marked impact on the upper-half wage inequality. Again, cognitive skills and socioemotional traits appear to function as a determinant of the polarization of the recent U.S. wage structure among prime-aged workers.

<< Figure 2 about here >>

These findings help elaborate the conclusion of Dunifon and Duncan (1998) and Dunifon, Duncan, and Brooks-Gunn (2001) that early differences in skills and traits have a significant effect on wages at much later ages. The long-run effect of cognitive skills and socioemotional traits is manifest in both between- and within-education group wage inequality. There are several scenarios that have the potential to disentangle this pattern. First, employers need a substantial amount of time to assess workers' general skills. Second, as workers reach their prime ages in the labor market, skills and traits formed during the early life stage synergize requirements for high ranking jobs, such as a sense of organization, efficiency, and a future orientation. Third, workers with higher levels of such skills and traits are more likely to participate in on-the-job-training, which would result in higher wages at later ages. Fourth, they perform better in wage bargaining in job mobility processes. While each scenario remains to be empirically tested, the results clearly show that the wage effect of early differences in skills and traits is positively associated with the larger effect of the college wage premium among older and more experienced workers.

DISCUSSION AND CONCLUSION

This paper has sought to provide a refinement of the account based on the economic return to education with emphases on the multidimensionality of skills and within-education group wage inequality. To this end, I have assessed the wage effect of socioemotional traits alongside cognitive skills by (1) conceptualizing them as a form of cultural capital and a critical factor to cope with the principal-agent problem in the labor market and (2) estimating quantile regression models to simultaneously evaluate the impact of such skills and traits on between- and within-education group wage inequality.

Four main findings emerge from the quantile regression analysis. First, the economic return to education is by and in itself a robust explanation for wage inequality. The college wage premium is highly significant, substantial in magnitude, and larger above the median of the wage distribution, even after holding individual skills and traits constant. Cognitive skills and socioemotional traits developed in schools, school quality, and educational credentials ("sheep-skin effect") appear to represent the college wage premium. Second, however, I find strong evidence that individual skills and traits as pre-college and pre-labor market factors contribute significantly to reducing the college wage premium and wage dispersion within college graduates. This result is mostly driven by the stronger impact of both cognitive skills and socioemotional traits in the upper portion of the wage distribution, leveling off the larger effect of the college premium above the median. In this vein, these skills and traits function as an important factor of the polarization of the recent U.S. wage structure, because they are more highly rewarded among high wage jobs.

A third finding is that cognitive skills and socioemotional traits play quite different roles in between- and within-education group wage inequality. The quantile regression interaction models show that when interacting with the college premium, cognitive skills are more influential in reducing wage differentials between high school and college graduates, whereas socioemotional traits are more pronounced in accounting for wage dispersions within college graduates, especially at the upper tail of the wage distribution. These results suggest that in high-paying jobs, employers facing the principal-agent problem provide a wage premium for college-educated workers with a high level of socioemotional traits. Given that these jobs allow more autonomy, those who possess cultural capital are more likely to respond positively to the employer-setting incentive structure. Finally, early differences in individual skills and traits have the long-run effect on between- and within-education group wage inequality. As workers approach their prime ages in the labor market, their effect becomes more pronounced in both the high school-college wage gap—especially at the upper tail of the wage distribution—and wage inequality within college graduates. It suggests a cumulative nature of the association between the wage effect of early differences in skills and traits and workers' time spent in the labor market, which is consistent with Heckman and his colleagues' claim that "skills beget skills" (Carneiro and Heckman 2003).

While these findings shed new lights on the dynamics of the economic return to education, there are several research foci that deserve further attention. First, a closer examination of early skill formation is needed to uncover the process by which family background is associated with socioeconomic outcomes. A better understanding of the parent-child relationship and the gene-environment interactions is a high priority. In so doing, elaboration of measures of individual skills and traits should be given another priority. Although the pre-college, pre-labor market measures constructed in this study alleviate the measurement error problem, they need to be improved in that the NLSY79 only gathered information on AFQT and personality traits. Assessing multiple indices of aptitude and behavioral traits (e.g., child problem behaviors) seems promising in that regard. A second research focus is on specifying the mechanisms by which workers' early differences in skills and traits affect their labor market performance under various forms of institutional arrangements. Taking the finding of the direct wage effect of individual skills and traits as a starting point, one could examine their relation into more proximate indicators of wage determination that reflect educational system and occupational structure. Among such indicators are advanced degree credentials, job mobility, job tenure, and job-specific skills required at the firm and occupation levels.

Third, sources other than skills and traits of within-education group wage inequality need to be addressed. This paper shows the contribution of cognitive skills and socioemotional traits to explaining wage inequality within college graduates, but its large portion is still left unexplained. Overeducation, school quality, and the different field of study could drive larger wage dispersion among college graduates (Martins and Pereira 2004). Those factors can be important to the extent that the highly educated end up getting low wage jobs because there are so many qualified people for high wage jobs, colleges are more stratified in terms of school quality and reputation, and individuals' choice of the field of study matters in wage determination. Studies of within-education group wage inequality should consider these factors along with differences in skills and traits. Lastly, but not least, more research should be done to link the wage effect of cognitive skills and socioemotional traits with wage inequality by gender and race/ethnicity. Supplemental analyses (available upon request from the author) find that the wage effect of such skills and traits play a more meaningful role in reducing the wage gap by race/ethnicity than by gender. Future research needs to examine how potential institutional constraints (e.g., female wage penalty or statistical discrimination by race/ethnicity) are intertwined with the relationship between individual skills and traits and wage inequality.

Despite such limitations, my results have substantive implications for the social stratification literature. Given that cognitive and socioemotional development is highly dependent on parental socioeconomic status and parenting behaviors, this paper gives credence to the research that emphasizes the family as an important institutional actor responsible for wage inequality. The finding that early differences in skills and traits are consequential to both between- and within-education group wage inequality suggests that the current discourse about upward mobility should put together equal access to college education and early childhood education. Even with a college education, children from disadvantaged families are more likely to be placed in lower portion of the wage distribution due to low levels of cognitive skills and socioemotional traits. From a social policy perspective, this implies that early interventions aimed at skill development during childhood may be critical for reducing inequalities in the labor market as well as education (Heckman 2007). Family-level response to the demand for skills, therefore, should be taken seriously in addition to the impacts of economic and political institutions on social inequality (Leicht 2008; Morris and Western 1999; Neckerman and Torche 2007).

A careful consideration of differences in cognitive skills and socioemotional traits enriches research on the economic return to education by extending its premise to both between- and within-education group wage inequality in contemporary U.S. society. In this respect, this paper joins an emerging literature that calls more attention to the relationship between intergenerational mobility and socioeconomic inequality (Breier 1995). Despite an intuitive connection, studies of mobility and inequality have been strikingly detached to each other (Hout 2004). I expect that social scientific efforts to link these two will benefit from developing sound frameworks for the early skill formation process and its lasting impact across the life course.

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APPENDIX

A. Rotter's Locus of Control Scale

Item 1: a) What happens to me is my own doing; b) Sometimes I feel that I don't have enough control over the direction my life is taking.

Item 2: a) When I make plans, I am almost certain that I can make them work; b) It is not always wise to plan too far ahead, because many things turn out to be a matter of good or bad fortune anyhow.

Item 3: a) In my case, getting what I want has little or nothing to do with luck; b) Many times we might just as well decide what to do by flipping a coin.

Item 4: a) Many times I feel that I have little influence over the things that happen to me; b) It is impossible for me to believe that chance or luck plays an important role in my life.

B. Rosenberg's Self-Esteem Scale

Item 1: I feel that I'm a person of worth, at least on an equal basis with others.

Item 2: I feel that I have a number of good qualities.

Item 3: All in all, I am inclined to feel that I am a failure.

Item 4: I am able to do things as well as most other people.

Item 5: I feel I do not have much to be proud of.

Item 6: I take a positive attitude toward myself.

Item 7: On the whole, I am satisfied with myself.

Item 8: I wish I could have more respect for myself.

Item 9: I certainly feel useless at times.

Item 10: At times I think I am no good at all.

Table 1. Descriptive Statistics by Educational Attainment, NLSY79 2002 Sample (unweighted)

Variable	All	Highest Education Completed			
		< High School	High School	Some College	College and More
Dependent Variable					
Log Hourly Wages	2.95	2.69	2.80	2.97	3.33
	(0.58)	(0.50)	(0.52)	(0.52)	(0.59)
Gap between Groups[a]		0.11	–	0.18	0.54
Variance within Each Group		0.25	0.27	0.27	0.35
Individual Skills and Traits					
Cognitive Skills	0.06	-0.42	-0.31	0.09	0.91
	(1.02)	(0.79)	(0.92)	(0.88)	(0.86)
Gap between Groups[a]		0.11	–	0.40	1.22
Variance within Each Group		0.63	0.84	0.88	0.74
Socioemotional Traits	0.01	-0.18	-0.19	0.11	0.33
	(0.99)	(0.94)	(0.91)	(1.04)	(0.99)
Gap between Groups[a]		-0.01	–	0.30	0.52
Variance within Each Group		0.88	0.84	1.08	0.99
Control Variables					
Sex (Male=1)	0.51	0.59	0.53	0.43	0.51
White (reference)	0.43	0.31	0.41	0.37	0.60
Black	0.29	0.33	0.32	0.35	0.18
Hispanic	0.18	0.25	0.18	0.22	0.12
Other Race	0.09	0.11	0.10	0.07	0.11
Two Biological Parent Family at Age 14 (reference)	0.68	0.53	0.67	0.66	0.80
Step Family at Age 14	0.09	0.14	0.10	0.07	0.05
Single Mother Family at Age 14	0.18	0.24	0.18	0.20	0.12
Other Family Structure at Age 14	0.06	0.09	0.06	0.07	0.03
Parental Education at Age 14: Less Than High School	0.32	0.54	0.38	0.30	0.11
Parental Education at Age 14: High School (reference)	0.41	0.37	0.48	0.40	0.32
Parental Education at Age 14: Some College	0.12	0.07	0.08	0.16	0.17
Parental Education at Age 14: College or More	0.15	0.03	0.05	0.13	0.40
Parental Occupation in 1979: Professional/Management	0.19	0.10	0.10	0.19	0.39
Family Income in 1979/$1000	17.12	12.79	15.87	16.24	22.81
	(11.13)	(7.70)	(9.80)	(9.61)	(13.89)
Number of Siblings in 1979	3.62	4.52	3.91	3.40	2.78
	(2.57)	(2.93)	(2.58)	(2.57)	(1.98)
Residence in the South at Age 14	0.38	0.44	0.39	0.40	0.31
Urban Residence at Age 14	0.79	0.82	0.76	0.80	0.80
Full-/Part-Time Work Status	0.84	0.78	0.85	0.85	0.87
Actual Work Experience	17.68	15.46	17.71	17.89	18.86
	(4.54)	(5.22)	(4.68)	(4.43)	(3.24)
Residence in the South	0.42	0.45	0.42	0.44	0.36
Urban Residence	0.75	0.77	0.69	0.77	0.80
Unemployment Rate ≥ 6%	0.53	0.54	0.55	0.53	0.49

Notes: *N*=2,527; Standard deviations for interval variables in parentheses; Missing indicators for parental occupation and family income are included in the analysis but not shown.

[a] indicates difference between each education group and high school graduates.

Table 2. Parameter Estimates from Quantile Regression Models for Log Hourly Wages with No Control for Education, NLSY79 2002 Sample

	Quantile Regression														OLS	
	q.05		q.10		q.25		q.50		q.75		q.90		q.95			
A. Cognitive Skills																
Cognitive Skills	0.082	*	0.083	*	0.092	*	0.140	*	0.141	*	0.179	*	0.176	*	0.124	*
	(0.025)		(0.020)		(0.016)		(0.015)		(0.016)		(0.026)		(0.032)		(0.012)	
B. Socioemotional Traits																
Socioemotional	0.046	*	0.032	*	0.053	*	0.059	*	0.081	*	0.079	*	0.126	*	0.069	*
Traits	(0.019)		(0.017)		(0.012)		(0.013)		(0.017)		(0.024)		(0.032)		(0.011)	
C. Individual Skills and Traits																
Cognitive Skills	0.064	*	0.069	*	0.084	*	0.124	*	0.124	*	0.155	*	0.144	*	0.110	*
	(0.028)		(0.019)		(0.018)		(0.015)		(0.016)		(0.026)		(0.036)		(0.013)	
Socioemotional	0.034	†	0.028	†	0.032	*	0.036	*	0.043	*	0.055	*	0.064	†	0.044	*
Traits	(0.021)		(0.016)		(0.015)		(0.014)		(0.016)		(0.023)		(0.036)		(0.011)	

Notes: *N*=2,527; Bootstrap standard errors in parentheses (300 replications); Each model does not include education attainment variables; Each model includes all control variables but not shown.

† $p < .10$; * $p < .05$ (two-tailed tests).

Table 3. Parameter Estimates from Quantile Regression Models for Log Hourly Wages with Control for Education, NLSY79 2002 Sample

	Quantile Regression														OLS	
	q.05		q.10		q.25		q.50		q.75		q.90		q.95			
A. College Premium																
College Premium	0.242	*	0.288	*	0.432	*	0.459	*	0.475	*	0.489	*	0.477	*	0.423	*
	(0.059)		(0.046)		(0.039)		(0.032)		(0.043)		(0.069)		(0.076)		(0.029)	
Within-Group[a]			q.95 vs. q.05:		0.235	*			q.90 vs. q.10:		0.201	*				
					[0.020]						[0.011]					
B. College Premium + Cognitive Skills																
College Premium	0.198	*	0.234	*	0.397	*	0.397	*	0.414	*	0.387	*	0.404	*	0.369	*
	(0.068)		(0.047)		(0.042)		(0.035)		(0.051)		(0.066)		(0.082)		(0.031)	
Cognitive Skills	0.032		0.058	*	0.043	*	0.076	*	0.060	*	0.085	*	0.101	*	0.060	*
	(0.028)		(0.021)		(0.017)		(0.015)		(0.021)		(0.026)		(0.031)		(0.013)	
Between-Group[b]	0.044		0.054		0.036		0.062		0.060		0.102		0.073		0.054	
% Explained	18.3		18.7		8.3		13.5		12.7		20.9		15.3		12.7	
Within-Group[a]			q.95 vs. q.05:		0.206	*			q.90 vs. q.10:		0.153	†				
					[0.043]						[0.051]					
% Explained					12.3						24.1					
C. College Premium + Socioemotional Traits																
College Premium	0.235	*	0.287	*	0.406	*	0.450	*	0.433	*	0.408	*	0.431	*	0.403	*
	(0.063)		(0.042)		(0.035)		(0.033)		(0.042)		(0.069)		(0.081)		(0.029)	
Socioemotional	0.036	†	0.035	*	0.027	†	0.038	*	0.055	*	0.067	*	0.081	*	0.045	*
Traits	(0.019)		(0.013)		(0.014)		(0.012)		(0.015)		(0.024)		(0.032)		(0.010)	
Between-Group[b]	0.007		0.001		0.027		0.009		0.042		0.081		0.046		0.020	
% Explained	2.9		0.4		6.2		2.0		8.9		16.5		9.6		4.7	
Within-Group[a]			q.95 vs. q.05:		0.196	*			q.90 vs. q.10:		0.121					
					[0.049]						[0.117]					
% Explained					16.6						39.7					
D. College Premium + Individual Skills and Traits																
College Premium	0.185	*	0.243	*	0.370	*	0.396	*	0.387	*	0.338	*	0.372	*	0.362	*
	(0.067)		(0.045)		(0.042)		(0.034)		(0.044)		(0.070)		(0.085)		(0.031)	
Cognitive Skills	0.030		0.042	†	0.037	*	0.061	*	0.055	*	0.076	*	0.101	*	0.050	*
	(0.030)		(0.021)		(0.019)		(0.015)		(0.019)		(0.028)		(0.033)		(0.013)	
Socioemotional	0.032		0.030	*	0.025		0.025	*	0.046	*	0.054	*	0.039		0.037	*
Traits	(0.021)		(0.015)		(0.015)		(0.012)		(0.017)		(0.024)		(0.034)		(0.010)	
Between-Group[b]	0.058		0.045		0.062		0.063		0.088		0.151		0.105		0.061	
% Explained	23.8		15.6		14.4		13.7		18.4		30.9		22.0		14.4	
Within-Group[a]			q.95 vs. q.05:		0.188	†			q.90 vs. q.10:		0.095					
					[0.087]						[0.251]					
% Explained					20.0						52.9					

Notes: *N*=2,527; Bootstrap standard errors in parentheses (300 replications); *p*-values from *F*-statistics in brackets; Each model includes all control variables but not shown.

[a] tests statistical difference in the college wage premium coefficients between the lower and upper tails in the wage distribution.

[b] indicates differences in the college wage premium coefficients before and after controlling for individual skills and traits across the wage distribution.

† $p < .10$; * $p < .05$ (two-tailed tests).

Table 4. Percent Reduction in Wage Inequality within College Graduates by Individual Skills and Traits, NLSY79 2002 Sample

	Predicted Hourly Wages in 2000 Dollars			
	q.10	q.90	Diff.	% Explained
Model A. College Premium	14.567	56.559	41.992	
Model B. A + Cognitive Skills	13.741	51.630	37.889	10%
Model C. A + Socioemotional Traits	14.328	53.206	38.878	7%
Model D. A + B + C	13.877	50.387	36.509	13%

Notes: The predicted hourly wages are calculated by averaging each respondent's value on all covariates except for being a college graduate and individual skills and traits. Both types of skills and traits are set to their sample means; The resulting predicted log hourly wages are exponentiated to be shown in dollar terms; Each model includes all control variables.

Table 5. Parameter Estimates from Quantile Regression Interaction Models for Log Hourly Wages, NLSY79 2002 Sample

	Quantile Regression														OLS	
	q.05		q.10		q.25		q.50		q.75		q.90		q.95			
A. College Premium X Cognitive Skills																
College Premium	0.188	*	0.243	*	0.345	*	0.315	*	0.317	*	0.304	*	0.232	*	0.314	*
	(0.079)		(0.050)		(0.048)		(0.035)		(0.049)		(0.071)		(0.096)		(0.035)	
Cognitive Skills	0.011		0.035		0.037		0.065	*	0.058	*	0.069		0.104	†	0.041	*
	(0.040)		(0.024)		(0.024)		(0.020)		(0.026)		(0.043)		(0.056)		(0.019)	
College Premium X	0.017		0.029		0.034		0.064	*	0.087	*	0.095	†	0.113		0.068	*
Cognitive Skills	(0.068)		(0.044)		(0.045)		(0.030)		(0.044)		(0.057)		(0.073)		(0.029)	
B. College Premium X Socioemotional Traits																
College Premium	0.186	*	0.257	*	0.381	*	0.365	*	0.355	*	0.318	*	0.320	*	0.346	*
	(0.077)		(0.047)		(0.043)		(0.041)		(0.045)		(0.064)		(0.093)		(0.032)	
Socioemotional	0.015		0.031		0.022		0.037	†	0.058	*	0.036		-0.046		0.033	†
Traits	(0.029)		(0.022)		(0.024)		(0.021)		(0.027)		(0.040)		(0.053)		(0.018)	
College Premium X	0.038		0.020		0.008		0.029		0.053		0.144	*	0.183	*	0.053	*
Socioemotional Traits	(0.062)		(0.045)		(0.040)		(0.034)		(0.036)		(0.066)		(0.082)		(0.027)	
C. College Premium X Cognitive Skills and College Premium X Socioemotional Traits																
College Premium	0.188	*	0.226	*	0.355	*	0.329	*	0.317	*	0.308	*	0.328	*	0.307	*
	(0.086)		(0.054)		(0.049)		(0.035)		(0.049)		(0.066)		(0.085)		(0.035)	
Cognitive Skills	0.027		0.036		0.034		0.068	*	0.043		0.073	†	0.155	*	0.041	*
	(0.039)		(0.027)		(0.025)		(0.022)		(0.026)		(0.043)		(0.055)		(0.019)	
Socioemotional	0.023		0.027		0.023		0.038	†	0.053	†	0.038		-0.054		0.035	*
Traits	(0.031)		(0.020)		(0.026)		(0.021)		(0.030)		(0.043)		(0.060)		(0.018)	
College Premium X	0.019		0.042		0.035		0.053		0.076		0.039		-0.037		0.060	*
Cognitive Skills	(0.074)		(0.048)		(0.048)		(0.035)		(0.048)		(0.063)		(0.076)		(0.030)	
College Premium X	0.025		0.022		0.015		0.016		0.048		0.131	*	0.196	*	0.044	
Socioemotional Traits	(0.065)		(0.047)		(0.043)		(0.031)		(0.036)		(0.062)		(0.081)		(0.027)	

Notes: *N*=2,527; Bootstrap standard errors in parentheses (300 replications); Models A and B also estimate the main effect of socioemotional traits and cognitive skills, respectively, but not shown; Each model includes all control variables but not shown.

† $p < .10$; * $p < .05$ (two-tailed tests).

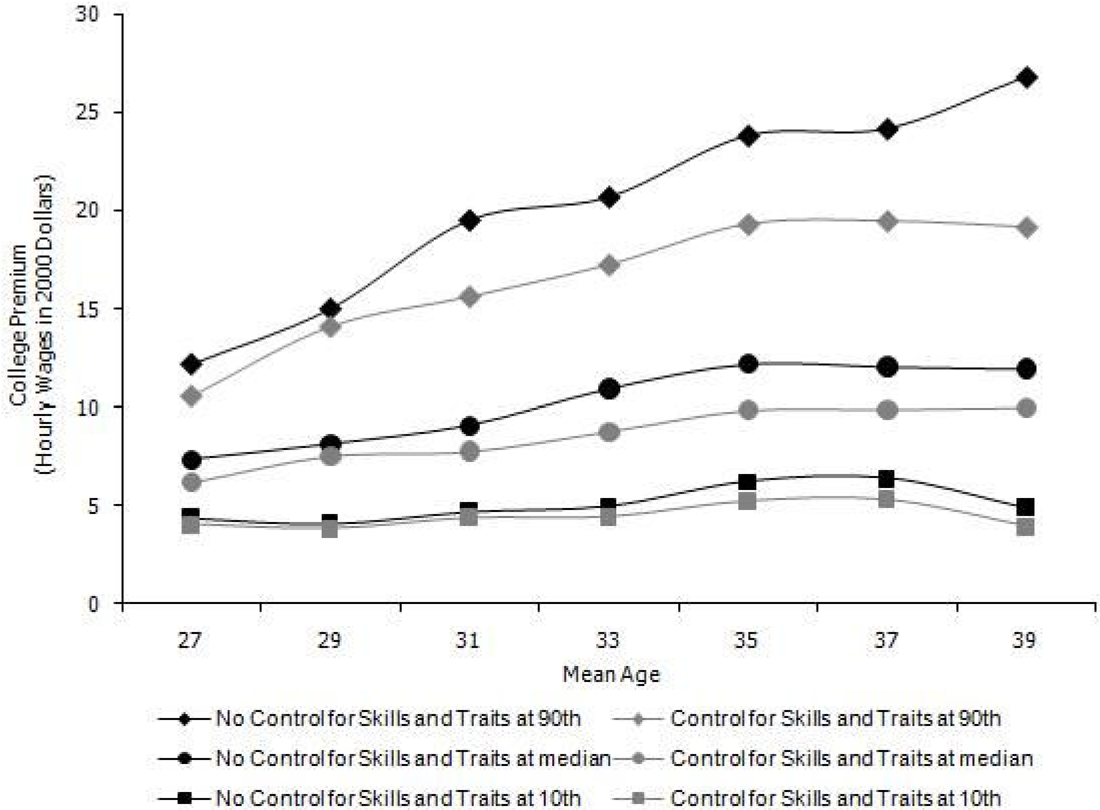

Figure 1. Evolution of the College Wage Premium, NLSY79 1990-2002 Samples
Notes: Figure 1 is based on quantile regression models in Table 3 that are estimated for each biannual sample; Each model includes all control variables.

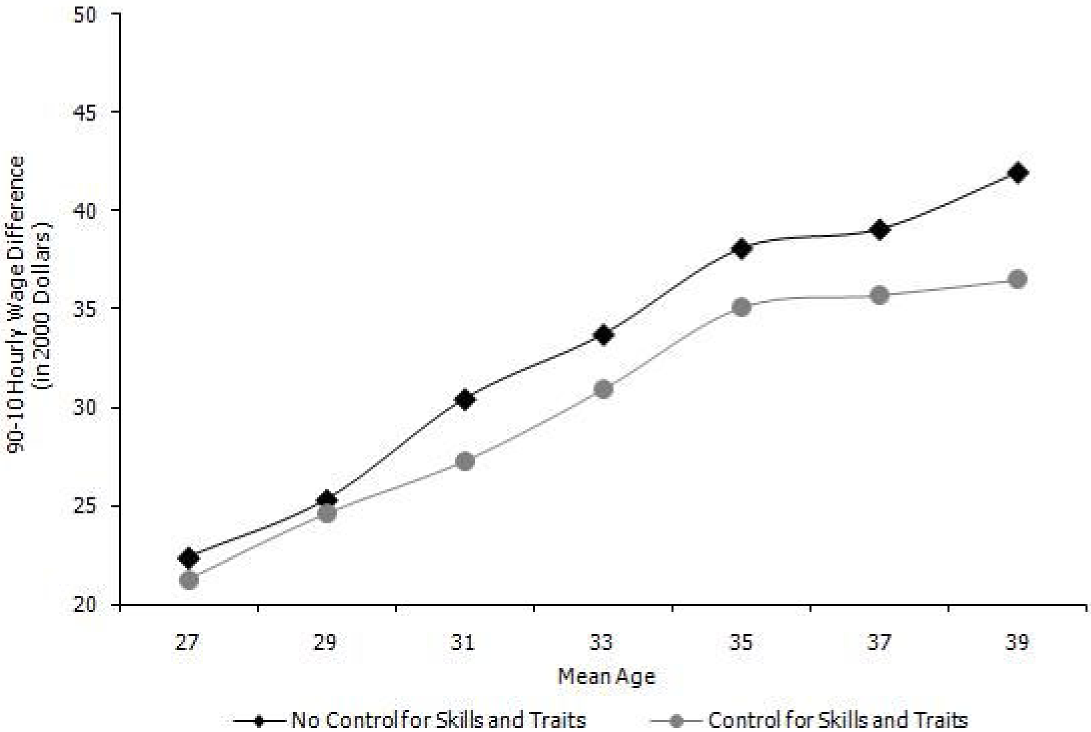

Figure 2. Evolution of Wage Inequality within College Graduates, NLSY79 1990-2002 Samples
Notes: Figure 2 is based on quantile regression models in Table 4 that are estimated for each biannual sample; Each model includes all control variables.