2011

Examining the Effect of Psychological Traits on Earnings and the Gender Wage Gap within a Young Sample of U.S. Employees

Marika May
Claremont McKenna College

CLAREMONT McKENNA COLLEGE

Examining the Effect of Psychological Traits on Earnings and the Gender Wage Gap within a Young Sample of U.S. Employees

SUBMITTED TO

PROFESSOR HEATHER ANTECOL

BY

MARIKA MAY

FOR

SENIOR THESIS

SPRING 2011

APRIL 25, 2011

Table of Contents

Abstract

This paper examines the effect of psychological traits on earnings and furthermore whether it helps explain the gender wage gap. Public-use data collected from *The National Longitudinal Study of Adolescent Health* is used to evaluate the impact on earnings on seven psychological factors: masculine traits, self esteem, analytical problem solving approach, willingness to work hard, impulsiveness, problem avoidance, and self-assessed intelligence. Findings show that gender differences in psychological traits are significant and returns to observable characteristics differ somewhat by gender as well. Among the young sample of U.S. employees evaluated in this study, I find that up to 21 percent of the gender wage gap can be explained, with psychological factors specifically explaining up to 1.5 percent of this gap.

I. Introduction

Measured wage discrimination is a particular form of discrimination referring to an unfair distribution of wages between people who display equal characteristics (Becker, 1957). Blinder (1973) and Oaxaca (1973) investigated the notion of wage discrimination by formally decomposing the gender wage gap into two components: an explained component and an unexplained component. The decomposition analysis revealed that a substantial wage gap existed (i.e., a large unexplained component) even when they controlled for gender differences in observable characteristics.

These two papers led to a flurry of research on the determinants of the gender wage gap. Whether it is human capital factors (Bacolod and Blum, 2010; Manning and Swaffiled, 2008; Mincer and Polachek, 1974), wage structure (Barth and Dale-Olsen, 2009; Blau and Kahn, 2000), or occupational segregation (Baron and Cobb-Clark, 2010; Blau and Kahn, 1999), researchers have found that these various factors contributed in explaining at least *some* of the gender earnings gap. Furthermore, researchers have also found that the gender wage gap has narrowed over time, especially in the 1980s (Blau and Kahn, 2006; O'Neill and Polachek, 1993; Weinberger and Kuhn, 2010). The biggest factors of this convergence are that women's work experience, schooling, and the acquisition of skills that enhance their qualifications, increased rapidly during this period. However, despite findings suggesting the narrowing of the gender wage gap, there is still a significant portion of the gap that is unexplained. What researchers believe can account for this unexplained portion of the wage gap is either other variables that may have been omitted or discrimination.

In recent years, researchers have shed light on the impact of psychological factors (e.g., personality traits, cognitive and noncognitive skills/abilities) on worker productivity and how accounting for it helps explain the gender wage gap. Through the use of several psychological measurements (e.g., the Rotter Locus of Control scale and the Five Factor Model) it has been found that psychological factors affect males and females differently, which in turn accounts for some of the gender earnings gap (Fortin, 2008; Mueller and Plug, 2006; Semykina and Linz, 2007). For example, Semykina and Linz (2007) who assess the effects of personality traits (locus of control and challenge-affiliation) on earnings find only female wages are significantly affected by personality. Furthermore, they find that psychological factors helped explain as much as 8 percent of the gender wage gap.

Although there is a large body of research either looking at the gender wage gap or the effects of psychological characteristics on labor market outcomes, studies bridging the two areas of study are still scarce. The purpose of this study is to further our understanding of the importance of controlling for psychological traits when decomposing the gender wage gap using data from *The National Longitudinal Study of Adolescent Health (Add Health)*. This data is ideal because it provides details on a wide range of the participant's psychological traits, prior to their entry into the labor market. Psychological traits that have not been looked at when analyzing the gender wage gap in the past can now be assessed due to the detailed nature of the survey. This, combined with the comprehensive demographic information that is available with the data source, allows for more control over various observable characteristics when decomposing the gender wage gap. There are two reasons why the use of this data set will be useful. One is that this study will contribute to the already scarce literature looking at the effect psychological traits has in explaining the gender gap. The second is that through the use of an alternate measurement of psychological characteristics, we may gain insight to how other traits influence labor market outcomes.

Results show that returns to observable characteristics differ somewhat by gender. Willingness to work hard significantly increases wages for both genders, although I find that males are rewarded more for this trait. Furthermore, females find that impulsiveness and self-assessed intelligence are also statistically significant, although being impulsive negatively affects wages. When the wage gap is decomposed, I find that up to 21.89 percent of the gender wage gap can be explained, although it is important to note that psychological factors explain a very small portion of the gap.

The remainder of the paper is as follows. Section II gives an overview of the literature. Sections III and IV present the data and the estimation strategy and results, respectively. Finally, Section V concludes.

II. Literature Review

For decades, researchers have been investigating the underlying sources of the gender wage gap to determine if there is discrimination. The seminal paper by Oaxaca (1973) studied whether female workers in the United States, when compared to their male counterparts, were being discriminated against. Specifically, this paper provided a quantitative assessment of the sources of the male-female wage differential and concluded that indeed, there is a distinguishable gender wage gap amongst workers participating in the urban labor market. Oaxaca's findings supported previous notions made by other scholars that the majority of the gender wage gap was not accounted for by "unequal pay for equal work," but in fact created by the disproportionate number of women represented in the lower end of the pay distribution.

At the same time, Blinder (1973) also found evidence suggesting the existence of discrimination. Unlike Oaxaca however, he examined two different pairs of people. One was the wage differential between white men and black men and the other, the difference between men and women. Indeed, Blinder finds that even after adjusting for differences in gender and/or race characteristics, a wage gap between these two groups of workers still existed. Subsequent research on the gender wage gap focused primarily on further explaining the unexplained component of the gender wage gap by controlling for a richer and more varied set of observable characteristics (e.g., actual labor market experience, education).[1]

Despite the flood of research examining the gender wage gap controlling for various different characteristics, researchers are still unable to fully explain the remainder of the earnings gap. However, there is a recent rise in the body of research bridging the study of psychology and economics together, where researchers have started to look at how people's psychological traits affect labor market returns such as earnings. This is promising as connecting these two seemingly unrelated fields together could help explain the gender wage gap further.

Before discussing previous research on the effect of psychological traits on labor market outcomes, I will first discuss two of the most commonly used measures of such attributes – the Rotter Locus of Control and the Five Factor Model. Psychological factors

[1] See for example, Bacolod and Blum, 2010; Baron and Cobb-Clark, 2009; Barth and Dale-Olsen, 2009; Blau and Kahn, 1999; Manning and Swaffiled, 2008; Mincer and Polachek, 1974.

are traits that help conceptualize characteristics such as personality traits, cognitive and non-cognitive skills/abilities. The Rotter Locus of Control scale was devised by Julian Rotter in 1966. The concept of locus of control refers to how much a person thinks the outcome of events they experience are under their control (Rotter, 1966). For example, a person who exhibits an internal locus of control believes all outcomes or events are a consequence of their own behavior, ability, or effort.

The Five Factor or the Big Five model was devised through a number of different studies (Fiske, 1949; Hogan,1991; Norman, 1963), although Goldberg (1993) is believed to be the first to clearly formularize these traits. The Five Factor model shows that there are five distinct traits- openness, conscientiousness, extraversion, agreeableness, and neuroticism (or emotional stability)- that are responsible in shaping a person's personality. Each trait is measured on a scale comprised of more specific characteristics and the more of these characteristics you exhibit, the higher you will score on that specific trait. As mentioned earlier, these measurements are crucial in conceptualizing psychological traits. Furthermore, it has recently been found that these traits also affect labor market outcomes.

Researchers have found that childhood cognitive development greatly affects future labor market performances. For example, maladjusted children were less likely to land prestigious positions and/or advance in their careers (Silles, 2010). Furthermore, psychological skills have been found to greatly affect the rate of employment (Cobb-Clark and Tan, 2009) and wages (Groves, 2005; Heckman, Stixrud, and Urxua, 2006) as well. Specifically, Groves (2005) and Heckman, Stixrud, and Urzua (2006) using the Rotter Locus of Control scale, find that in general exhibiting an internal locus of control (i.e., belief that outcome of events are directly related to one's own actions or skills) is correlated with higher wages.

Heckman *et al.* (2006) even go further and state that psychological factors strongly influence schooling decisions and these abilities were as important as cognitive skills in explaining labor market outcomes. Other studies (Barrick and Mount, 1991; Bowles, Gintis, and Osborne, 2001; Osborne, 2000; Silles, 2010) similarly observed that psychological traits significantly affected other work-related returns even when different measurements such as the Five Factor model are used.

From studies of psychological factors, researchers find that not only were there economic consequences of possessing certain psychological factors but these characteristics were also rewarded and penalized differently across gender. Specifically, Nyhus and Pons (2005) used data from the DNB Household Survey (DHS) in order to see how psychological traits influenced earnings and how it varied between genders. From a very large sample of people in the Dutch population, the researchers find that there was in fact a gender difference in rewards and penalties for possessing certain psychological factors, through the use of the Five Factor model. Although emotional stability affected wages positively for both males and females, agreeableness affected female pay negatively. Furthermore, Nyhus and Pons also find that openness to experience, as years of experience increased, played a significant role in increasing male wages.

In another study, Cobb-Clark and Tan (2009) looked at how psychological factors influenced the probability of employment and wages differently across genders. Using the Household, Income, and Labour Dynamics in Australia (HILDA) data, the researchers find that psychological factors significantly affect occupational attainment.

They also find the effects are different across gender as well. Not only did men and women with similar skills enter the work force at different times but women also observed slight wage rewards for their psychological traits. In a related study, Antecol and Cobb-Clark (2010) find that psychological factors help explain occupational segregation in entry-level jobs. Specifically they find that females are less likely to enter a field or occupation that is male-dominated and people's psychological characteristics relates to the decisions they make regarding education and occupation.

Given researchers are finding that psychological factors influence men and women differently, it is not surprising that they are now becoming interested in how psychological factors influence the unexplained component of the gender wage gap. In particular, Mueller and Plug (2006) examine the effects of psychological traits on the wages of male and female workers who graduated high school in Wisconsin in 1957. The same sample was interviewed again in 1992 to update participant information. Through the use of a modified version of the Five Factor model, they find that men who were more open to experience, emotionally stable, and non-agreeable enjoyed higher wages than men who did not possess these traits. Conversely, women's earnings are found to be higher the more conscientious and open they were to experience. Openness to experience is correlated with increasing wages for both genders while agreeableness is found to be the trait that had the most impact in generating the gender wage gap. In general, men were more non-agreeable than women and men were the only ones who experienced positive earnings for possessing this trait. They find that about 3-4 percent of the gender wage gap can be explained in their study, with psychological factors specifically explaining 16 percent of that gap.

Fortin (2008) also looked at the extent to which psychological factors helped explain the gender wage gap. However, the psychological factors she utilized were the Rosenberg self-esteem and the Rotter Locus of Control scales. Through the use of the National Longitudinal Study of the High School Class of 1972 (NLS72) and the National Education Longitudinal Study of 1988/94 (NELS88), Fortin finds that typically masculine or feminine psychological factors such as the importance of money or work and importance of people or family, are indeed gender specific and play a significant role in explaining the gender wage gap in the 1980s. Locus of control and the importance of people/family negatively affected wages, although this effect was not always significant. On the other hand, self-esteem and the importance of money/work significantly affected wages positively and also had the most impact in driving the gender wage gap apart. When a modified version of the Oaxaca-Blinder decomposition is used, Fortin finds that up to 34 percent of the explained portion of the gender wage gap can be explained by psychological factors. In a similar study conducted by Semykina and Linz (2007) using employment data from over 2,600 Russian workers, they also find that gender differences in psychological traits are significant and that it helped explain as much as 8 percent of the gender wage gap, when the Oaxaca-Blinder estimation strategy is used.

Despite the aforementioned studies, research specifically looking at the role psychological factors play in explaining the gender wage gap is still extremely limited. Moreover, the existing literature is often based on non-U.S. employees, demonstrating how little knowledge researchers have on this topic in the U.S. The goal of this study is to add to the limited literature on psychological traits and the gender wage gap using a young sample of U.S. employees. The Add Health survey also asks a wide array of questions regarding demographic and psychological information, allowing for a more comprehensive investigation into whether these factors can indeed help explain the gender wage gap. In addition, because such a unique longitudinal data set is used in the study, we may gain information regarding this particular psychological measurement and its particular effects on labor market outcomes. The ultimate goal of this study is to add to the scarce literature that is available looking at how exactly observable characteristics, specifically one's psychological traits, can help explain the gender wage gap.

III. Data

I use Public-use data from *The National Longitudinal Study of Adolescent Health* (Add Health). Add Health is a longitudinal study, which began looking at a representative sample of adolescents in the U.S. during the 1994-1995 school year, when the participants were between grades seven through twelve.[2] All of those who participated were asked to complete a series of questions at school and complete an interview conducted at their homes during the collection of Wave I data. So far, the same individuals have been followed and been re-interviewed in 1996, 2001-02, and 2007-08, each of which represents data in Wave II, Wave III, and Wave IV, respectively. However since results from Wave IV are not available for public use, only data up to Wave III was considered in this research.

The Add Health data is ideal for this study because it provides information regarding participant's psychological traits prior to entering the labor market as well as a variety of demographic information and questions regarding personal relationships and labor market experiences or outcomes. This detailed and comprehensive questionnaire

[2] Add Health website, http://www.cpc.unc.edu/projects/addhealth.

also allows for a more complete view of the respondent's psychological characteristics. Furthermore, since the Add Health survey only targets students studying in the U.S., the results will provide a better explanation for what effects psychological traits have on the gender wage gap in the *United States.*

The sample used for this study is restricted to the respondents who did not skip any questions on any of the variables of interest in all three Waves. Individuals who also did not respond as the same gender throughout the three Waves, are not making earnings, or are making less than $1 or over $100 an hour are also omitted. This results in a sample consisting of 2,384 respondents; 1,247 females and 1,137 males. From the original 4,882 respondents who participated in all three Waves, the drops include about half of this sample.

III.A Wages

I construct a measure of hourly wages based on hours worked per week and wages which were reported in different units: hourly, daily, weekly, monthly, and annually. For wages not reported hourly, I first determine the number of hours worked by a respondent depending on the unit reported for their wages. Given hours were reported weekly no further calculation was need for hours worked per week. I calculated hours worked per day as the reported weekly hours divided by 5. I reported bi-weekly hours worked as the reported weekly hours multiplied by 2.167. I calculated hours worked bi-monthly as the reported weekly hours multiplied by 2. I reported hours worked per month as the reported weekly hours multiplied by 4. Finally I calculated the hours worked per year as the reported weekly hours multiplied by 52. The problem with this approach is that since there was insufficient information regarding the hours worked, an arbitrary number is constructed for each individual. This means that the hourly wage rate for those who did not work as much as the constructed hours is underestimated whilst for those who worked more than the constructed hours, their wage is overestimated.

I then determine hourly wages by dividing wages by the number of hours a respondent worked corresponding to the unit reported for their wages. For example, if wages are given by a daily rate, the daily wage rate is divided by hours worked per day. An analogous calculation is made for weekly, monthly and annual wages. I also convert hourly wages into the natural log of hourly wages to take into account outliers in the data.

Table 1 reveals that on average, males earn a higher hourly wage of $10.48 compared to $9.18 for females, representing a raw gender wage gap of roughly 12.4 percent (or 12.5 log points). The existence of this wage gap is exactly what this paper attempts to explain by accounting for demographic and psychological factors that will be defined below. However, the actual wage gap is lower than that of previous literature. This may be due to the fact that the group of people who are examined in this paper is a young sample so there may not be as severe a wage gap as what may exist for an older demographic.

III.B Demographic Factors

As in the existing literature of the gender wage gap, I control for a number of demographic characteristics. The demographic information is based on Wave III data with the exception of a respondent's race which is based on Wave I data.

First, I created three indicator variables for race: white, black, and other race. In particular, White equals one if the respondent identifies with being white, and zero otherwise. Black equal one if the respondent identifies with being black, and zero otherwise. Finally, other race equals one if the respondent identifies with being Hispanic, Asian, Native American, and zero otherwise. According to Table 1, the majority of the respondents, both male and female, identify their race as white (70.2 and 66.8 percent respectively). The remainder of male and female respondents identified as being black (15.9 and 19.6 percent, respectively) or another race (13.6 percent and 13.9 percent, respectively).

In order to proxy for potential labor market experience, I include controls for age and age squared, as well as education.[3] The respondent's age variable is constructed by subtracting a respondent's birth date year from the year that the Wave III interview was conducted. The average age of both men and women in the sample is roughly 22 years of year. I create indicator variables for the highest degree obtained: less than high school, high school, some college, and college (i.e., Bachelor's, Master's, Professional, or equivalent degree). According to Table 1, more males than females have listed that the highest degree they earned is either less than high school (9.6 and 5.8 percent, respectively) or high school degree (75.1 and 73.1 percent, respectively). Furthermore, fewer males than females have listed that the highest degree they earned is some college (6.7 and 8.5 percent, respectively) or college (8.6 and 12.7 percent, respectively).

[3] I could not include a control for potential Mincer experience (age-years of education-6) because years of education as reported by Add Health appeared to be misreported. This was determined by comparing the years of education reported to the highest degree earned. The two measured did not match up and the information provided by the highest degree earned seemed more reasonable.

Additional variables concerning labor market experiences are also included in the analysis. Specifically, the number of jobs currently working for and the status of employment of the respondent are included. Working full-time equals one if the respondent is working for pay for at least 35 hours per week, and zero otherwise. On average, males were 15 percent more likely to be employed full-time relative to their female counterparts while both males and females currently have had roughly 1.1 jobs (see Table 1).

Finally, I also created a variable indicating whether or not the respondent is currently married, whether or not English is the predominant language spoken at home, and whether or not the respondent currently lives with roommates. Table 1 reveals that over 90 percent of respondents spoke English as their primarily language at home and over 85 percent of them are currently living with roommates. Moreover, females are more likely to be currently married than their male counterparts (18.3 and 12.1 percent, respectively).

III.C Psychological Factors

As previously stated, the main advantage of the Add Health data is that it has retrospective information on psychological traits. Specifically, respondents who participated in the Wave I and Wave II survey responded to a large number of questions pertaining to psychological factors. Although this section of the survey asked the respondents to describe a wide range of attributes, these attributes were not based off of any standard psychological measures such as the Rotter Scale or the Five Factor model.

This could potentially be problematic as the measure that will be used is not necessarily reliable or valid, unlike the standard psychological measures.

Following Antecol and Cobb-Clark (2010), I focus on seven different psychological factors: masculine traits, self-esteem, analytical problem solving approach, willingness to work hard, impulsiveness, problem avoidance, and self-assessed intelligence.[4] The underlying components of each of these factors are listed in Appendix 1. These seven traits are the sums of underlying components asked in the survey, to which respondents decided how likely the characteristic described them. The ranking ranges from strongly agree (1) to strongly disagree (5). This ranking is reversed for interpretation purposes for this study, with the exception of three questions asked in Wave II regarding how shy, sensitive, and emotional respondents think they are.

Table 2 shows the summary statistic for each of the seven attributes, as well as their underlying components by gender. Not surprisingly, males scored about half a point higher in masculine traits overall than females (15.737 and 15.107, respectively). Although females reported they were significantly less shy than males, more males were significantly less sensitive and emotional. Females reported significantly lower levels of self-esteem than males (49.277 and 50.789, respectively) and on most of the underlying components that comprised self esteem as well. This is consistent with Hagger and Stevenson's (2010) research where they find males tend to display higher levels of self-esteem. Males are slightly more inclined than females to believe that when they get what they desired, it was as a result of their hard work (8.022 and 7.894, respectively), consistent with Semykina and Linz's (2007) research where they find males score highly

[4] Antecol and Cobb-Clark (2010) used factor analysis in order to group certain similar features together to create seven distinct psychological attributes. For more information, refer to their study for more detail.

on internal locus of control, which is very similar to the concept of willingness to work hard. Males also display significantly higher levels of impulsivity than females (12.372 and 11.156, respectively), which is consistant with past findings that there is a significant gender difference in impulsiveness (Chapple and Johnson, 2007). In general, females are also more likely to be avoidant than males (13.751 and 13.401, respectively); similarly consistent with past findings that women are more likely to use avoidance as a coping technique when dealing with problems (Howerton and Van Gundy, 2009). Furthermore, the means of analytical or self-assessed intelligence traits are found that they are not significantly different between the two genders.

III.D Log Earnings by Psychological Traits

Before formally looking at whether accounting for psychological traits can help explain the gender wage gap, I compare the raw differences in the log of hourly wages between those who score in the 25th and 75th percentile of each attribute by gender. This allows one to informally determine whether psychological traits influence the gender wage gap.

Table 3 reveals that for all seven attributes, the gender differences in wages are significantly different within percentiles. That is for each trait, males earn more than females at both ends of the distribution. For example at the 75th percentile for the willingness to work hard trait, males (females) earn 2.270 (2.157) log of hourly wages while at the 25th percentile, males (females) earn 2.182 (2.071) log of hourly wages. With the exception of self-assessed intelligence, wages across gender is not significantly different between the two percentiles for each trait. Specifically, the gender wage gap at the top of the distribution suggests males earn 0.071 log of hourly wages more than females while at the bottom of the distribution, males on average earn 0.197 log of hourly wages more than females. This suggests that there is a limited role for psychological traits in explaining the gender wage gap.

In an attempt to further investigate this, the remainder of the paper formally analyzes the influence of psychological factors on the gender wage gap.

IV. Estimation Strategy and Results

IV.A Wages

To assess the effects of psychological factors on earnings, I estimate a model of the following form:

$$\ln W_i = M\gamma + X\beta_i + P\delta_i + \varepsilon \qquad (1)$$

where $\ln W$ is the natural log of hourly wages, i indicates whether the model is explaining male (m) or female (f) characteristics, M is an indicator variable for male, X is a vector of personal characteristics (race, age, whether English spoken at home, whether currently living with a roommate(s), highest educational degrees earned, number of jobs, whether working full-time, and marital status), P is a vector of psychological traits (masculine traits, self esteem, analytical problem solving, willingness to work hard, impulsiveness, problem avoidance, and self-assessed intelligence), and ε is an error term with the usual properties. The regression is first run with just psychological factors alone and then personal characteristics are added in the second regression analysis. I then estimate Equation (1) separately by gender (excluding the male indicator variable).

Previous research has found that the antagonistic characteristic, based on the Five Factor model, is positively correlated with earnings (Mueller and Plug, 2006). Given that antagonistic characteristics is similar to the masculine trait that I consider, I hypothesize that respondent's with high scores on the masculine trait will earn higher wages (holding all else constant). Fortin (2008) finds that people with higher self esteem experience higher earnings, leading me to hypothesize those with higher self esteem scores will earn more. Semykina and Linz (2007) previously find that those who display an internal locus of control got rewarded for displaying this trait. Given that locus of control is similar to the willingness to work hard trait (i.e., belief that outcome of events was a result of self *working hard*), there is reason to believe scoring high on the work hard trait will translate to higher earnings as well. Since it is known that those who earn higher wages also display socially desirable psychological traits (Harrell, 1969), I hypothesize that high earners will probably be more likely to be analytical and believe (s)he is more intelligent than their peers.

On the other hand, Mueller and Plug (2006) find that women are rewarded for conscientiousness, which is essentially the opposite spectrum of impulsiveness. Therefore I hypothesize that individuals who score high on impulsiveness will observe lower wages. Furthermore, Silles (2010) find that children who were withdrawn or passive aggressive growing up were disadvantages in the labor market. This may suggest that those who score highly on problem avoidance may be penalized for possessing such trait as well. The reason why demographic factors are included in the wage regression is to control for the regression results as much as possible. What this means is that accounting for observable characteristics such as demographic factors allow for the control over respondent characteristics as much as possible. Furthermore, it is also crucial to include other observable information such as living with roommates, number of jobs currently held, and marital status in the regression. The reason behind this is because it has previously been noted that psychological characteristics affect various social behaviors (Herrnstein and Murray, 1994).

IV.B Wage Regression Results

The first two columns of Table 4 present the results for Equation (1) without and with demographic controls, respectively. The male variable is also included in both specifications. There are several noteworthy results. First, when demographic controls are excluded from the analysis (see Column 1), men earn 0.137 log points more than their female counterparts. Moreover, only two psychological factors are statistically significant at conventional levels: the willingness to work hard and self-assessed intelligence. Both of these traits positively influence wages. Specifically, scoring one point higher on the willingness to work hard scale (self-assessed intelligence) increases log of hourly wages by 2.16 (1.02) log points. Interestingly, when demographic controls are added to the model (see Column 2), men continue to outperform their female counterparts although to a lesser extent. In addition, only the self-assessed intelligence remains statistically significant at conventional levels.

When demographic controls are included in the analysis, Black respondents earn significantly lower wages than their "other race" counterparts as well as those who attained an educational degree that is high school or less. In addition, those who attain a college or an equivalent degree, are fully-employed, or married see it significantly increases their log of hourly wages.

Turning to the analysis run separately by gender (see Columns 3 through 6 of Table 4) it can be seen that the returns to observable characteristics differ somewhat by gender. For both males and females, willingness to work hard is statistically significant at conventional levels in the specification excluding demographic controls, although the effect is larger for males. Moreover for females, impulsiveness and self-assessed intelligence are also statistically significant while the same is not true for men. Specifically, a one unit increase in self-assessed intelligence (impulsiveness) increases (decreases) women's hourly wages by 0.0198 (-.0096) log points. When demographic characteristics are included, psychological traits do not determine male wages while self-assessed intelligence continues to matter for female respondents. The explanation behind this could be due to the fact that psychological traits or *this* measurement specifically, does not greatly affect log of hourly wages in this sample.

When demographic controls are included in the analysis, attaining a college or an equivalent degree and being fully employed significantly increases both male and female wages. For males, being married also significantly increases wages while the same is not true for women. Moreover for females, responding as Black significantly decreases log of hourly wages, as well as attaining a high school degree or less. Specifically, responding as Black decreases wages by -0.0832 log points, while attaining a high school degree (or less) decrease women's hourly wages by -0.111 (-0.224) log points.

IV.C Decomposition of the Gender Wage Gap

To determine an explanation for the differences in male and female earnings, the size of the wage gap is investigated. This can be done by looking at what will happen to the wage gap with females with male characteristics or males with female characteristics, hypothetically. In order to do this, the estimation strategy and method devised by Oaxaca (1973) and Blinder (1973) is followed to further decompose the earnings profile for each gender. The following equations represent the two approaches that is used to decompose the gender wage gap.

$$\overline{\ln \mathrm{W_m}} - \overline{\ln \mathrm{W_f}} = (\overline{\mathrm{X_m}} - \overline{X_f})\hat{\beta}_{m,} + \overline{X_f}(\hat{\beta}_m - \hat{\beta}_f) \tag{2}$$

or,

$$\overline{\ln \mathrm{W_m}} - \overline{\ln \mathrm{W_f}} = (\overline{\mathrm{X_m}} - \overline{X_f})\hat{\beta}_{f,} + \overline{X_m}(\hat{\beta}_m - \hat{\beta}_f) \tag{3}$$

The bars denote sample means, m and f denote male and female, respectively, the vector of coefficients ($\hat{\beta}$) are from the regression results presented in Table 4 (Columns 3-6), and the means of the observable characteristics ($\bar{X}$) are presented in Table 1 and 2. Equation (2) looks at the effect on the gender wage gap if females face the same returns as men for their observable characteristics and Equation (3) looks at the effect on the wage gap if males face the same returns as women for their observable characteristics. In other words, Equation (2) uses male weights while Equation (3) uses female weights.

In both Equations (2) and (3), the first term on the right hand side represents the portion of the wage differences that is explained or more specifically, the gender wage gap resulting from the differences in observable characteristics. This refers to the demographic, educational, labor market experience, and psychological trait variables. On the other hand, the second term on the right hand side represents the portion of the wage gap that is unexplained by the model. What is unexplained by the model is perceived as the effect of gender discrimination or the effect of omitted variables. The reason why two approaches are necessary to decompose the wage equation is because you need to test the counterfactual to see what could happen to the wages of females with male characteristics or males with female characteristics.

IV.D Wage Decomposition Results

Table 5 presents the decomposition results. The first row indicates that the actual gap is equal to 12.8 log points. Depending on the counterfactual considered, as little as 8.12 % of the total gender wage gap (using female weights) and as much as 21.89% of the gender wage gap can be explained by observable characteristics (using male weights). Interestingly, psychological traits are found to play a very limited role. For example, while demographic characteristics explain 20.4 percent, psychological characteristics are found to explain 1.5 percent using male weights. Irrespective of which weights are utilized, the majority of the gender wage gap remains unexplained.

The results found in this study with respect to the relative role psychological factors play in explaining the gender wage gap are generally in sharp contrast to the existing literature. The range of estimates from the previous literature are 8.4 percent (Semykina and Linz, 2007) to up to 34 percent (Fortin, 2008); Mueller and Plug (2006) fall in the middle at 16 percent. As mentioned above, at *best*, I find that only 1.5 percent of the gender wage gap can be explained by psychological factors.

The possible explanations for the disparity in the results in this analysis and the previous literature may be a result of the differences in measurement of psychological factors. Previous literature tend to use psychological measurements (such as, the Big Five or Rotter Locus of Control scales) in order to assess the effects of psychological traits on the gender wage gap.[5] Both of these measurements have been tested in other psychological journals for their validity and reliability. However, the Add Health data did not use these externally validated scales. Instead, they collected information on a range of observed attributes that were then combined into seven psychological factors based on factor analysis (see Antecol and Cobb Clark, 2011 for details).

Another puzzle with the results in this study is why so little of the gender wage gap is explained in this analysis. I offer two potential explanations. The first possibility may be due to how little information is available in the Public-Use file of the Add Health data. For example, information on cognitive skills (i.e., vocabulary test scores) is not available in the public file. Cognitive skills have been found to be an important determinant of earnings (Heckman, Stixrud, and Urxua, 2006) and the omission of such a variable may result in a larger portion of the gender wage gap being attributed to unobservable characteristics.

The second possibility for the large unexplained component is because Wave III captures the respondent's data very early in their working career, the overall size of the gender wage gap observed in this analysis is very small to begin with. The gender wage gap tends to get larger in older samples as women have generally taken time out of the labor market to care for their children and are penalized upon their return. Because the female respondents in this sample are in their early 20s they have not yet begun their families, nor off-ramping out of and on-ramping into the labor market (Hewlett, 2007).

[5] Fortin (2008); Mueller and Plug (2006); Semykina and Linz (2007).

V. Conclusion

The existence of the gender wage gap has led researchers to try and solve the possible reason behind it for over 35 years. Using a decomposition strategy first proposed by Oaxaca (1973) and Blinder (1973), researchers have looked at the relative role an array of observable characteristics play in explaining the gender wage gap. Recently, there has been an increased interest in the effect psychological traits play in explaining the gender wage gap.

Using *The National Longitudinal Study of Adolescent Health*, this paper seeks to add to this literature by creating an alternative measure of psychological traits as well as use information of students only from the United States. This is beneficial because much of the previous literature uses data based on non-U.S. employees. Furthermore, since the Add Health survey asks a wide array of psychological as well as demographic information, it allows for a more comprehensive investigation into the gender wage gap within a young sample of U.S. employees.

Findings show that returns to observable characteristics differ somewhat by gender. For both genders, willingness to work hard is statistically significant, although males are rewarded more for this trait. Furthermore, females observe that impulsiveness and self-assessed intelligence also significantly affect log of hourly wages, although impulsiveness works to decrease wages. Although effects of some characteristics differ by gender, it is important to note that when both psychological and demographic factors are controlled for in the regression, psychological traits do not determine male wages while self-assessed intelligence continues to matter only for female respondents. This could be indicating that these psychological factors do not really affect log of hourly wages. Using an Oaxaca (1973) and Blinder (1973) decomposition approach, I find very little of the gender wage gap can be explained by observable characteristics, including psychological traits.

The hope for this study was to contribute to the existing literature on how psychological traits can help explain the gender wage gap. However, the inconclusive results suggest there is still a lot to investigate regarding this topic. It is a known fact that psychological factors significantly affect labor market outcomes.[6] In addition, research has found that certain psychological characteristics are also rewarded and penalized differently across gender.[7] If this is the case, there may still be a role for psychological factors helping to explain the gender wage gap. In order to expand this area of study, alternative samples need to be investigated. This can perhaps be done through a sample that includes all working age individuals and not just individuals at their entry-level. Furthermore, the psychological measurements used in the study should be tested against ones that has been validated in psychological journals. This way it ensures the respondent's psychological traits are accounted for in a reliable way.

---

[6] Barrick and Mount (1991); Bowles, Gintis, and Osborne (2001); Groves (2005); Heckman, Stixrud, and Urxua (2006); Osborne (2000); Silles (2010).

[7] Nyhus and Pons (2005).

References

Bacolod, M. P., & Blum, B. S. (2010). Two sides of the same coin: U.S. 'residual' inequality and the gender gap. *Journal of Human Resources, 45*(1), 197-242.

Baron, J. D., & Cobb-Clark, D. (2010). Occupational segregation and the gender wage gap in private- and public-sector employment: A distributional analysis. *Economic Record, 86*(273), 227-246.

Barrick, M. R., & Mount, M. K. (1991). The big five personality dimensions and job performance: A meta-analysis. *Personnel Psychology, 44*(1), 1-26.

Barth, E., & Dale-Olsen, H. (2009). Monopsonistic discrimination, worker turnover, and the gender wage gap. *Labour Economics, 16*(5), 589-597.

Becker, G. S. (1957) 1971. *The Economics of Discrimination*. 2nd ed. Chicago: University of Chicago Press.

Blau, F. D., & Kahn, L. M. (1999). Analyzing the gender pay gap. *Quarterly Review of Economics and Finance, 39*, 625-646.

Blau, F. D., & Kahn, L. M. (2000). Gender differences in pay. *Journal of Economic Perspectives, 14*(4), 75-99.

Blau, F. D., & Kahn, L. M. (2006). The U.S. gender pay gap in the 1990s: Slowing convergence. *Industrial and Labor Relations Review, 60*(1), 45-66.

Blinder, A. S. (1973). Wage discrimination: Reduced form and structural estimates. *Journal of Human Resources, 8*(4), 436-455.

Bowles, S., Gintis, H., & Osborne, M. (2001). The determinants of earnings: A behavioral approach. *Journal of Economic Literature, 39*(4), 1137-1176.

Chapple, C. L., & Johnson, K. A. (2007). Gender differences in impulsivity. *Youth Violence and Juvenile Justice, 5*(3), 221-234.

Cobb-Clark, D., & Tan, M. (2009). *Noncognitive skills, occupational attainment, and relative wages.* CEPR Discussion Papers, 612. Australian National University.

Fiske, D. W. (1949). Consistency of the factorial structures of personality ratings from different sources. *The Journal of Abnormal and Social Psychology, 44*(3), 329-344.

Fortin, N. M. (2008). Symposium on noncognitive skills and their development: The gender wage gap among young adults in the United States: The importance of money versus people. *Journal of Human Resources, 43*(4), 884-918.

Goldberg, L. R. (1993). The structure of phenotypic personality traits. *American Psychologist, 48*(1), 26-34.

Groves, M. O. (2005). How important is your personality? Labor market returns to personality for women in the US and UK. *Journal of Economic Psychology, 26*(6), 827-841.

Hagger, M. S., & Stevenson, A. (2010). Social physique anxiety and physical self-esteem: Gender and age effects. *Psychology & Health, 25*(1), 89-110.

Harrell, T. W. (1969). The personality of high earning MBA's in big business. *Personnel Psychology, 22*(4), 457-463.

Heckman, J. J., Stixrud, J., & Urzua, S. (2006). The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. *Journal of Labor Economics, 24*(3), 411-482.

Herrnstein, R. J., & Murray, C. A. (1994). *The bell curve: Intelligence and class structure in American life*. New York, NY US: Free Press.

Hewlett, S. A. (2007). *Off-ramps and on-ramps: Keeping talented women on the road to success.* Boston, MA US: Harvard Business School Press.

Hogan, R. T. (1991). Personality and personality measurement. In L. M. Hough (Ed.), *Handbook of industrial and organizational psychology, vol. 2 (2nd ed.).* (pp. 873-919). Palo Alto, CA US: Consulting Psychologists Press.

Howerton, A., & Van Gundy, K. (2009). Sex differences in coping styles and implications for depressed mood. *International Journal of Stress Management, 16*(4), 333-350.

Manning, A., & Swaffield, J. (2008). The gender gap in early-career wage growth. *Economic Journal, 118*(530), 983-1024.

Mincer, J., & Polachek, S. (1974). Family investment in human capital: Earnings of women. *Journal of Political Economy, 82*(2), S76-s108.

Muller, G., & Plug, E. (2006). Estimating the effect of personality on male-female earnings. *Industrial and Labor Relations Review, 60*(1), 3-22.

Norman, W. T. (1963). Toward an adequate taxonomy of personality attributes: Replicated factor structure in peer nomination personality ratings. *The Journal of Abnormal and Social Psychology, 66*(6), 574-583.

Nyhus, E. K., & Pons, E. (2005). The effects of personality on earnings. *Journal of Economic Psychology, 26*(3), 363-384.

Oaxaca, R. (1973). Male-female wage differentials in urban labor markets. *International Economic Review, 14*(3), 693-709.

O'Neill, J., & Polachek, S. (1993). Why the gender gap in wages narrowed in the 1980s. *Journal of Labor Economics, 11*(1), 205-228.

Osborne, M. A. (2000). The power of personality: Labor market rewards and the transmission of earnings. University of Massachusetts.

Rotter, J. B. (1966). Generalized expectancies for internal versus external control of reinforcement. *Psychological Monographs: General & Applied, 80*(1), 1-28.

Semykina, A., & Linz, S. J. (2007). Gender differences in personality and earnings: Evidence from Russia. *Journal of Economic Psychology, 28*(3), 387-410.

Silles, M. A. (2010). Personality, education and earnings. *Education Economics, 18*(2), 131-151.

Weinberger, C. J., & Kuhn, P. J. (2010). Changing levels or changing slopes? The narrowing of the gender earnings gap 1959-1999. *Industrial and Labor Relations Review, 63*(3), 384-406.

Tables

Table 1. Demographic Characteristics by Gender

	Female		**Male**	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
White 1	0.668	0.471	0.702	0.458
Black 1	0.196	0.397	0.159*	0.366
Others 1	0.136	0.342	0.139	0.346
Age 3	21.818	1.601	22.161**	1.700
Age 32	478.585	69.965	493.994**	75.513
English 3	0.944	0.230	0.935	0.247
Roommates 3	0.877	0.328	0.865	0.341
Less than High School 3	0.058	0.233	0.096**	0.295
High School 3	0.731	0.444	0.751	0.433
Some College 3	0.085	0.279	0.067	0.250
College 3	0.127	0.333	0.086**	0.281
Number of Jobs 3	1.138	0.401	1.134	0.393
Full Employment 3	0.594	0.491	0.745**	0.436
Hourly Wage 3	9.176	5.305	10.476**	5.462
Log of Hourly Wage 3	2.115	0.440	2.243**	0.457
Married 3	0.183	0.387	0.121**	0.327
	1247		1137	

* Significance at the 5% level and ** significance at the 1% level for differences in mean between male and female for indicated variable. Number at the end of the variable name indicate which wave the data was extracted from.

Table 2. Psychological Characteristic by Gender

	Female		**Male**	
	Mean	Std. Dev.	Mean	Std. Dev.
Masculine Traits 2	15.107	2.434	15.737**	2.361
Independent 2	4.156	0.792	4.128	0.791
Assertive 2	3.729	0.901	3.735	0.843
(Not) Shy 2	3.302	1.240	3.191*	1.188
(Not) Sensitive 2	1.763	0.719	2.055**	0.789
(Not) Emotional 2	2.156	0.963	2.628**	0.975
Self Esteem 12	49.277	6.365	50.789**	5.688
Good Qualities 1	4.224	0.670	4.325**	0.633
Proud of Self 1	4.269	0.715	4.359**	0.676
Like Self 1	3.798	0.995	4.198**	0.849
Just Right 1	3.658	0.901	3.850**	0.825
Socially Accepted 1	4.062	0.763	4.158**	0.726
Feel Loved 1	4.302	0.726	4.322	0.668
Good Qualities 2	4.306	0.638	4.375**	0.628
Proud of Self 2	4.354	0.659	4.407	0.635
Like Self 2	3.888	1.002	4.266**	0.783
Just Right 2	3.828	0.871	3.943*	0.830
Socially Accepted 2	4.196	0.716	4.229	0.706
Feel Loved 2	4.395	0.656	4.358	0.648
Analytical 1	15.128	2.499	15.199	2.519
Judge Solutions 1	3.758	0.809	3.816	0.834
Judge Alternatives 1	3.581	0.853	3.647	0.906
Get the Facts 1	3.825	0.844	3.791	0.865
Alternative Solutions 1	3.964	0.731	3.945	0.788
Work Hard 12	7.894	1.495	8.022*	1.395
Word Hard 1	3.852	0.881	3.904	0.868
Work Hard 2	4.042	0.915	4.118*	0.840
Impulsive 12	11.156	2.749	12.372**	2.809
Gut Feeling 1	2.851	1.100	3.116**	1.117
Gut Feeling 2	2.778	1.139	3.026**	1.138
Take Risks 2	3.345	1.090	3.690**	0.978
Live for Today 2	2.182	0.942	2.539**	1.085
Avoidance 12	13.751	2.788	13.401**	2.679
Avoid Problems 1	3.036	1.041	3.235	1.028
Upset by Problems 1	3.661	0.959	3.405**	1.023
Avoid Problems 2	3.322	1.151	3.410	1.094
Upset by Problems 2	3.732	1.031	3.352**	1.058
Self-Assessed Intelligence 12	7.811	1.817	7.774	1.905
Self-Assessed Intelligence 1	3.854	1.033	3.836	1.078
Self-Assessed Intelligence 2	3.957	1.048	3.938	1.075
	1247		1137	

* Significance at the 5% level and ** significance at the 1% level for differences in mean between male and female for indicated variable. Number at the end of the variable name indicate which wave the data was extracted from.

Table 3. Log Earnings by Psychological Traits at the 25th and 75th Percentile

Psychological Trait Percentile	Log of hourly wages				
	75 Percentile		25 Percentile		
Variable	Female	Male	Female	Male	Difference at quartile significant?
Masculine Traits 2	2.102567	2.238865**	2.124323	2.221934**	No
Self Esteem 12	2.132223	2.247761**	2.113996	2.218828**	No
Analytical 1	2.125359	2.243073**	2.100197	2.244612**	No
Work Hard 12	2.156513	2.269606**	2.071337	2.182344**	No
Impulsive 12	2.035845	2.239401**	2.151041	2.271264**	No
Avoidance 12	2.121554	2.257008**	2.134936	2.259223**	No
Self-Assessed Intelligence 12	2.181796	2.253084*	2.070888	2.268309**	Yes**

* Significance at the 5% level and ** significance at the 1% level for differences in mean between male and female for indicated percentile. Number at the end of the variable name indicate which wave the data was extracted from.

Table 4. Regression Results

OLS estimates for the log of hourly earnings of the whole sample and then by gender.

	Pooled		**Male**		**Female**	
	(1)	(2)	(3)	(4)	(5)	(6)
Male 3	0.137***	0.108***				
	(0.0191)	(0.0185)				
Others 1		0.0381		0.0139		0.0542
		(0.0273)		(0.0400)		(0.0374)
Black 1		-0.0685***		-0.0564		-0.0832***
		(0.0237)		(0.0370)		(0.0308)
Age 3		0.129		0.148		0.160
		(0.120)		(0.171)		(0.176)
Age 32		-0.00216		-0.00248		-0.00299
		(0.00272)		(0.00384)		(0.00402)
English 3		-0.0531		-0.0307		-0.0776
		(0.0393)		(0.0563)		(0.0553)
Roommates 3		0.0280		0.0211		0.0360
		(0.0263)		(0.0388)		(0.0360)
Lshs 3		-0.143***		-0.0878		-0.224***
		(0.0454)		(0.0673)		(0.0634)
Hs 3		-0.0658**		-0.0207		-0.111***
		(0.0331)		(0.0530)		(0.0423)
College 3		0.167***		0.134**		0.184***
		(0.0417)		(0.0680)		(0.0526)
Numjob 3		-0.00747		0.0138		-0.0357
		(0.0219)		(0.0332)		(0.0291)
Fullemploy 3		0.170***		0.191***		0.146***
		(0.0197)		(0.0310)		(0.0255)
Married 3		0.0446*		0.132***		-0.0134
		(0.0252)		(0.0416)		(0.0315)
Masculine 2	-0.00468	-0.00296	-0.00155	-0.000695	-0.00731	-0.00478
	(0.00399)	(0.00378)	(0.00595)	(0.00571)	(0.00537)	(0.00502)
Esteem 12	-0.00127	0.00166	-8.47e-05	0.00314	-0.00252	0.000894
	(0.00167)	(0.00161)	(0.00260)	(0.00254)	(0.00218)	(0.00208)
Analytical 1	0.00196	-0.00199	-0.000166	-0.00225	0.00456	-0.00146
	(0.00395)	(0.00375)	(0.00576)	(0.00554)	(0.00543)	(0.00509)
Workhard 12	0.0197***	0.00945	0.0222**	0.00832	0.0160*	0.00668
	(0.00672)	(0.00638)	(0.0103)	(0.00999)	(0.00885)	(0.00827)
Impulsive 12	-0.00579	-0.00273	-0.00213	-0.00200	-0.00962**	-0.00264
	(0.00356)	(0.00342)	(0.00525)	(0.00509)	(0.00486)	(0.00462)
Avoidance 12	-0.00129	0.00347	-0.00164	0.00186	-0.00154	0.00552
	(0.00354)	(0.00339)	(0.00540)	(0.00526)	(0.00468)	(0.00442)
Intelligence 12	0.00989*	0.0109**	0.000443	0.00522	0.0198***	0.0189***
	(0.00526)	(0.00514)	(0.00767)	(0.00769)	(0.00724)	(0.00695)
Constant	2.067***	0.151	2.141***	-0.166	2.128***	-0.0162
	(0.120)	(1.336)	(0.185)	(1.920)	(0.161)	(1.943)
Observations	2,384	2,384	1,137	1,137	1,247	1,247
R-squared	0.030	0.145	0.005	0.105	0.020	0.169

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Number after variable name indicate which wave the data was extracted from.

Table 5. Wage Decomposition Results

Actual Gap	0.1281929				
Females with Male Characteristics (2)			**Males with Female Characteristics (3)**		
Explained			**Explained**		
XmBm-XfBm	0.0280652	21.89%	XmBf-XfBf	0.0104067	8.12%
Explained by:			**Explained by:**		
Demographic	0.0261385	20.39%	Demographic	0.0171525	13.38%
Psychological	0.0019265	1.50%	Psychological	-0.0067458	-5.26%
Unexplained			**Unexplained**		
XfBm-XfBf	0.1001279	78.11%	XmBm-XmBf	0.1177864	91.88%
Exp+Unexp	0.1281931		Exp+Unexp	0.1281931	

Appendix 1. Description of Psychological Factors

Variable Name	Question
	Respondents are asked whether they agree or disagree with each of the following statements:
Masculine 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 just the way you are.
Just Right 12	You feel like you are doing everything 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 was 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 because you worked hard for it.
Impulsiveness 12	
Gut Feeling 12	When making decisions, you usually 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 very upset.
	Respondents are asked to rate their intelligence:
Self-Assessed Intelligence 12	
Self-Assessed Intelligence 12	Compared with other people your age, how intelligent are you?

*Respondents are asked to rank how well each of these questions described them ranging from strongly agree (1) to strongly disagree (5). However for interpretation purposes, the ranking is reversed, except for some of the attributes that constructed masculine traits (shy, sensitive, and emotional). Furthermore, the intelligence trait ranges from moderately below average (1) to extremely above average (6) and this ranking is also not reversed either.