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Abstract

This paper investigates the role of non-cognitive skills in the occupational segregation of young workers entering the U.S. labor market. We find entry into male-dominated fields of study and male-dominated occupations are both related to the extent to which individuals believe they are intelligent and have "male" traits while entry into male-dominated occupations is also related to the willingness to work hard, impulsivity, and the tendency to avoid problems. The nature of these relationships differs for men and women, however. Non-cognitive skills (intelligence and impulsivity) also influence movement into higher-paid occupations, but in ways that are similar for men and women. On balance, non-cognitive skills provide an important, though incomplete, explanation for segregation in the fields that young men and women study as well as in the occupations in which they are employed.

JEL-Classification: J24, J16, J31

Keywords: non-cognitive skills, occupation, youth, gender

1. Introduction

One of the most enduring features of the labor market is that men and women do very different kinds of work. A shift in the occupational mix towards traditionally female-dominated jobs and the entry of women into traditionally male-dominated jobs have reduced the extent of occupational segregation over time (Blau et al. 1998), however, it remains the case that in the United States more than half of female (or male) employees would have to change jobs in order to equalize the occupational distributions of men and women (Blau et al. 2010; Jacobs 1999, 2003; Blau and Kahn 2000). Occupational segregation appears to be even higher in Europe, particularly among highly-educated workers (Dolado et al. 2002). These employment patterns are the combined result of decisions made by both employers (e.g. regarding hiring, promotion, retention, training etc.) and workers (e.g. regarding human capital acquisition, labor market participation, job mobility, etc.). Consequently, theoretical explanations of gender segregation in occupations typically center around 1) gender differences in labor market skills or ability; 2) gender differences in preferences for job characteristics; or 3) discrimination (see Polachek 1981; Anker 1997). The relative contribution of each of these to employment patterns across occupations is not well understood, however, and remains the focus of current debate.

In particular, a recent upsurge in interest in the labor market returns to non-cognitive skills more generally has highlighted the potential link between non-cognitive skills and occupational choice. Personality traits, for example, have wage returns that appear to be both occupation- and gender-specific (see Nyhus and Pons 2005; Mueller and Plug 2006; Cobb-Clark and Tan 2010) leading the expected benefit of entering different occupations to depend on ones personality in ways that differ for men and women. Moreover, there is evidence that workers' non-cognitive skills are often matched to the requirements of the specific occupations they have chosen. Workers with positive core self-evaluations (i.e., high self-esteem, high self-efficacy, internal locus of control, and high emotional stability) typically look for more challenging jobs (Judge et al. 2000), achieve better job performance (Judge and Bono 2001), and are particularly adept at translating early advantages into later economic success (Judge and Hurst 2007). Those with high self-efficacy experience faster occupational advancement (Andrisani 1977), while women are employed in safer jobs (DeLeire and Levy 2004; Grazier and Sloane 2008) or in jobs with lower earnings risk (Bonin et al. 2007) consistent with their tendency to be more risk averse than men (see Eckel and Grossman 2008 for a review). Finally, workers who are more social or gregarious are more likely to choose jobs that involve more interpersonal interactions (Borghans et al. 2008; Krueger and Schkade 2008).

This paper contributes to this growing literature by analyzing the role of non-cognitive skills in the occupational segregation of young workers entering the U.S. labor market. We begin by assessing whether or not college students' non-cognitive skills are related to their decision to study disciplines dominated by men. To this end, we take advantage of data from the National Longitudinal Study of Adolescent Health (Add Health) which provide unusually rich information about the psycho-social characteristics of a representative sample of young people at multiple points in time. The detail of the survey makes it possible to focus on a range of attributes (e.g. self-esteem, analytical approach to problem solving, impulsiveness, traditional male traits, conflict avoidance, etc.) that have not previously factored into analyses of occupational choice and which collectively can be thought of as non-cognitive skills. We then move on to consider whether or not there is a link between graduates' non-cognitive skills and their employment in traditionally male jobs. The panel nature of the survey is important in allowing us to measure respondents' non-cognitive skills prior to their job choices. Separate consideration of both field-of-study and employment outcomes helps us to understand whether any link between non-cognitive skills and occupational segregation is likely to be a supply-side or a demand-side phenomenon. Although most researchers focus only on occupational attainment, educational presorting is an important driver of occupational segregation (Borghans and Groot 1999). Finally, we investigate the potential link between occupational segregation and gender wage gaps by analyzing whether or not non-cognitive skills have differential effects on the movement into higher-paid as opposed to male-dominated occupations.

Understanding the role of non-cognitive skills in the occupational segregation of young workers is important for a number of reasons. First, occupational segregation may have implications for other labor market outcomes. The gender wage gap in particular is often attributed to gender segregation across occupations, industries, or jobs (see for example Groshen 1991; Blau and Kahn 2000; Mumford and Smith 2007), although others argue that occupational segregation may be relatively unimportant for women's wages (Bettio 2002; Fortin and Huberman 2002; Barón and Cobb-Clark 2010). This complex relationship between occupational segregation and other key labor market outcomes makes it important to understand the process that leads men and women to work in different jobs. Second, although researchers have traditionally focused on the importance of gender differences in human capital and labor market discrimination, new estimates of the role of preferences in occupational choice are beginning to suggest that a substantial fraction of the gender gap in occupations may stem from men's and women's preferences over job attributes (Daymont and Andrisani 1984; Turner and Bowen 1999; Rosenbloom et al. 2008; Zahfar 2009). Men are often shown to be more responsive than women to expected earnings when choosing their fields of study, for example (Freeman and Hirsch 2008; Montmarquette et al. 2002; Boudarbat and Montmarquette 2007; Zafar 2009). This disparity has profound implications for gender equity more generally. In particular, Daymont and Andrisani (1984) argue that eliminating discrimination will not result in equality of earnings unless there is greater similarity in men's and women's preferences. It is an open question whether these gender differences in preferences can also be linked to gender differences in non-cognitive skills. Finally, a focus on young workers just entering the labor market may provide the best opportunity for understanding the way that occupational segregation will evolve into the future. The presence of glass ceilings in many fields implies of course that similarity in occupational distributions at labor market entry is no guarantee that occupational segregation will remain small as workers' careers progress. However, there is little reason to believe that within cohort segregation will decline over time, suggesting that any decline in occupational segregation is likely to come from increasing equality among younger cohorts (see also Morgan 2008).

We find entry into male-dominated fields of study and male-dominated occupations are both related to the extent to which individuals believe they are intelligent and have "male" traits while entry into male-dominated occupations is also related to the willingness to work hard, impulsivity, and the tendency to avoid problems. The nature of these relationships differs for men and women, however. Non-cognitive skills (intelligence and impulsivity), on the other hand, influence movement into higher-paid occupations in a similar way for men and women. On balance, non-cognitive skills provide an important, though incomplete, explanation for segregation in the fields that young men and women study as well as in the occupations in which they are employed.

In the next section of the paper we provide details about the Add Health data and our estimation sample. Our conceptual framework and estimation strategy are outlined in Section 3.

Our results are discussed in section 4, while our conclusions and suggestions for future research follow in Section 5.

2. Data: The Adolescent Health Survey

We use data from the National Longitudinal Study of Adolescent Health (Add Health) which includes longitudinal data from 1994-2008 for a nationally representative sample of adolescents in grades 7-12 in the United States in the 1994-1995 academic school year (Harris 2009).[1] The data are ideal for our purposes as they allow us to look at the relationship between youth outcomes (i.e., field of study and occupational choice) in Wave III (when young people are 18 – 28 years old) and a wide range of factors including predetermined non-cognitive skills (i.e., personality, test scores, and future expectations) measured at Waves I and II (during the youths' high school years)[2] and demographic characteristics (i.e., age, race, immigrant status, marital status, fertility) measured at Wave III.

In order to rank occupations, we merge in information on the male share of employment and the average wage level in each occupation based on 4-digit Standard Occupational Classification [SOC] codes from the *Integrated Public Use Microdata Series* (IPUMS) 5% sample of the 2000 United States Census.[3] To compute the male share of the occupation we restrict the Census sample to include workers between the ages of 25 and 64. In calculating average wages within occupations, we further restrict the sample to include workers who are not

[1] Wave I in-home interviews were conducted between April and December 1995; Wave II in-home interviews were conducted between April and August 1996; and Wave III interviews were conducted were conducted between August 2001 and April 2002. In addition, data from a fourth wave of interviews conducted between April and June 2007 and January and February 2008 have recently been made available. Given our interest in early-career jobs, we focus on labor market outcomes captured at Wave III.

[2] Youth are 11-21 and 11-23 years old in Waves I and II, respectively.

[3] For individuals with missing 4-digit (4,936 observations from a total of 15,196 observations) SOC codes in the Add Health data, if available, we either assigned them their three-digit (70 observations) or their two-digit (43 observations) SOC codes.

self-employed and who have non-missing hourly wages (computed as annual wages divided by weeks worked times usual hours of work in the past calendar year).[4]

In addition, we merge in information on the male share of students in each field of study from the U.S. Department of Education, National Center for Education Statistics, Integrated Postsecondary Education Data System (IPEDS) in order to compare the gender composition of various discipline areas.[5] Unfortunately, IPEDS and Add Health data did not have a unique field-of-study "key" to merge on. We created the key across the two survey instruments based on the description of the field of study and the data labels used in the Add Health survey. We base our field of study measure on the respondents' highest level of completed education (above high school degree) for 99.5 percent of the observations and on the respondents' current highest field of study for 0.5 percent of the observations.[6] Add Health comprises of 16.0 percent of respondents with field of study information at the 4-digit level (e.g., African Studies), 57.9 percent at the 2-digit level (e.g., Area Studies total), and 26.1 percent at the 1-digit level (e.g., Area, Ethnic, and Cultural studies total).[7]

A total of 8,594 respondents between the ages of 20 and 25 in the Wave III cross-section have non-missing values for all of the variables of interest in all three waves.[8] This narrow age

[4] A detailed list of occupations is available upon request.

[5] IPEDS did not have information on the male share in trade certificate fields (i.e., funeral, cosmetic, and food preparation). For these fields we assume the gender balance is the same as in the occupation and used information on the male share in the occupation using the IPUMS 2000 Census data.

[6] While 9.35 percent of the field of study sample is currently enrolled in school, we generally do not have information on their current field of study. Thus we utilize field of study from the highest level of completed education (above high school degree). The field of study sample comprises 37.7, 58.5, 2.5, and 1.2 percent of respondents with (completing) an associates, a bachelors, a masters, and a professional degree, respectively

[7] In almost half of the cases (42.0 percent) we are have an exact match between the Add Health and IPEDS data, that is, we merge the field of study information at the same level of detail. In 42.8 percent of the cases where four-digit information is not available in IPEDS, we instead merge based on two-digit information. In the cases where neither two- or four-digit level information is available (15.2 percent) in IPEDS, we merge on one-digit information. A detailed list of fields of study is available upon request.

[8] Wave I in-home interviews included 20,745 adolescents; Wave II in-home interviews included 14,738 adolescents, and Wave III in-home interviews included 15,197 young adults. The number of respondents that have information in all three waves is 11,621. The Wave I in-home sample included the core sample from each community plus a

range allows us to focus explicitly on young workers at the beginning of their careers. From this group we draw two estimation samples. The field of study sample is further restricted to respondents who have higher than a high school degree in Wave III. The occupational attainment sample is further restricted to respondents who completed their formal education and were employed in Wave III. This produces two estimation samples of 1,653 (field of study) and 3,935 (occupational attainment) respectively.

2.2 Gender Differences in Field of Study and Occupational Attainment

The distribution of men and women between the ages of 20 and 25 with (or completing) degrees beyond their high school diplomas at Wave III across fields of study is provided in Figure 1.[9] To facilitate comparisons, we have ranked discipline areas by the proportion of men choosing to study them. The most common field of study for both men and women is business. One in five men (20.6 percent) and nearly one in five women (17.7 percent) attending college study a business-related field including business management or administrative services. These patterns are consistent with other evidence that there is gender balance among business students. In 2005 – 2006, for example, half of all bachelor's degrees in business management, business administration, and marketing were awarded to women in comparison to only 8.5 percent in 1965-1966 (Blau et al. 2010, pg. 157). In other fields, the gender gap continues to be much larger. Men in our sample are much more likely than women to study engineering for example

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number of over-samples (saturated schools, disabled, blacks from well-educated families, Chinese, Cuban, Puerto Rican, and adolescents residing with a twin). The Wave II in-home sample was the same as the Wave I in-home sample with the following exceptions: the majority of respondents in grade 12 were excluded from Wave II because they exceeded grade eligibility requirement; the Wave I disabled sample was not re-interviewed in Wave II; and a small number of respondents participated in Wave II but not Wave I. The Wave III in-home sample was the same as Wave I in-home sample conditional on locating the Wave I respondents. For more information on the samples see http://www.cpc.unc.edu/projects/addhealth/design.

[9] This includes 1,595 women and 1,062 men, respectively. This sample does not impose the extra restriction that individuals must have non-missing values on all the Wave III variables of interest. The distributions look similar if we instead focus on the restricted sample and are available upon request.

(13.5 vs. 2.1 percent), while women are much more likely than men to study for careers as health professionals (14.7 vs. 2.4 percent). These gender gaps are consistent with the fact that only 19.4 percent of engineering degrees in 2005-2006 were awarded to women, while women received 86.0 percent of bachelor's degrees in health (Blau et al. 2010, pg. 157).

Figure 1 Here

There are also gender differences in the occupations in which the young men and women in our sample are employed. Men are most often employed in construction and extraction (15.3 percent), sales (11.3 percent), and installation, maintenance, and repair (9.9 percent) jobs (see Figure 2).[10] Young women, on the other hand, are virtually never employed in construction or installation jobs (less than 0.5 percent each), but are over represented in sales (18.2 percent) and office and administrative support (15.9 percent).[11] In other occupations, for example management and art, design, entertainment, sports and media there is virtually no gender gap. Previous research suggests that it is reasonable to believe that this occupational segregation among the young workers in our data is almost certainly related to the educational presorting discussed above. Borghans and Groot (1999) conclude, for example, that over the 1980s educational presorting accounted for approximately two-thirds of occupational segregation in the Netherlands. At the same time, the link between occupation and field of study is stronger in some fields (e.g. law, education, engineering, etc.) than in others (e.g. English, history, humanities). This implies that the degree to which educational presorting drives occupational

[10] This includes 2,882 women and 3,172 men between the ages of 20 and 25, respectively. This sample does not impose the extra restriction that individuals must have non-missing values on all the Wave III variables of interest. The distributions look similar if we instead focus on the restricted sample and are available upon request.

[11] Using data from the 2000 U.S. Census, we find women between the ages of 40-60 continue to virtually never be employed in construction or installation jobs and are over-represented in sales and office and administrative support. Moreover, we find that while men between the ages of 40-61 are most often employed in management, construction and extraction continues to be a male dominated field. Interestingly, while management was roughly a gender neutral field for 18-28 year olds (5.52 and 6.03 percent female and male, respectively), it slowly diverges. Specifically, the percent female and male are 7.25 and 9.90 for 29-39 year olds, 7.79 and 12.76 for 40-50 year olds, and 7.64 and 14.11 percent for 51-61 year olds, respectively.

segregation will also vary across occupations. Moreover, Morgan (2008) argues that gender wage gaps are smaller within bachelor's degree professional majors and graduate degree professional majors in part because these fields of study have tighter links to jobs. As a result, the implications of educational presorting for the gender wage gap will also vary across occupations.

Figure 2 Here

2.3 Non-cognitive Skills

Respondents to the Add Health Survey were asked in Waves I and II to describe how well a detailed list of attributes described them and their behavior.[12] We use factor analysis to determine if the large number of observed attributes can be explained largely (or entirely) in terms of fewer unobserved variables called *factors* for modeling purposes.[13] As is common in factor analysis, we rely on two "rules of thumb" in selecting the number of factors to be considered. We set the number of factors equal to the number of eigenvalues that are greater than 1 (Kaiser 1960),[14] as well as restricting the rotated factor loadings (i.e., the correlation coefficients between the observed variables and the factors) to be greater than 0.4 for the central factor and 0.25 for the other factors (Raubenheimer 2004).[15] Moreover, we ensure that the Cronbach's alpha statistic (i.e., a measure of the *internal consistency reliability* of factor

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[12] Add Health also includes a number of questions on attributes related to health (lot of energy, seldom sick, heal fast, coordination, physical fitness) and attributed related to interpersonal style (never argue, never sad, never criticize.) We do not consider these in our analysis. We confirm with factor analysis that these variables indeed do not appear to be the same concepts as the other non-cognitive skill measures.

[13] Although we use principal factor analysis (PFA), we could have used an alternative approach, principal component analysis (PCA). Results using PCA are similar and available upon request. Factor analysis was based on a sample of 11,160 respondents providing complete information on their observed attributes in Waves I and II.

[14] We have 9 factors with eigenvalues greater than 1 (we began with 33 observed attributes) and these 9 factors explain 58 percent of the total variance.

[15] Another rule of thumb is to have loadings of 0.70 as this indicates that roughly half of the variance in the indicator is explained by that factor, this rule however is very restrictive in real world data. We use rotation as it makes the output more understandable because observed variables cannot load on multiple factors. In particular, we rely on VARIMAX rotation, which is the most commonly used rotation, as it makes it as easy as possible to identify each observed personality variable with a single factor.

analysis) is greater than 0.80 for the central factor and 0.50 for the other factors. The groupings of indicators obtained through factor analysis can be thought of as indicative of the underlying patterns in the data. Consequently, we use them as well as casual empiricism to guide our final set of attributes to be considered.

The factor analysis led us to consider seven separate attributes: 1) male traits; 2) self-esteem; 3) analytical problem solving approach; 4) willingness to work hard; 5) impulsiveness; 6) problem avoidance; and 7) self-assessed intelligence. We will refer to these attributes collectively as "non-cognitive skills".[16] The detailed questions that comprise each of these seven attributes are listed in Appendix Table 1. While the possible responses to each of the individual questions (with the exception of intelligence) ranged from 1 (strongly agree) to 5 (strongly disagree), for interpretive ease we reversed the ranking for all but three of the questions (shy, sensitive, and emotional). Intelligence ranges from 1 (moderately below average) to 6 (extremely above average). Appendix Table 2, which presents the factor loadings and Cronbach's alpha statistics, illustrates that all but the first attribute (male traits) meet the "rules of thumb" tests discussed above. Male traits, on the other hand, include a set of attributes (independent, assertive, (not) shy, (not) sensitive, (not) emotional) that were not considered to be a "factor" but which we argue should indeed be grouped together as a single attribute. Specifically, we rely on the BEM Sex Role Inventory (BSRI) TEST; which is an instrument used to judge how masculine or feminine a person is (Bem 1976).[17] The attributes that we consider to be male traits coincide with those considered to be masculine in the BSRI test.

[16] Following common practice in the economics literature, we use the term "non-cognitive skills" to distinguish between a range of personality traits or social skills from other productivity-related skills which are generally seen as more "cognitive". See Kuhn and Weinberger (2005) for a discussion.
[17] A version of the BSRI test is available at:
http://www.siprep.org/faculty/cdevincenzi/documents/HS_A1b_Bem_Androgyny_Test.pdf.

Table 1 documents the degree to which non-cognitive skills measured in this way vary across gender for the full sample of 8,594 Wave III respondents. Means (and standard deviations) are presented by gender both for skills as a whole as well as for their individual components. Bolding (and shading) indicates those gender differences in skills that are statistically significant. Adolescent boys have significantly higher levels of the traits that are generally ascribed to men and lower levels of traits generally ascribed to women (BEM 1976). Interestingly, however, while this is true across this trait in aggregate, there are exceptions among its individual components. Adolescent girls report significantly lower (rather than higher) levels of shyness than do teenage boys, while the gender gap in assertiveness and independence among young people is not significant.

Table 1 Here

Teenage girls are also as likely as teenage boys to report that they take an analytical approach to problem solving by getting the facts, judging and considering alternative solutions, and then judging the outcome after carrying out a solution. Moreover, there is no significant difference in the extent to which teenage girls and boys see themselves as "intelligent". Despite this, teenage boys have significantly higher levels of self-esteem. They are more likely to say that they have many good qualities, are proud of themselves, like themselves, are 'just right', are socially accepted, and feel loved. They are also significantly more likely to say that they are willing to work hard.

Consistent with many studies of teenage risk taking (see Byrnes et al. 1999 for a review), adolescent boys report higher levels of impulsiveness than do adolescent girls. Boys are more likely to report that they follow their gut feelings, take risks, and live for today. Finally, adolescent boys are also somewhat more likely than their female counterparts to report that they try to avoid problems, despite the fact that they are substantially less likely to report that they get upset by problems. Overall, teenage boys score somewhat lower on our overall measure of problem avoidance than do teenage girls.

2.4 Observable Characteristics

Our analysis also includes a number of demographic characteristics. These are all based on Wave III except for one (indicated below). Age is the respondent's age as of the Wave III survey (restricted to range from 20 to 25). Female is an indicator variable equal to one if the respondent is female and zero otherwise. White is an indicator variable equal to one if the respondent reported he or she is white only, and zero otherwise.[18] Married is an indicator variable equal to one if the respondent reported he or she is currently married (including couples who are not currently living together), and zero otherwise. We also include controls for the number of children less than 6 years of age and the number of children between 6 and 12 years of age. Finally we include the Add Health Picture Vocabulary Test Score (which is an adapted version of the Peabody Picture Vocabulary Test) from Wave I standardized by age (each group having a mean of 100 and standard deviation of 15) (Dunn and Dunn 2007).

Finally, we include two measures of future expectations. Specifically, the Add Health survey asked "What do you think are the chances that each of the following will happen to you: you will have a middle income at age 30 and you will be married by age 25". Possible responses include 1 (almost certain), 2 (a good chance), 3 (a 50-50 chance), 4 (some chance, probably not), and 5 (absolutely no chance). Once again for interpretive ease, we reverse the scale.

[18] Respondents were allowed to report multiple races, thus an individual who reported white in addition to another race is coded as zero.

Summary statistics by gender are presented in Appendix Table 3 for the full sample of 8,594 Wave III respondents. Females and males are roughly the same age on average, 21.76 and 21.88, respectively. The sample is predominantly white (i.e., roughly 74 percent white) and native-born (roughly 95 percent non-immigrant). Given the young age of the sample, very few respondents are married (21.4 and 11.6 percent for females and males, respectively) or have children, especially children older than 6 years of age. Males performed slightly better on average on the picture vocabulary test (102.6) relative to their female counterparts (101.3). Finally, males, relative to females, are slightly more likely to believe they will have a middle income at age 30 and be married by age 25.

3. Estimation Strategy

Our objective is to understand how this diverse set of non-cognitive skills, measured in high school, influences the occupational choices of young people as they enter the labor market. In what follows, we outline the conceptual framework which guides our thinking, drawing an explicit distinction between occupational choice and occupational attainment. We then discuss the implications of this framework for empirical models like ours that seek to estimate the determinants of the gender composition and wage level of occupations.

3.1 Conceptual Framework: Occupational Choice and Occupational Attainment

Building on the work of Gupta (1993), we begin with a simple conceptual framework in which young people's occupational choices are driven by their expectations of the life-time, net benefits associated with alternative career paths. In particular, we assume that the expected utility at time *t* of individual *i* entering occupation *j* is given by the following:

$$E_t[U_{ij}] = E_t[X_i\beta_j + \gamma_{ij} + \varepsilon_{ij}] \quad (1)$$

where X_i is a vector of productivity-related characteristics (including both cognitive and non-cognitive skills), β_j is a vector of occupation-specific pecuniary returns, and γ_{ij} captures the individual-specific non-pecuniary benefits (or costs) associated with employment in occupation *j*. Finally, ε_{ij} is an error term which may reflect, for example, optimization errors or uncertainty about future returns.[19] This framework implies that the net benefit of entering each occupation is driven by individuals' expectations about the labor market return to their own human capital (i.e. expected wages) when employed in that occupation as well as their individual preferences for working in that occupation. Those who expect to face hiring or wage discrimination from employers -- and hence have low expected future wages -- may choose to avoid entering particular occupations (Blau et al. 2010).

The probability that individual *i* chooses to enter—and train for—occupation *j* (P_{ij}^C) is then given by:

$$P_{ij}^C = \Pr ob(c_{ij} = 1) = \Pr ob(E_t[U_{ij}] > E_t[U_{ik}]) \quad \text{for all } k \neq j \quad (2)$$

In this context, individuals choose different occupations either because they have characteristics that lead them to be more productive in some occupations than others (and hence enjoy higher returns) or because they have idiosyncratic preferences for certain occupations over others (see also Filer 1986). This implies then that non-cognitive skills will affect occupational choices through future productivity (and hence expected future wages) as well as preferences over occupation-specific employment conditions.

[19] O'Donoghue and Rabin (2001) review the evidence from the psychological literature on adolescent decision making focusing particularly on risk taking. Many of the types of optimization errors discussed by O'Donoghue and Rabin have implications for decisions about future career paths.

Occupational attainment, however, reflects both the decisions of potential workers to train and apply for entry into specific occupations as well as employers' choices about which applicants to hire. Let the productivity of worker *i* when employed in occupation *j* (w_{ij}) be given by:

$$w_{ij} = X_i \beta_j + \mu_{ij} \tag{3}$$

where μ_{ij} is an error term capturing the firm's uncertainty about worker productivity which results perhaps from information asymmetries. Firms are assumed to hire a job applicant if his or her occupation-specific productivity exceeds a specific threshold $\overline{w_j}$. This implies that the probability of an applicant being hired into occupation *j* (P_{ij}^H) is given by

$$P_{ij}^H = \Pr ob(h_{ij} = 1 \mid c_{ij} = 1) = \Pr ob(w_{ij} - \overline{w_j} > 0) \tag{4}$$

The probability that individual *i* is employed in occupation *j* can then be written as:

$$P_{ij} = \Pr ob(o_{ij} = 1) = \Pr ob(c_{ij} = 1) * \Pr ob(h_{ij} = 1 \mid c_{ij} = 1)$$

$$= P_{ij}^C P_{ij}^H \tag{5}$$

Given this framework, the distribution of men and women across fields of study can be seen as largely revealing individuals' choices to enter and train for particular occupations. In effect, it is individuals' beliefs about (and preferences over) the future returns to and non-pecuniary aspects of various career paths that underpin the decision to enter specific fields of study. Non-cognitive skills influence individuals' field of study choices by affecting expectations regarding both productivity in and preferences for specific occupations. Actual occupational attainment, however, also reflects the outcome of firms' hiring decisions and changes in individuals' occupational choices as a result of updated information they may have acquired along the way. Both combine to produce job mobility that may either exacerbate or mitigate the pre-occupational sorting that occurs before individuals enter the labor market (see Borghans and Groot 1999; Spookram and Strobel 2009). Non-cognitive skills may have a differential effect on the field-of-study and occupational attainment distributions either because non-cognitive skills affect employers' hiring and pay decisions in ways that students do not completely anticipate, or because students have not fully anticipated the non-pecuniary costs and benefits of being employed in particular occupations.

3.2 Estimation Model

Given our data, we are not able to directly estimate the model of occupational choice and occupational attainment described above. Despite this, it is a useful framework for highlighting the demand-side (through worker productivity) and supply-side (through anticipated returns and worker preferences) effects of non-cognitive skills on occupational outcomes. Importantly, the way in which individuals' non-cognitive skills are matched to occupations is likely to differ for young men and young women. It seems reasonable to expect, for example, that non-cognitive skills may be one more basis on which labor market discrimination can occur. In addition, men and women appear to have different preferences over the job attributes inherent in different occupations (Daymont and Andrisani 1984; Turner and Bowen 1999; Montmarquette et al. 2002; Boudarbat and Montmarquette 2007; Freeman and Hirsch 2007; Rosenbloom et al. 2008; Zahfar 2009). The process generating gender differences in preferences is complex and not well understood, but is likely to stem from social expectations about appropriate gender roles, disparity in educational experiences (including discrimination), information asymmetries, etc. Unfortunately, our estimation strategy will not provide us with a way of separately identifying these demand- and supply-side influences.[20] Consequently, the interpretation of our estimates of the effect of non-cognitive skills on occupational choice and occupational attainment must admit all of these possibilities.

Our interest is not in the way that non-cognitive skills are related to the propensity to enter specific occupations, but rather in the extent to which non-cognitive skills provide an explanation for occupational segregation overall. This interest in vertical integration requires us to quantify occupations in some way (see Miller 1987). Consequently, we assign to each field of study code the proportion of students in that field who are men. Occupation codes are assigned both the proportion of workers in that occupation who are men and average occupation-specific wages (see Section 2.2). We then estimate the determinants of the vertical integration of individual *i*'s field of study and occupation (Y_i^n) as follows:

$$Y_i^n = Z_i\delta + \Gamma_i\psi^g + \mu_i \tag{6}$$

where *n* indexes our three estimation models (i.e., field-of-study gender composition, occupation gender composition, and occupation average wages), g indexes gender, Z_i is a vector of individuals' productivity-related, personal characteristics and cognitive skills, Γ_i captures non-cognitive skills, δ and ψ are vectors of parameters to be estimated, and μ_i is an iid error term with classical properties (see Greene 2008).

The model given by equation (6) allows the effect of non-cognitive skills on moving into male-dominated (or higher-wage) occupations to differ across gender.[21] We consider three

[20] Brown et al (2005; 2008) present an econometric framework for modeling occupational choice which separately accounts for both supply-side and demand-side influences. Identification is achieved by specifying some factors that affect 1) only supply-side choices and 2) only demand-side choices. In their case, family background and gender are assumed to be supply-side factors, while work experience, schooling and qualifications are assumed to be demand-side factors. Unfortunately, we do not see a clear argument for making a similar distinction with respect to the range of non-cognitive skills we consider.

alternative specifications. The first represents our baseline specification and includes measures of both personal characteristics and non-cognitive skills. The second drops indicators for marital status and the presence of children instead accounting for expectations about future income and marital status. Finally, the third specification includes marital status and child indicators along with our measures of expectations. Equation (6) is estimated using Ordinary Least Squares (OLS) which allows us to consider between 192 (field of study) and 346 (occupations) detailed occupational categories.[22] Results (OLS coefficients and robust standard errors) are provided in Table 2 (field of study) and in Tables 4 and 5 (occupation).

4. Results

4.1 Non-cognitive Skills and Male-Dominated Fields of Study

It is no surprise that we find women are less likely than men to enter male-dominated fields of study. Everything else equal, women are majoring in discipline areas in which the proportion of all students who are men is 21.8 percentage points lower than is the case for their male counterparts (see Table 2). It is important to note that this gap in the gender composition of women's discipline areas is not explained by gender differences in the personal characteristics, cognitive skills (as measured by vocabulary test scores) or non-cognitive skills which are accounted for in the estimation. Although the gap could be evidence of pre-market discrimination in educational opportunities, this seems unlikely given other evidence that in recent years girls have outperformed boys in many areas (including in reading and in grade point

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[21] We also estimated a model that allowed personal characteristics and future expectations to differ across gender. Given the patterns found for non-cognitive skills generally remain unchanged as do the effects of personal characteristics and future expectations (i.e., the level terms generally display the same patterns and the interaction terms are generally insignificant), we do not present these results here. These results are available upon request.

[22] Ordered probit regression is also occasionally used to examine the determinants of occupational rankings (e.g. Miller 1987). However, estimation of ordered probit models requires analysis of more aggregated occupations which typically combine finer occupational categories that have very different gender ratios and average wages.

averages overall), have narrowed their test-score gap in math, and are enrolling in high school math and science courses that are at least as challenging as those undertaken by boys (see Freeman 2004; Blau et al. 2010 for reviews). It seems more likely that gender segregation in discipline areas stems in part from the different preferences that men and women have for the job attributes associated with different occupations.

Table 2 Here

Individuals' non-cognitive skills are related to the educational choices that they are making. Entry into male-dominated fields of study is most closely related to the extent to which individuals believe they are intelligent and have "male" traits, i.e. are independent, assertive, not shy, not sensitive, and not emotional. These two non-cognitive traits have substantively different effects on the behavior of men and women, however. Each one standard deviation increase the extent to which men report that they have traditional male traits is associated with a 3.3 percentage point increase in the proportion of their classmates who are men. The effect of having traditional male traits on entry into traditionally-male fields of study is significantly smaller for women. Thus, contrary to common perceptions, women who exhibit traits commonly associated with men are only slightly more likely than other women to enter discipline areas dominated by men. Moreover, each one standard deviation increase in the extent to which men report that they are intelligent is associated with a reduction of 3.0 percentage points in the proportion of individuals in their chosen field of study who are men. In contrast, the effect of self-perceived intelligence on the extent to which ones discipline area is male-dominated is significantly larger (4.9 percentage points), and overall positive, for women.[23] For both men and

[23] The marginal effect of each unit increase in self-perceived intelligence is 1.9 percentage points for women, i.e. the sum of the overall effect for men and the interaction term, and -3.0 percentage points for men.

women, self-assessed intelligence is associated with entry into fields of study that are relatively less traditional for ones gender.

Other non-cognitive skills – i.e., self-esteem, analytical approach to problem solving, willingness to work hard, impulsivity, and problem avoidance – are not significantly related to the gender composition of an individual's chosen discipline area. Although adolescent boys have significantly higher self-esteem and are significantly more likely to report that they are willing to work hard, are impulsive, and want to avoid problems (see Table 1), after controlling for these differences, we find no evidence that the process which matches these non-cognitive skills to fields of study differs for young men versus young women.

Additionally, personal characteristics such as age, race, immigrant status, marital status, and the presence of children and cognitive ability as reflected in vocabulary test scores are unrelated to individuals' decision to study disciplines dominated by men. Fields of study are also unrelated to individuals' expectations (while in high school) about their marital status at age 25. This is somewhat inconsistent with previous research which links women's occupational choices to their future need to balance family and work commitments (see Polachek 1981; Anker 1997). At the same time, the higher are high school students' expectations about their salaries at age 30, the higher is the proportion of men enrolled in their chosen field of study while they are in their twenties. Specifically, each one standard deviation increase the extent to which respondents report that they expect to be middle income earners at age 30 is associated with a 1.4 percentage point increase in the proportion of their classmates who are men. Finally, we note that the estimated effect of non-cognitive skills on the gender composition of individuals' chosen discipline area is virtually identical across our three specifications. This implies that while expectations about income at age 30 have some effect on the decision to enter traditionally-male fields of study, this effect is independent to those associated with non-cognitive skills.

4.2 Occupational Rankings

Occupational rankings (based on 2000 U.S. Census data) are provided in Table 3 separately for younger women aged 18 – 28 and older women aged 25 – 64. We consider 23 specific occupations. Each is ranked on the basis of the proportion of the workforce that is male as well as on average wages.

Interestingly, there is little difference in occupational rankings based on gender composition across the two age samples. In only two cases, legal studies and food preparation and serving, do the rankings across the age groups differ by more than two ranks. In particular, food preparation and serving is more male-dominated (has a higher rank) among younger workers aged 18 – 28 than among older workers 25 – 64. The legal occupation is more female-dominated among younger workers. There are more differences in the occupational rankings based on average wages. In total, the ranking of five of the 23 occupations considered differs by more than two ranks across the two samples of workers. Three occupations –management, sales, and military specific – are relatively better paid among older workers than among younger workers. Production and business operations and financial specialist jobs are relatively better paid among younger workers. Overall, the ranking of occupations, particularly with respect to the gender ratio, appear to be quite stable across age groups.

Table 3 Here

In contrast, occupational rankings based on average wages are fundamentally different to those based on gender composition. With only two exceptions – architecture and engineering (all workers) and personal care and service (workers aged 18 – 28) occupations – rankings based on wages differ to those based on the proportion of the workforce that is male by more than two places. In short, high wage occupations are not necessarily those in which men are over-represented. For example, the legal occupation is the highest paid occupation for workers aged 25 – 64, but is only 13th in terms of the proportion of the jobs that are held by men. Farming, fishing and forestry jobs pay the least, but are relatively male dominated (ranked 7th). A similar disparity exists in the occupational rankings of workers aged 18 – 28.

These patterns highlight the importance of considering multiple dimensions of occupations when analyzing the drivers and consequences of occupational integration. Much of the previous literature has focused on understanding the extent to which the gender wage gap could be reduced by reducing gender segregation across fields of study or occupations (e.g. Daymont and Andrisani 1984; Miller 1987; Groshen 1991; Morgan 2008; Cobb-Clark and Tan 2010; Zafar 2009). At the same time, the results in Table 3 highlight the fact that encouraging women to move into male-dominated occupations is not necessarily the same thing as encouraging them to move them into highly-paid occupations.

4.3 Non-cognitive Skills and Entry into Male-Dominated and High-Wage Occupations

The estimated relationship between workers' non-cognitive skills and the gender composition of their occupations is presented in Table 4. As before, we consider three alternative specifications which are increasing in controls.

Women on average are employed in occupations in which the proportion of workers that are men is nearly thirty percentage points lower than is true for the occupations in which otherwise similar men work (see Table 4). This disparity in the gender composition of the occupations in which men and women are employed is somewhat larger than the 21.8 percentage point gap in the gender composition of men's and women's fields of study (see Table 2). Thus, the occupations in which men and women work are more segregated along gender lines than are the discipline areas in which they study. A number of things might account for this divergence. First, demand-side factors, in particular firms' hiring and promotion decisions, may produce a wedge between the occupations that individuals train for and the occupations in which they are employed (see Section 3.1). This wedge is likely to be larger in some occupations than in others (Morgan 2008) and may either result in more or less segregation (Borghans and Groot 1999; Spookram and Strobel 2009). Second, there may be less gender segregation among the highly-educated young people for whom we have information about fields of study than there is among workers as a whole. Finally, the diversity in men's and women's preferences over occupations may intensify after they enter the labor market and begin working.

Table 4 Here

The effect of having "male" traits (i.e., independent, assertive, not shy, not sensitive, not emotional) and being intelligent on entry into male-dominated occupations is much the same as on entry into male-dominated fields of study.[24] Each one standard deviation increase the extent to which men report that they have traditional male traits is associated with a 2.7 percentage point increase in the proportion of their workmates who are men, while each one standard deviation increase in the extent to which men report that they are intelligent is associated with a reduction of 3.8 percentage points in the proportion of workers in their occupation who are men. In contrast, the effect of self-perceived intelligence on the extent to which women are employed in male-dominated occupations is essentially zero.

[24] The exception is that the interaction between being female and having male traits while negative is not statistically significant when we consider occupational attainment.

At the same time, the willingness to work hard, impulsivity, and the tendency to avoid problems, although unrelated to the gender composition of field of study areas, are linked to the gender composition of the occupations in which men and women work. Men and women who report that they are willing to work hard are employed in occupations which are more male-dominated, while the tendency to avoid problems is related to working in occupations with relatively more women. Women who describe themselves as “impulsive” (i.e., go with their gut feelings, take risks, and live for today) are employed in occupations which are significantly more male-dominated than are the occupations of men who also see themselves as impulsive. These results suggest that firms’ hiring and promotion decisions may push those workers who are willing to work hard, tackle (rather than avoid) problems, and (for women) take risks into male-dominated occupations.

Although personal characteristics are unrelated to the gender composition of individuals/ fields of study (see Table 2), we find that older workers, white workers, and those with children between the ages of 6 and 12 are employed in occupations in which the proportion of workers who are men is significantly higher (see Table 4). Finally, expectations about future marital status and income have no significant effect on the extent to which workers are employed in male-dominated occupations. Moreover, the estimated effect of non-cognitive skills on the gender composition of individuals’ occupations is unaffected by the inclusion of these variables in the estimation model. Thus, we find no evidence for the proposition that individuals who anticipate having high incomes or family responsibilities in the future are more likely to be employed in occupations dominated by men.

Thus far we have been concerned with segregation into male- versus female-dominated occupations. Our conceptual framework, however, highlights the importance of expected wages in driving occupational choice, while Section 4.2 demonstrates that an occupational ranking based on gender composition differs substantially to that based on average wages. Given this, we turn now to consider the effect of non-cognitive skills on occupation-specific wage levels.

Table 5 reveals that self-assessed intelligence is associated with a substantial increase in within-occupation average wages ($0.81 for each standard deviation change), while impulsiveness is related to a reduction in average wages ($0.61 for each standard deviation change). The interaction between being female and having these non-cognitive skills is insignificant implying that, in terms of occupation-specific wages, women's return to these non-cognitive skills is the same as men's. Taken together, these results suggest that the occupation-specific wage returns to women's non-cognitive skills are at least as large as those for men.

Table 5 Here

Individuals' personal characteristics are unrelated to the gender composition of their chosen fields of study (see Table 2) and only loosely related to the gender composition of the occupations in which they work (see Table 4). There are strong links, however, between workers' personal characteristics and the average wage levels in their occupations. Occupation-specific wages are higher among older workers ($0.53 for each year of age) and among immigrants ($1.34). Cognitive skills (as reflected in vocabulary test scores) are also associated with modestly higher average wages ($0.06 for each standard deviation increase). Children, on the other hand, are related to a reduction in average wages of between $0.50 (children less than 6) and $0.47 (children aged 6 – 12). It is important to note that these results pertain to the average wage level in the occupation as a whole and not to an individual's own wage. Nonetheless, they highlight that access to high-wage occupations varies across demographic groups in a way that entry into male-dominated occupations does not.

Finally, the more high school students expect to earn at age 30, the lower is their occupation-specific wage when they are between the ages of 18 and 28. In contrast, expecting to be married at age 25 is associated with being in a higher-paid occupation in ones twenties. These patterns may reflect the fact that adolescents often have difficulty in forming expectations about the future (see O'Donoghue and Rabin 2001). At the same time, many young workers in the early stages of their careers progress rapidly through a number of occupations suggesting that their early occupations are not completely indicative of the occupations in which they will spend the majority of their working lives.

5. Conclusions

Men and women tend to be employed in very different occupations. While occupational segregation has declined over time, in the U.S., for example, more than half of female (male) employees would have to change jobs in order to eliminate occupational segregation (see Blau et al. 2010). This persistence in occupational segregation is commensurate with the persistent gender gap in the college majors that men and women choose (Turner and Bowen 1999). Both demand-side factors (e.g., firm's hiring, promotion, retention, training, etc.) and supply-side factors (e.g., worker's human capital acquisition, labor market participation, job mobility, job flexibility, etc.) play a role in explaining occupational segregation as well as educational presorting, however, the factors underlying these processes are still a subject of debate.

Using Add Health data, we shed light on this debate by examining the role non-cognitive skills play in the occupational segregation of young workers entering the U.S. labor market. Specifically, we model the effect of non-cognitive skills on the gender composition of college students' field of study as well as on the gender composition and average wage level of the occupations in which young people are employed. This allows us to shed light on the extent to which educational presorting is an important driver of occupational segregation (see Borghans and Groot 1999).

Not surprisingly, we find that women (holding all else constant) are less likely to enter male-dominated fields of study and male-dominated occupations, although the extent of gender segregation is more acute in occupations in which men and women work. While demand-side factors, particularly firms' hiring and promotion decisions, may produce this wedge between the occupations that individuals train for and the occupations in which they are employed, supply-side factors, particularly men's and women's different preferences for job attributes associated with different occupations, may explain why gender segregation in fields of study and occupations persist despite controls for non-cognitive skills, personal characteristics, and future expectations. It is important to note, however, that young men and women are equally likely to be employed in highly-paid occupations implying that young women do not suffer a wage penalty as a result of these occupational choices.[25]

We also find that individuals' non-cognitive skills are related to the educational and occupational choices that they are making. Specifically, entry into male-dominated fields of study and male-dominated occupations are both related to the extent to which individuals believe they are intelligent and have "male" traits (i.e., are independent, assertive, not shy, not sensitive, and not emotional) while only entry into male-dominated occupations is related to the willingness to work hard, impulsivity, and the tendency to avoid problems. Moreover, the effect of non-cognitive skills on field of study and occupational attainment (based on percent male) tends to differ by gender (e.g., women who are intelligent are more likely to study/work in male-

[25] This is not to say that there is no gender wage gap among young workers. A wage gap may still exist if there is a gender wage gap within occupations.

dominated fields of study). Non-cognitive skills (intelligence and impulsivity) are also found to influence the movement into higher-paid occupations, yet the occupation-specific wage returns to women's non-cognitive skills are the same as men's.

What can we conclude then about the role of non-cognitive skills in explaining the occupational segregation of men and women? Is there any reason to expect that work will become more integrated in the future? Educational pre-sorting and occupational attainment are clearly related to non-cognitive skills such as impulsivity, self-assessed intelligence, and traditionally male traits. Thus, non-cognitive skills provide an important explanation for the disparity in the fields that men and women study as well as in the occupations in which they are employed. This is consistent with previous research documenting the link between non-cognitive skills and college enrollment (Jacob 2002), the effect of preferences on college major choices (Daymont and Andrisani 1984; Turner and Bowen 1999; Freeman and Hirsch 2008; Rosenbloom et al. 2008), and the occupation- and gender-specific nature of the returns to non-cognitive skills (Nyhus and Pons 2005; Mueller and Plug 2006; Cobb-Clark and Tan 2010). At the same time, there remains a large gap -- despite our extensive controls -- in the gender composition of the fields of study and occupations that men and women are entering. Young women continue to be more likely than their male peers to train for and work in occupations dominated by other women making it likely that occupational segregation will remain a feature of many labor markets. Fortunately, our results suggest that the link between gender segregation and gender pay gaps may not be as close as is often thought.

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Figure 1. Field of Study by Gender

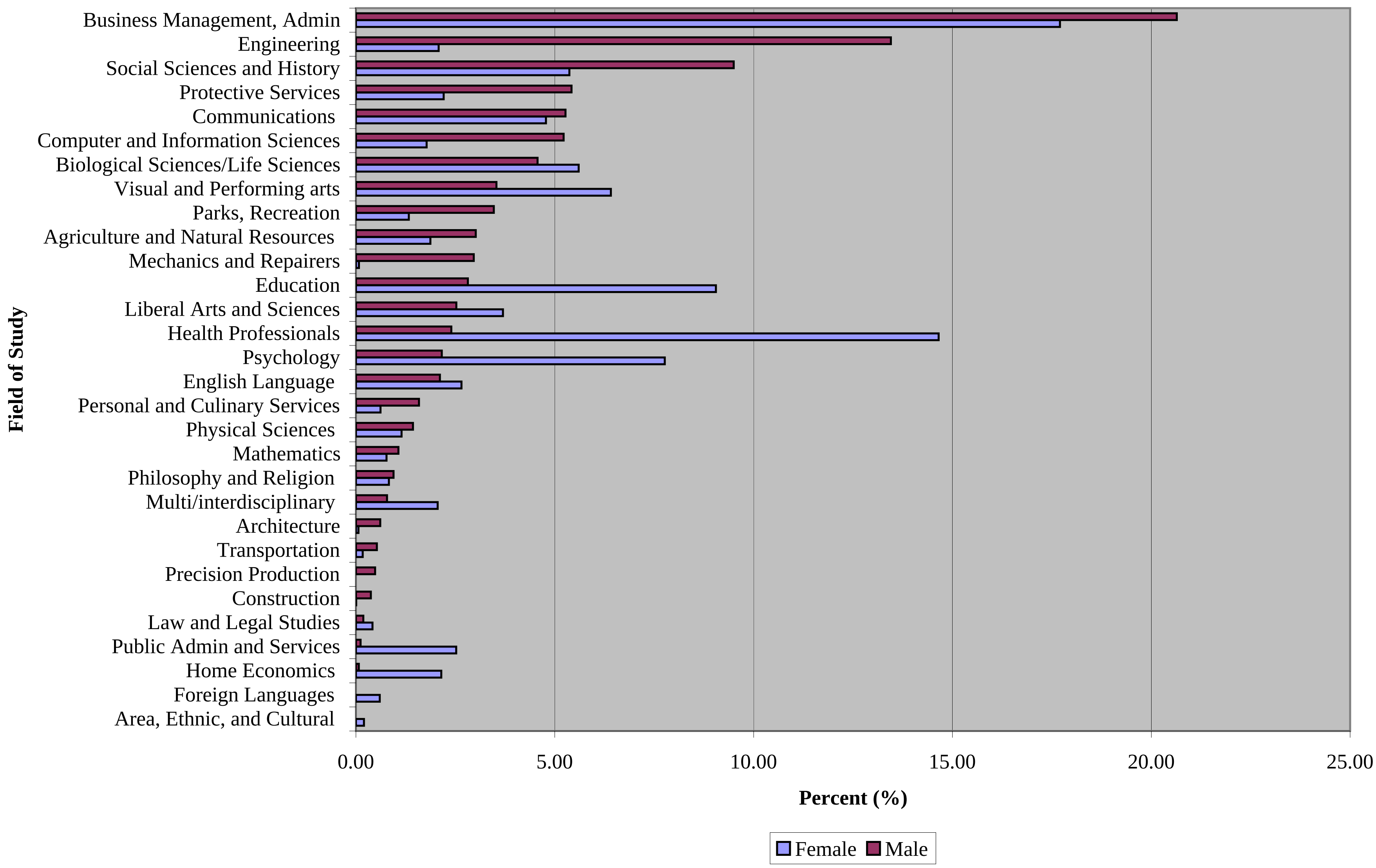

Figure 2. Occupation by Gender

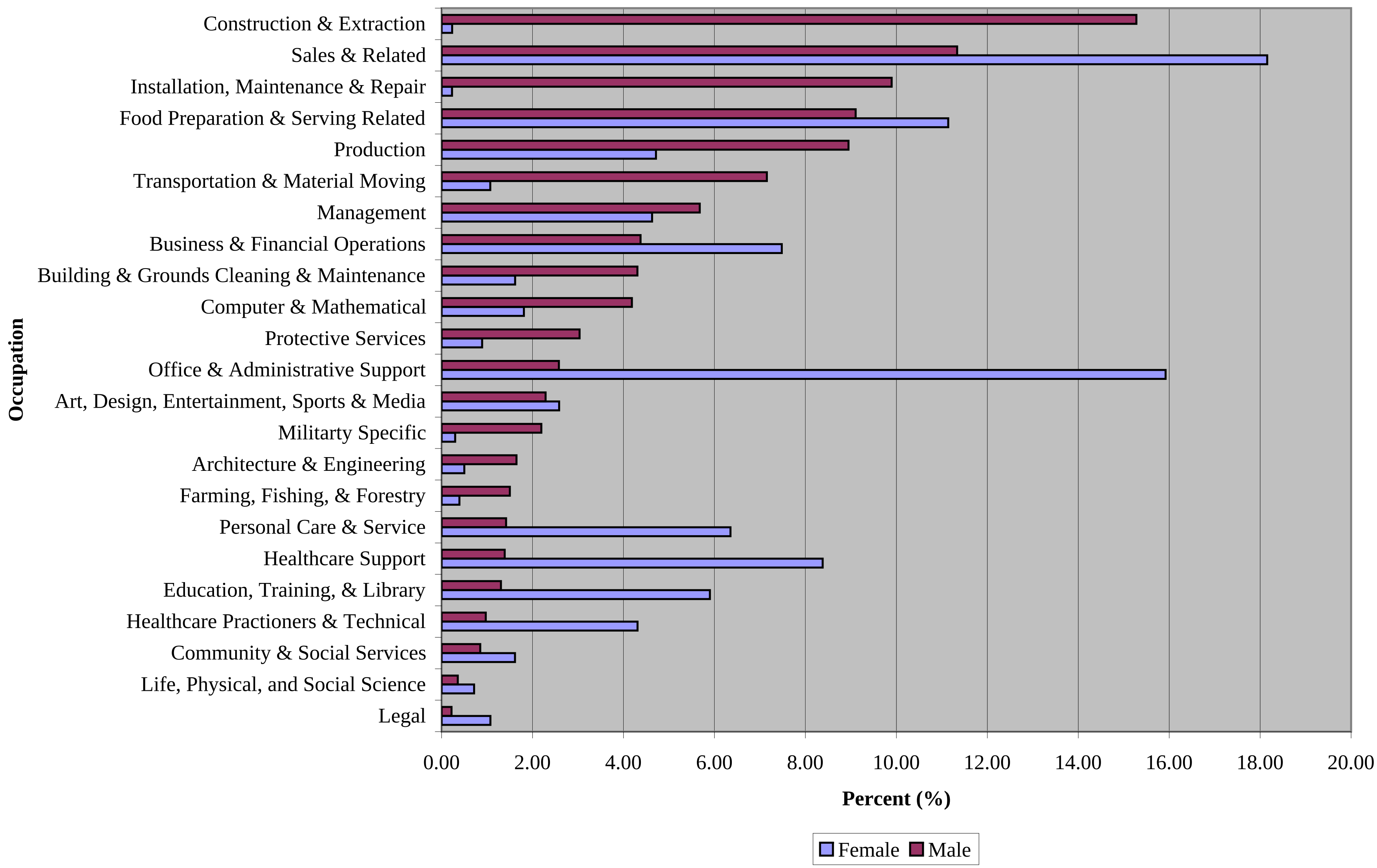

Table 1. Non-Cognitive Skills by Gender

	Female		**Male**	
	Mean	Std. Dev.	Mean	Std. Dev.
Male Traits 2	15.011	2.370	**15.658**	2.324
Independent 2	4.143	0.795	4.108	0.792
Assertive 2	3.716	0.886	3.723	0.863
(Not) Shy 2	3.249	1.248	**3.175**	1.200
(Not) Sensitive 2	1.783	0.733	**2.047**	0.802
(Not) Emotional 2	2.120	0.937	**2.605**	0.982
Self Esteem 12	48.608	6.502	**50.553**	5.883
Good Qualities 1	4.176	0.678	**4.319**	0.629
Proud of Self 1	4.202	0.749	**4.356**	0.675
Like Self 1	3.763	1.018	**4.177**	0.861
Just Right 1	3.622	0.912	**3.852**	0.851
Socially Accepted 1	3.981	0.793	**4.136**	0.746
Feel Loved 1	4.228	0.758	**4.321**	0.689
Good Qualities 2	4.276	0.642	**4.360**	0.623
Proud of Self 2	4.305	0.698	**4.382**	0.667
Like Self 2	3.862	0.990	**4.231**	0.810
Just Right 2	3.770	0.897	**3.912**	0.849
Socially Accepted 2	4.102	0.756	**4.188**	0.731
Feel Loved 2	4.321	0.707	4.319	0.697
Analytical 1	15.076	2.477	15.153	2.559
Judge Solutions 1	3.766	0.816	3.796	0.848
Judge Alternatives 1	3.553	0.867	**3.616**	0.912
Get the Facts 1	3.797	0.847	3.790	0.882
Alternative Solutions 1	3.961	0.738	3.951	0.796
Work Hard 12	7.872	1.483	**8.005**	1.400
Work Hard 1	3.842	0.893	**3.911**	0.860
Work Hard 2	4.029	0.893	**4.093**	0.844
Impulsive 12	11.347	2.824	**12.444**	2.813
Gut Feeling 1	2.872	1.104	**3.122**	1.133
Gut Feeling 2	2.834	1.140	**3.023**	1.131
Take Risks 2	3.386	1.070	**3.723**	0.988
Live for Today 2	2.255	0.991	**2.577**	1.083
Avoidance 12	13.860	2.702	**13.451**	2.796
Avoid Problems 1	3.082	1.032	**3.225**	1.051
Upset by Problems 1	3.677	0.957	**3.379**	1.021
Avoid Problems 2	3.322	1.121	**3.458**	1.071
Upset by Problems 2	3.779	0.987	**3.389**	1.067
Intelligent 12	7.816	1.862	7.840	1.949
Intelligent 1	3.853	1.079	3.875	1.115
Intelligent 2	3.963	1.050	3.965	1.103
	4526		4068	

Notes: 1 and 2 reflect Waves 1 and 2, respectively. Bold (shaded) indicates males are significantly different from females at the 5 (10) % significance level. Individual components range from 1 (strongly disagree) to 5 (strongly agree).

Table 2. Determinants of the Rank of Field of Study: Percent Male (OLS Regression)

	Specification 1		Specification 2		Specification 3	
	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.
Female	**-0.218**	0.016	**-0.216**	0.016	**-0.217**	0.016
Non-Cognitive Skills						
Male Traits 2	**0.033**	0.011	**0.035**	0.010	**0.034**	0.010
Self Esteem 12	-0.007	0.012	-0.006	0.012	-0.006	0.012
Analytical 1	0.002	0.011	0.002	0.011	0.002	0.011
Work Hard 12	0.011	0.011	0.012	0.011	0.011	0.011
Impulsive 12	-0.014	0.013	-0.015	0.013	-0.015	0.013
Avoidance 1	0.000	0.010	-0.001	0.010	0.000	0.010
Intelligent 12	**-0.030**	0.012	**-0.029**	0.012	**-0.028**	0.012
Female*Male Traits 2	-0.022	0.013	-0.022	0.013	-0.022	0.013
Female*Self Esteem 12	0.000	0.015	0.000	0.015	0.001	0.015
Female*Analytical 1	0.004	0.014	0.005	0.014	0.004	0.014
Female*Work Hard 12	-0.019	0.015	-0.019	0.015	-0.020	0.015
Female*Impulsive 12	0.002	0.016	0.002	0.016	0.001	0.016
Female*Avoidance 1	0.000	0.013	0.001	0.013	0.000	0.013
Female*Intelligent 12	**0.049**	0.015	**0.048**	0.015	**0.048**	0.014
Personal Characteristics						
Age 3	-0.006	0.006	-0.005	0.006	-0.005	0.006
White 3	-0.005	0.015	-0.008	0.015	-0.004	0.016
Immigrant 3	0.042	0.028	0.040	0.028	0.041	0.028
Married 3	0.000	0.019			0.001	0.019
Children Less Than 6 3	0.019	0.015			0.018	0.015
Children 6-12 3	0.001	0.021			0.002	0.022
Vocabulary Test Score 1	0.001	0.001	0.001	0.001	0.001	0.001
Future Expectations						
Middle Income at 30 2			**0.014**	0.007	**0.014**	0.007
Marriage at 25 2			-0.004	0.007	-0.003	0.007

Notes: 1, 2 and 3 reflect Waves 1, 2, and 3, respectively.Bold (Shaded) significant at the 5 (10) % level.
Non-cognitive skills and future expectations included as deviations from the mean.
Male share of field of study calculated from statistics obtained from the U.S. Department of Education, National Center for Education Statistics, Integrated Postsecondary Education Data System (IPEDS). These shares were merged into the AddHealth data based on respondent's field of study (see text for more details).
The sample size is 1653 and includes men and women who have greater than a high school degree.

Table 3. Occupation by Rank

Occupation	25-64 **Rank** %Male	Wage	18-28 **Rank** %Male	Wage
Management	10	2	11	6
Business Operations Specialist & Financial Specialists	16	7	15	4
Computer & Mathematical	8	3	7	1
Architecture & Engineering	4	4	5	3
Life, Physical & Social Science	11	6	12	7
Community & Social Services	17	14	18	13
Legal	13	1	17	2
Education, Training & Library	19	9	20	9
Arts, Design, Entertainment, Sports, Media	14	8	13	8
Healthcare Practioners & technical	20	5	22	5
Healthcare Support Occupations	23	20	23	18
Protective Service	6	10	8	10
Food Preparation and Serving	18	22	14	22
Building and Grounds Cleaning and Maintenance	12	21	10	20
Personal Care and Service	22	19	21	21
Sales	15	11	16	17
Office and Admin Support	21	18	19	16
Farming, Fishing and Forestry	7	23	6	23
Construction and Extraction	1	13	1	12
Installation, Maintenance, and Repair	2	12	2	11
Production	9	17	9	14
Transportation and Material Moving	5	16	4	15
Military Specific	3	15	3	19

1=Highest
23=Lowest
*Source: U.S. Census 2000.

Table 4. Determinants of the Rank of Occupation: Percent Male (OLS Regression)

	Specification 1		**Specification 2**		**Specification 3**	
	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.
Female	**-0.299**	0.011	**-0.298**	0.011	**-0.300**	0.011
Non-Cognitive Skills						
Male Traits 2	**0.027**	0.007	**0.027**	0.007	**0.027**	0.007
Self Esteem 12	0.001	0.009	0.000	0.009	0.000	0.009
Analytical 1	0.000	0.008	0.001	0.008	0.000	0.008
Work Hard 12	**0.022**	0.009	**0.022**	0.009	**0.022**	0.009
Impulsive 12	-0.015	0.008	-0.015	0.008	-0.014	0.008
Avoidance 1	**-0.019**	0.008	**-0.019**	0.008	**-0.019**	0.008
Intelligent 12	**-0.038**	0.008	**-0.040**	0.008	**-0.039**	0.008
Female*Male Traits 2	-0.009	0.010	-0.010	0.010	-0.010	0.010
Female*Self Esteem 12	0.000	0.012	0.001	0.012	0.000	0.012
Female*Analytical 1	-0.005	0.011	-0.006	0.011	-0.005	0.011
Female*Work Hard 12	-0.011	0.012	-0.012	0.012	-0.011	0.012
Female*Impulsive 12	**0.026**	0.012	**0.027**	0.012	**0.026**	0.012
Female*Avoidance 1	0.001	0.011	0.001	0.011	0.000	0.011
Female*Intelligent 12	**0.038**	0.011	**0.038**	0.011	**0.039**	0.011
Personal Characteristics						
Age 3	**0.008**	0.004	**0.008**	0.004	**0.008**	0.004
White 3	**0.035**	0.013	**0.029**	0.013	**0.034**	0.013
Immigrant 3	0.015	0.026	0.011	0.026	0.013	0.025
Married 3	-0.004	0.013			-0.004	0.013
Children Less Than 6 3	0.013	0.008			0.012	0.008
Children 6-12 3	**0.030**	0.011			**0.030**	0.011
Vocabulary Test Score 1	0.000	0.000	0.000	0.000	0.000	0.000
Future Expectations						
Middle Income at 30 2			-0.008	0.006	-0.009	0.006
Marriage at 25 2			0.000	0.006	0.001	0.006

Notes: 1, 2 and 3 reflect Waves 1, 2, and 3, respectively.Bold (Shaded) significant at the 5 (10) % level.
Non-cognitive skills and future expectations included as deviations from the mean.
Male share of occupation is based on statistics obtained from the U.S. Census 2000.
These shares were merged into the AddHealth data based on respondent's occupation (see text for more details).
The sample size is 3935 and includes men and women who have completed their formal education.

Table 5. Determinants of the Rank of Occupation: Wage (OLS Regression)

	Specification 1		**Specification 2**		**Specification 3**	
	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.
Female	-0.049	0.269	-0.180	0.263	-0.084	0.267
Non-Cognitive Skills						
Male Traits 2	0.238	0.165	0.235	0.164	0.240	0.164
Self Esteem 12	0.132	0.180	0.112	0.178	0.092	0.179
Analytical 1	-0.044	0.161	-0.062	0.161	-0.038	0.161
Work Hard 12	0.062	0.167	0.026	0.165	0.039	0.166
Impulsive 12	**-0.605**	0.184	**-0.531**	0.182	**-0.538**	0.184
Avoidance 1	-0.129	0.177	-0.108	0.177	-0.118	0.177
Intelligent 12	**0.805**	0.184	**0.765**	0.179	**0.736**	0.180
Female*Male Traits 2	-0.005	0.241	-0.025	0.240	-0.031	0.239
Female*Self Esteem 12	-0.217	0.256	-0.215	0.253	-0.191	0.254
Female*Analytical 1	0.190	0.241	0.227	0.239	0.196	0.240
Female*Work Hard 12	0.229	0.234	0.239	0.231	0.222	0.232
Female*Impulsive 12	0.403	0.278	0.347	0.274	0.380	0.276
Female*Avoidance 1	-0.077	0.253	-0.122	0.253	-0.111	0.252
Female*Intelligent 12	-0.073	0.311	-0.022	0.308	-0.040	0.309
Personal Characteristics						
Age 3	**0.527**	0.084	**0.502**	0.083	**0.520**	0.084
White 3	-0.296	0.300	-0.158	0.297	-0.288	0.304
Immigrant 3	**1.336**	0.571	**1.339**	0.573	**1.298**	0.568
Married 3	-0.046	0.279			-0.011	0.278
Children Less Than 6 3	**-0.498**	0.166			**-0.491**	0.167
Children 6-12 3	**-0.472**	0.187			**-0.449**	0.188
Vocabulary Test Score 1	**0.060**	0.010	**0.060**	0.010	**0.056**	0.010
Future Expectations						
Middle Income at 30 2			**-0.574**	0.129	**-0.568**	0.130
Marriage at 25 2			**0.329**	0.128	**0.292**	0.129

Notes: 1, 2 and 3 reflect Waves 1, 2, and 3, respectively.Bold (Shaded) significant at the 5 (10) % level.
Non-cognitive skills and future expectations included as deviations from the mean.
The wage level in an occupation occupation is based on statistics obtained from the U.S. Census 2000.
These levels were merged into the AddHealth data based on respondent's occupation (see text for more details).
The sample size is 3935 and includes men and women who have completed their formal education.

Appendix Table 1. Description of Non-Cognitive Skills

Variable Name	Question
Male Traits 2	
Independent 2	You are independent.
Assertive 2	You are assertive.
(Not) Shy 2	You are shy.
(Not) Sensitive 2	You are sensitive to other people's feelings.
(Not) Emotional 2	You are emotional.
Self Esteem 12	
Good Qualities 12	You have a lot of good qualities.
Proud of Self 12	You have a lot to be proud of.
Like Self 12	You like yourself the way you are.
Just Right 12	You are doing things just about right.
Socially Accepted 12	You feel socially accepted.
Feel Loved 12	You feel loved and wanted.
Analytical Problem Solving 1	
Judge Solutions 1	When you are attempting to find a solution to a problem, you usually try to think about as many different ways to approach the problem as possible.
Judge Alternatives 1	When making decisions, you generally use a systematic method for judging and comparing alternatives.
Get the Facts 1	When you have a problem to solve, one of the first things you do is get as many facts about the problem as possible.
Alternative Solutions 1	After carrying out a solution to a problem, you usually try to analyze what went right and what went wrong.
Willingness to Work Hard 12	
Work Hard 12	When you get what you want, it's usually b/c you worked hard for it.
Impulsiveness 12	
Gut Feeling 12	When making decisions, you uusally go with your "gut feeling" without thinking too much about the consequences of each alternative.
Take Risks 2	You like to take risks.
Live for Today 2	You live your life without much thought for the future.
Problem Avoidance 12	
Avoid Problems 12	You usually go out of your way to avoid having to deal with problems in your life.
Upset by Problems 12	Difficult problems make you upset.
Self-Assessed Intelligence 12	
Intelligent 12	Compared with other people your age, how intelligent are you?

Appendix Table 2. Factor Analysis/Correlation
(Rotated Factor Loadings (Pattern Matrix) and Unique Variances)

Variable	Factor1	Factor2	Factor3	Factor4	Factor 5	Factor 6	Factor 7	Factor 8	Factor 9
Good Qualities 1		0.609							
Proud of Self 1		0.703							
Like Self 1		0.640							
Just Right 1		0.601							
Socially Accepted 1		0.622							
Feel Loved 1		0.650							
Good Qualities 2	0.642								
Proud of Self 2	0.726								
Like Self 2	0.646								
Just Right 2	0.638								
Socially Accepted 2	0.662								
Feel Loved 2	0.687								
Judge Solutions 1			0.560						
Judge Alternatives 1			0.598						
Get the Facts 1			0.614						
Alternative Solutions 1			0.640						
Work Hard 1								0.418	
Work Hard 2								0.451	
Gut Feeling 1						0.392			
Gut Feeling 2						0.505			
Take Risks 2						0.390			
Live for Today 2						0.434			
Avoid Problems 1					0.381				
Upset by Problems 1					0.425				
Avoid Problems 2					0.455				
Upset by Problems 2					0.504				
Intelligent 1				0.608					
Intelligent 2				0.612					
Independent 2									
Assertive 2									0.316
(Not) Shy 2									0.346
(Not) Sensitive 2							0.475		
(Not) Emotional 2							0.496		
Alpha	0.854	0.844	0.740	0.685	0.555	0.556	0.502	0.524	0.301

*Factors 10 through 14 do not have values above 0.30 so they are not reported.

Appendix Table 3. Summary Statistics by Gender

	Female		Males	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Rank of Field of Study (Percent Male)*	0.376	0.176	0.573	0.197
Rank of Occupation (Percent Male)^	0.363	0.243	0.675	0.261
Rank of Occupation (Wage)^	17.514	6.346	17.641	5.923
Personal Characteristics				
Age 3	21.762	1.345	21.879	1.405
White 3	0.743	0.437	0.742	0.437
Immigrant 3	0.049	0.215	0.050	0.219
Married 3	0.214	0.410	0.116	0.321
Children Less Than 6 3	0.475	0.771	0.233	0.650
Childrent 6-12 3	0.110	0.399	0.112	0.673
Vocabulary Test Score 1	101.291	13.839	102.648	14.208
Future Expectations				
Middle Income at 30 2	2.594	0.995	2.738	1.020
Marriage at 25 2	2.703	1.083	2.894	1.077
N	4526		4068	

^Number of observations are 1874 and 2061 for females and males, respectively.
*Number of observations are 980 and 673 for females and males, respectively.