Explaining personality pay gaps in the UK

Alita Nandi and Cheti Nicoletti

ISER, University of Essex

2009

JEL: J71; C21; J31

Keywords: Big Five trait, decomposition, wage

Contact: Alita Nandi, ISER University of Essex, Wivenhoe Park, CO4 3SQ Colchester, UK, Tel. 01206 873536. email anandi@essex.ac.uk

Acknowledgments

We would like to thank participants at the ESPE and the BHPS conferences in 2009, Guido Heineck and Jon Burton for their helpful comments. The support by the Economic and Social Research Council through the MiSoC research centre and *Understanding Society*: The UK Household Longitudinal Study are kindly acknowledged.

Abstract

Using the British Household Panel Survey we examine how the Big Five personality traits – openness to experience, conscientiousness, extroversion, agreeableness, and neuroticism – affect wages. We estimate mean and quantile pay gaps between people with low and high levels of each of the Big Five, and decompose these pay gaps in the part explained by differences in workers' characteristics and in the residual unexplained part. We find that openness to experience is the most relevant personality trait followed by neuroticism, agreeableness and extroversion. Openness and extroversion are rewarded while agreeableness and neuroticism are penalized.

1. Introduction

In recent years there has been an increasing number of economic papers looking at the relationship between earnings and personality traits and there is strong evidence that personality matters (in the labor market) as much as cognitive skills or education. We add to this literature by deepening the understanding of why people with different personality traits get paid differently.

While it is generally considered fair that workers with better cognitive abilities or education be paid more, unequal pay across workers with different levels of a personality trait, but who are otherwise identical, could be considered unfair. In this paper we estimate the counterfactual pay gap between workers with different levels of a personality trait which we would observe if they were equal in terms of all other characteristics that are rewarded in the labor market.

In theory this counterfactual pay gap reflects an unequal and potentially unfair treatment of workers with different personality traits, but this could also reflect an omitted variables problem if we cannot observe some of the workers' characteristics which are relevant to capture their productivity. By using the British Household Panel Survey we control for a large set of characteristics which allows us to reduce, although not completely eliminate, the omitted variables problem. For example, a pay gap for high neurotic workers could be a consequence of a reduced productivity or of employer's prejudices against neuroticism. High levels of neuroticism which limit productivity are probably the consequence of a mental health problem. So we expect that once we control for the presence of health problems and for the extent to which health limits the amount of work, the reduced productivity effect of neuroticism will be eliminated (or reduced) and the estimated pay gap between high and low neurotic people will better reflect discrimination.

We use the Big Five trait taxonomy (openness to experience, conscientiousness, extroversion, agreeableness, and neuroticism) to classify people into different personality groups (e.g., high agreeable and low agreeable, high extrovert and low extrovert, etc.) and then decompose the pay gap between these groups into two additive components: a component explained by differences in workers' characteristics and a residual unexplained component (the counterfactual pay gap). We decompose further the explained component to identify the contribution of each specific characteristic in explaining pay differences (detailed decomposition). To implement the decomposition analysis we adopt an innovative method proposed by Firpo et al (2007) which overcomes some of the shortcomings of the Oaxaca-Blinder method.

Our main contribution to the literature is twofold. First, we conduct a detailed decomposition of the personality pay gap to identify the importance of differences in occupation, education, health and other characteristics in explaining these pay gaps. Second, we provide a more complete picture of the relationship between wage and personality traits by analyzing the personality pay gaps not just at the mean but also at different points of the wage distribution.

2. Background

Recently economists (see Goldsmith *et. al.* 1997, Bowles *et al*., 2001, Nyhus and Pons 2005, Mueller and Plug 2006, Cebi 2007, Heineck 2007, Viinikainen *et. al.* 2007, Heckman *et al.* 2008, Fortin 2008, Heineck and Anger 2009) have begun to study the effect of personality traits[1] on labor outcomes and in particular earnings. These studies, as well as earlier research by psychologists (Barrick and Mount 1991, Mount and Barrick 1998 and Saldago 1997), have found strong associations between personality traits and different labor outcomes.

Personality traits are generally defined as stable patterns of thought, feelings and behaviour (Borghans *et. al.* 2008). It does not mean that persons with certain traits behave in the exact same way in every situation, but that they have a higher tendency of behaving in particular ways than others. While these traits are relatively steady in adulthood, they can be affected by parental background, environmental factors and interventions, during childhood and also during adolescence (Cunha and Heckman 2008,

[1] Some researchers use the term non-cognitive skills rather than personality traits. As advised by Borghans *et. al.* (2008) we avoid the term non-cognitive skills because it seems to suggest, erroneously, that personality skills are independent of cognitive abilities. Henceforth we will use the term personality traits, characteristics, skills or abilities.

Cunha *et al*. 2006). This implies that early interventions targeted at improving personality skills can have effects on adult outcomes such as earnings (see Heckman *et al*. 2008).

It is possible to define a large number of personality traits, but here we restrict our attention to the Big Five personality traits taxonomy that includes openness to experience (vs. closed to experience), conscientiousness (vs. lack of direction), extraversion (vs. introversion), agreeableness (vs. antagonism) and neuroticism (vs. emotional stability), as it has received a general consensus among psychologists (see John and Srivastava 1999). The Big Five taxonomy does not have a theoretical background, but there is empirical evidence that the Big Five are the only replicable factors. Goldberg (1990) and Saucier and Goldberg (1996) analyze large sets of personality adjectives and find factor structures similar to the Big Five personality traits.

Recent studies that have examined the effect of Big Five personality traits on wages using different datasets (Nyhus and Pons 2005, Mueller and Plug 2006, Heineck 2007, Heineck and Anger 2009) find that agreeableness, openness to experience and neuroticism are significant in explaining pay even after controlling for other relevant explanatory variables; whereas Viinikainen *et. al*. (2008) find that only extraversion matters. Some of these studies have acknowledged that part of the wage differential is due to occupational sorting by personality types (Mueller and Plug 2006) but they have not tried to quantify how much of the personality pay differences is related to occupational sorting or to differences in other job and personal characteristics. In this paper we try to fill this gap by answering the following questions: Why are people with diverse personality traits paid differently? To what extent is it because persons with certain personality traits happen to have certain characteristics that are rewarded differently in the labor market? And how important is each of these characteristics in explaining pay gaps across personality groups?

To highlight why this may happen let us consider arguments for why we expect labor market earnings to differ by personality traits.

First, as with cognitive ability, personality skills may increase productivity and therefore wages. Of course certain traits may increase a person's productivity in certain activities and tasks but not necessarily all. Psychologists find, for example, positive associations between conscientiousness and job performance for all types of occupations and between extraversion and job performance for occupations which require social interaction or team work (see Mount and Barrick 1998). They also find that openness to experience makes training more effective, which in turn can increase productivity in some occupations. Finally, Bowles *et. al.* (2001) suggest that, in the presence of incomplete information, employers could be willing to pay a premium for persons with personality traits that are incentive enhancing as then employers can encourage higher productivity by using incentives.

Second, employers may pay persons with different personality traits differently for reasons other than their effect on productivity. We refer to this as taste based discrimination. It could be that employers prefer to work with people with certain types of personality traits and so are willing to pay more even if these persons are not necessarily more productive. Similarly, there can be employee (colleague) and consumer taste based discrimination against workers with specific personality traits. Consumers, for example, may prefer to buy from sellers who are more agreeable and extrovert and to buy from less agreeable or introvert sellers only if the price is reduced (see Altonji and Blank 1999).

Third, some personality traits can enhance the ability of wage bargaining or the workplace social networking and ultimately affect wages (Mueller and Plug 2006).

While personality traits may be rewarded differently for productivity or non-productivity enhancing reasons, we may also observe personality pay differences if people with diverse personality traits sort into different occupations and education levels (Filer 1986, Jackson 2006 and Krueger and Schkade 2008). This is what makes it difficult to interpret observed personality pay differences as rewards for different personality traits only.

3. Methods

There is a large literature on how to decompose pay differences between groups into two additive components: the composition component explained by differences in characteristics and the residual unexplained component (see Blinder 1973, Oaxaca 1973, DiNardo *et. al.* 1996, Barsky *et. al.* 2002, and Firpo *et. al.* 2007).

The most well-known and popular decomposition approach is the Blinder-Oaxaca method (Blinder, 1973; Oaxaca, 1973). This approach is based on the estimation of a linear regression of the outcome variable, y, on a set of explanatory variables x separately for the two groups to be compared, which we call the comparison and reference groups. In our analysis, the outcome variable is log wage and the explanatory variables are a set of personal and job characteristics. For each of the Big Five personality traits our comparison (reference) group is defined by people with high (low) levels of the personality trait. The estimated regression coefficients for the comparison group and the mean values of x observed for the reference group are used to predict the counterfactual mean log wage of the comparison group as if it had the same distribution (or at least the same mean) of x as that observed for the reference group. The difference between the counterfactual mean log wage of the comparison group and its observed mean log wage represents the explained component of the pay difference (composition effect), while the difference between the counterfactual mean and the mean observed for the reference group represents the residual unexplained pay difference.

If we represent the log wage regression by,

$$y_j = x_j \beta_j(\mu) + \varepsilon_j$$

where j takes value 1 for individuals belonging to the comparison group (group 1) and 0 for individual in the reference group (group 0), x_j is a vector of K explanatory variables (including the constant), $\beta_j(\mu)$ is the corresponding vector of coefficients, μ denotes mean regression coefficients, and ε_j is an error term. Let $\bar{x}_j$ be the mean of x_j, then the composition and residual effects are given by $(\bar{x}_1 - \bar{x}_0)\beta_1(\mu)$ and $\left(\bar{x}_0\beta_1(\mu) - \bar{x}_0\beta_0(\mu)\right)$, respectively.

Furthermore, the Blinder-Oaxaca method allows decomposing the explained component into additive parts representing the contribution of each explanatory variable to the pay difference:

$$(\bar{x}_1 - \bar{x}_0)\beta_1(\mu) = \sum_{k=1}^{K} \left(\bar{x}_{1,k} - \bar{x}_{0,k}\right)\beta_{1,k}(\mu)$$

where $\bar{x}_{j,k}$ is the *k-th* component of the vector variables $\bar{x}_j$.

The Blinder-Oaxaca method is the only statistical tool that allows us to estimate the separate contribution of each variable to explaining the mean pay gap and for this reason it is still largely used in applied economics papers (see for example Antecol et al. 2008 and Chiswick et al. 2008). Nevertheless, the Blinder-Oaxaca decomposition has three main disadvantages: first, it is not directly applicable to decompose differences in any statistics other than the mean; second, it imposes a linearity assumption between outcomes and explanatory variables; and third, when the range of possible values assumed by x differ for the comparison and reference groups, it computes the counterfactual mean by using out of the sample predictions.

A solution to the first disadvantage has been recently provided by Firpo et al (2007) who show how to extend the Blinder-Oaxaca mean decomposition to other statistics by using the recentered influence function (*RIF*) approach (see Firpo et al 2009). The recentered influence function for a statistic v of y is a function RIF(y,v) which satisfies the following properties[2]:

(a) its mean is equal to the actual statistic v, $E_y[RIF(y,v)]= v$;

(b) the mean of its conditional expectation given x, $E_y[RIF(y,v)|x]$, is again equal to the actual statistic v, i.e. $E_x\{E_y[RIF(y,v)|x]\}= v$.

Assuming a linear relationship between $RIF(y,v)$ and x for both the comparison and reference groups, we can estimate $E_y[RIF(y_j,v)|x_j]$ using a linear regression:

$$RIF(y_j,v)=x_j\,\beta_j(v)+u_j,$$

where j is, as before, the group indicator (0 or 1), x_j is a vector of K explanatory variables (including the constant), $\beta_j(v)$ is the corresponding vector of coefficients for the statistic v and u_j is an error term.[3] Given the properties (a) and (b), it is easy to prove that the difference between the statistic v for group 1 and 0 is

[2] For a more detailed definition of the recentered influence function and a full list of properties we refer to Firpo et al (2009).

[3] When the ν statistics is a quantile then the RIF-regression is an unconditional quantile regression (see Firpo et. al. 2009).

$$v_1 - v_0 = \mathrm{E_y}[RIF(y_1,v)|x_1] - \mathrm{E_y}[RIF(y_0,v)|x_0] = \bar{x}_1\beta_1(v) - \bar{x}_0\beta_0(v),$$

and can be decomposed into two additive components, the composition effect and the residual effect,

$$\bar{x}_1\beta_1(v) - \bar{x}_0\beta_0(v) = \left(\bar{x}_1 - \bar{x}_0\right)\beta_1(v) + \bar{x}_0\left(\beta_1(v) - \beta_0(v)\right).$$

This decomposition is equivalent to the Blinder-Oaxaca method with the only difference that it is based on the *RIF*-regression rather than the y-regression.

The *RIF* of the mean is equal to *y*. In this case the *RIF*-regression is equal to the y-regression so that the Blinder-Oaxaca decomposition of the mean difference is a special case of the *RIF* based decomposition. So, we call the *RIF* based decomposition the *generalized Blinder-Oaxaca* or *regression based method*.

This method can also be used also to produce a detailed decomposition to evaluate the contribution of each variable (see Firpo et. al. 2007),

$$v_1 - v_0 = \sum_{k=1}^{K}\left(\bar{x}_{1,k} - \bar{x}_{0,k}\right)\beta_{1,k}(v) + \bar{x}_0\left(\beta_1(v) - \beta_1(v)\right).$$

In our application we consider the decomposition of pay differences in quantiles and mean. The *RIF* of a τ-quantile is given by

$$RIF(y, q_\tau) = q_\tau + \frac{\tau - \mathrm{I}(y \le q_\tau)}{f(q_\tau)}$$

where q_τ is the τ-quantile, *I*(.) is the indicator function taking value *1* if the event between parenthesis is true and *0* otherwise, and *f*(.) is the density distribution of *y* computed at the τ-quantile. We estimate $RIF(y,q_\tau)$ by replacing q_τ with its sample estimate and computing the density distribution by using a nonparametric kernel estimation.

While the *generalized Blinder-Oaxaca* or *regression based method* does have the advantage of providing a decomposition of differences in statistics other than the mean such as quantile, variance, etc. the composition effect estimated provides only an approximation of the marginal effect on the statistic *v* of a change of the distribution of *x* from the comparison group to the reference group. Firpo et al (2009) prove that the approximation error goes to *0* for infinitesimal changes in the distribution of *x* or in the special case where v is equal to the mean. Also, this method is still based on a linearity assumption and on out of the sample predictions when the explanatory variables have a different range between the two groups compared (Barsky *et. al.* 2002).

A more robust way to decompose pay differences in mean, quantile or other statistics is by using weighting methods (DiNardo *et. al.* 1996, Barsky *et. al*. 2002). The counterfactual statistic (mean, quantile, etc) is estimated by simply computing the statistics using weights to equivalize the distribution of the explanatory variables (x) between the two groups compared. A counterfactual statistic for the comparison group, assuming the same distribution of x as that observed for the reference group, can be computed using weights, $w(x)$, given by the ratio between the probability of belonging to the reference group rather than the comparison group (conditional to the variable x) and its complement to one, i.e.

$$w(x)=Pr(d=1|x)/[1-Pr(d=1|x)],$$

where d is a dummy taking value 1 for the comparison group and 0 for the reference group.

The probability $Pr(d=1|x)$ can be estimated non-parametrically if the explanatory variables are low in number. On the contrary, when the set of variables is large some parametric assumptions are needed to avoid the curse of dimensionality. In our empirical application we consider a large set of explanatory variables and we assume a logit model. Notice that applying weighting methods is equivalent to applying propensity score methods (see for example Rosembaum and Rubin 1983, Hirano et al. 2003, Wooldridge 2002 and 2007), where the propensity score is defined by $Pr(d=1|x)$.

The main advantage of weighting (or propensity score) methods is that these require us to specify and estimate a model only for $Pr(d=1|x)$. On the other hand, their drawback is that they do not provide a detailed decomposition of the difference in v (*i.e.,* a decomposition where the contribution of each single explanatory variable can be separated out).

To compute counterfactual means, quantiles, variances and other summary statistics, it is also possible to combine weights and regression based methods. The combined method is equivalent to the counterfactual estimation used by Firpo et al (2007). The combined weighting regression method consists in estimating the RIF linear regression for the comparison group,

$$RIF(y_1,\nu)=x_1\ \beta_1^{WR}(\nu)\ +\mathrm{u}_1,$$

by using the above described weights, $w(x)$. The superscript *WR* in $\beta_1{}^{WR}$ (ν) stands for weighted regression. The estimation is consistent if either the weights (i.e. the logit model) are correctly estimated or the linear regression model is correctly specified.[4] The counterfactual statistics are computed as in the Blinder-Oaxaca decomposition but considering the coefficients estimated using the weighted RIF-regression, $\left(\bar{x}_o\beta_1^{WR}(\nu)\right)$. Given the counterfactual, we can again decompose the pay gap into two additive components:

$$\nu_1-\nu_0=\left[\bar{x}_1\beta_1(\nu)-\bar{x}_o\beta_1^{WR}(\nu)\right]+\left[\bar{x}_o\left(\beta_1^{WR}(\nu)-\beta_0(\nu)\right)\right].$$

The first addend between square brackets represents the composition effect, whereas the second addend is the unexplained residual. We can further decompose the composition effect into two parts:

$$\bar{x}_1\beta_1(\nu)-\bar{x}_o\beta_1^{WR}(\nu)=(\bar{x}_1-\bar{x}_0)\beta_1(\nu)+\bar{x}_0\left(\beta_1(\nu)-\beta_1^{WR}(\nu)\right),$$

with the first part equal to the composition effect based on the generalized Blinder-Oaxaca approach, and the second part equal to the difference between the composition effect in the generalized Oaxaca and in the combined weighting and regression based approach (and thus the reliability of the detailed decomposition). The first part, *i.e.*, the composition effect based on the generalized Blinder-Oaxaca approach, can be further decomposed into additive components reflecting the contribution of each explanatory variable, $\left(\sum_{k=1}^{K}\left(\bar{x}_{1,k}-\bar{x}_{0,k}\right)\beta_{1,k}(\nu)\right)$.

In our empirical application we apply both the generalized Blinder-Oaxaca decomposition and the more robust weighting and regression based approach. In all our

[4] In summary, the combined weighting and regression based estimation method is double consistent (Robins and Rotnitzky 1995).

estimation procedures we consider also weights to correct for the sampling design and for unit non-response (see for details Section 4).

4. Data

4.1 Sample definition

For our analysis we use data from the British Household Panel Survey (BHPS), a longitudinal survey of a representative sample of private households in the UK. The BHPS provides the ‘Big Five’ personality traits and detailed information on employment, education, income, and other socio-economic variables at individual and household levels making it particularly suitable for our study. Each year (wave) every adult (16+ years) member of the original sample of households is eligible for interview even when they move into a different household (as long as they are currently residing in UK).[5] All adult co-residents of these original sample members are also eligible for interview.

We use data primarily from the wave 15 (*i.e.*, year 2005) of the BHPS as the Big Five personality traits are measured in that wave. We restrict the sample to men interviewed in wave 15 who are between the ages of 24 and 64 years by December 2005, currently living in the UK and in paid employment (but not self-employed). This resulted in a sample of 3025 men. After dropping cases with missing values for the variables in our analysis we were left with 2688 observations (about 90% of the sample). In all our analyses we take account of the sampling design and unit non-response by using the cross-section weights for wave 15 provided in the publicly released BHPS data set.[6]

4.2 Variables

Personality traits

We consider the Big Five personality traits - openness to experience, conscientiousness, extraversion, agreeableness and neuroticism - which have been recognized by most psychologists as a way to summarize the large range of individual personality

[5] All children born to members of this original sample also become part of that sample and become eligible for interview when they turn 16.

[6] For details on the weighting procedure we refer to British Household Panel Survey User Manual Volume A, 2009, edited by Taylor M.F. with Brice J., Buck N., Prentice-Lane E.

characteristics (see John and Srivastava 1999). We measure these 5 personality traits by using the 15-item personality inventory available in the BHPS. The Big Five are usually assessed with a longer set of questions; however, there is empirical evidence supporting the reliability of measures based on concise inventory (see for example Benet-Martinez and John 1998 and Gosling *et. al.* 2003).

In Table 4.1 we report for each of the 5 personality traits the related personality facets or adjectives (as in John and Srivastava 1999) and the three questions asked in the BHPS to measure it. The BHPS asks each respondent to rate a set of claims on how they see themselves on a 7-point scale, from 1 "does not apply" to 7 "applies perfectly". We measure each personality trait as the average score of the responses to the three questions. We adopt the standard approach to assess measurement error problems by computing the standardized Cronbach's alpha reliability index.[7] We find an alpha reliability equal to 0.68, 0.57, 0.59, 0.56 and 0.69 for openness, conscientiousness, extraversion, agreeableness and neuroticism respectively. These are exactly the same as the reliability indexes found by Heineck (2007) who also uses the BHPS and very close to the ones found by Heineck and Anger (2009) who use the German Socio-Economic Panel and the same 15-item personality inventory, and they are better in 3 out of 5 cases than the reliability indexes computed by Gosling *et. al.* (2003) using an even more reduced number of questions (a 10-item personality inventory). On the other hand, these reliability measures are worse than in studies which use a larger number of items to measure each personality trait (see for example John and Srivstava 1999 or Mueller and Plug 2006).

We report the mean, standard deviation, first, second and third quartiles for each of the five personality traits in Table 4.2. In our analysis we use the median, the 25th and the 75th percentiles of each of these personality traits to distinguish between people with low and high, extremely low and extremely high levels of the trait. Each trait (*i.e.* the average of the three items used to measure it) takes values from 1 to 7. The largest standard deviation and inter-quartile range (which are measures of variability) are

[7] This alpha reliability index is given by the ratio between the variance of the true unobserved personality measure and the variance of the observed personality measure and it is computed under assumptions equivalent to the classic measurement error model (see Cronbach, 1951).

observed for neuroticism, followed by extroversion and openness. For conscientiousness and agreeableness there is less variability and more than 50% of the people have values higher than 5.

Wage

We compute hourly wage using the usual gross monthly wage of the current job and the number of hours normally worked per week. When the information is missing we consider the imputed value provided in the BHPS.[8] We find that the average log hourly wage for those with high levels (above the median) of a personality trait are different from those with low levels (below the median) of that personality trait (see Table 4.3).[9] The largest difference in mean is between high and low openness, 0.089, which corresponds to about £1.04 (10%) difference in hourly wage. Extroversion is also positively rewarded and implies on average an increase of about 5% (63 pence) of the hourly wage. On the contrary, high agreeableness and neuroticism are penalized in the labor market with an average reduction of the hourly wage of about 6% (72 pence).

Other control variables

In our empirical application we also control for a set of workers' characteristics relevant in the wage determination, which we describe below.

Every person in paid employment is asked to report verbatim what sort of work they do and their job title. BHPS provides the 3-digit Standard Occupational Classification (SOC 2000) of the current job based on the verbatim reports and we use that to classify people into nine occupational categories (*occupation*): managers and senior officials; associate professional and technical; administrative and secretarial; skilled trades; personal service; sales and customer service; process, plant and machine operatives; and elementary occupations .

We also use other information about the job that the respondents report – the firm size or rather whether the firm has fewer than 10 employees (*firm size*), whether the firm is public or not (*public*) and whether the job is temporary, i.e., fixed-term contracts,

[8] See for details on wage imputation British Household Panel Survey User Manual Volume A, 2009, edited by Taylor M.F. with Brice J., Buck N., Prentice-Lane E.
[9] Test results on significance of the pay differences are reported in Table 5.1 in Section 5.

seasonal or casual jobs (*temporary*). To identify whether a person is employed full-time or part-time we use the BHPS derived variable which codes all those whose total hours worked (including overtime) in a week is less than 30 as part-time employed and more than 30 hours as full-time employed (*part-time employed)*.

We compute the potential work experience (*experience)* of a person in the standard manner by subtracting the age the worker left full-time education (school, college or university) for the first time from his/her current age.

Using questions on the training received in the past three years we compute a variable to identify whether respondents have received training (of 30 hours or more per week) in the last three years (*past training*).

We also compute the proportion of time people have spent in unemployment since they were first interviewed (*past unemployment*).

We also consider a variable for the highest educational qualification achieved which we categorize in college or university degree, A-level or other higher education but below college degree, GCSE or O-level, and vocational or technical education (*education*).

Respondents are also asked to report whether they have any health problems or disabilities.[10] We summarize this information with a dummy variable indicating whether a person has any of these health problems (*any health problems*). We also consider the extent to which health limits the amount of work in a four-point scale – a lot, somewhat, just a little and not at all – (*health limits work*).

The BHPS provides also information on which standard region or metropolitan area the person lives in. We consider the following nine regions London, Rest of South-East, South-West, Anglia & Midlands, North West, Rest of the North, Wales, Scotland, Northern Ireland (*region*).

[10] More specifically, respondents report if they have health problems or disabilities connected with: arms, legs, hands, feet back, or neck (including arthritis and rheumatism); difficulty in seeing (other than needing glasses to read normal size print); difficulty in hearing; skin conditions/allergies; chest/breathing problems, asthma, bronchitis; heart/high blood pressure or blood circulation problems; stomach/liver/kidneys or digestive problems; diabetes; anxiety, depression or bad nerves, psychiatric problems; alcohol or drug related problems; epilepsy; migraine or frequent headaches; cancer; stroke; or other health problems .

In Table 4.4 we report the mean and standard errors for the variables just described.

5. Results

Relationship between wage and personality traits

We analyze the pay difference between workers with high and low levels (above and below the median) of each of the Big Five personality traits (openness, conscientiousness, extroversion, agreeableness and neuroticism). In Table 5.1 we report these pay differences computed at the mean as well as at the 10th, 25th, 50th, 75th and 90th percentiles. Pay (wage) is defined as the logarithm of hourly wage. As a consequence, differences in mean and quantiles are approximately equal to relative instead of absolute changes in mean and quantiles.

We observe statistically significant mean pay differences (different from 0 at the 5% level) for openness, agreeableness, neuroticism and extroversion. High agreeable and high neurotic people are paid on average less; whereas people with high openness and high extroversion tend to be paid more. Conscientiousness, however, does not lead to any statistically significant difference in pay. These results seem in line with previous studies by Letcher and Niehoff (2004) and Mueller and Plug (2006), who consider a sample of people graduated from high schools in Wisconsin, and with Heineck (2007) and Heineck and Anger (2009), who use the British and German Household Panel surveys.

Results in Table 5.1 suggest that the pay differentials are approximately invariant across the distribution for conscientiousness. On the contrary, neuroticism, agreeableness and introversion pay gaps are more significant for people at the bottom of the pay distribution, whereas openness to experience provides a pay advantage especially for people in the top half of the pay distribution. In other words, there seems to be a sticky floor effect for highly neurotic, highly agreeable people and highly introvert people and a glass ceiling effect for people who are closed to experience.

Pay differences observed for people with diverse personalities could be in part explained by the fact that people with different personality characteristics sort out in different occupations, level of education, etc. Previous papers find for example that conscientiousness and openness are correlated with education (see Barrick and Mount 1991, and Raad and Schouwenburg 1996) and this can explain part of the pay differences observed for conscientious and open people. This is confirmed by our decomposition results. Before moving to describe in detail these results, we provide some empirical evidence on the sorting out of people with diverse personalities in different occupations, levels of education and other characteristics which are usually rewarded in the labor market.

More precisely, we study how a personality trait relates to education, occupation, potential work experience and its square, part-time, temporary job, public sector, firm size, health dummies for bad health and for health problems limiting amount of work, past training and past unemployment experience, region dummies, and the other four personality traits (dummies for low and high level of each personality trait).[11] We analyze this multivariate relationship by considering logit models for the probability of having high rather than low levels of each of the Big Five personality traits.

In our logit model used to predict the probability of openness to experience, we find that it is statistically significantly positively related to college or university degree, and negatively related to no educational qualification and elementary occupations. The most significant explanatory variables positively related to conscientiousness are work experience and having a GCSE or O level, whereas dummies for part-time job and administrative-secretarial and sales or customer services occupations are statistically significantly negatively related. Agreeableness relates positively to no educational qualification as well as to college or degree education, and negatively to work experience. Neuroticism is positively correlated with bad health, health problems which limit amount of work, past unemployment experience and administrative and secretarial occupation, and negatively with past training. Finally, extroversion is positively correlated with having a GCSE or O level, past training and working in big firms, and negatively correlated with college or degree education, professional occupations and work experience.

[11] A more detailed description of these variables is provided in Section 4.

Decomposition results

As a first step towards estimating the decompositions, we estimate mean and unconditional quantile wage regressions separately for each personality group (unlike previous studies), therefore allowing the return to a personality trait to differ across occupations, levels of education and other explanatory variables. Next we decompose these pay differences for each personality trait, at the mean and at 5 different quantiles, into two main components: a component, called composition effect, which is explained by differences in the explanatory variables, and a residual unexplained component. These are computed using both the combined weighting and regression based method and the the generalized Blinder-Oaxaca method described in Section 2. The weights for the combined method are based on the logit models described above. In the second and third column of Tables 5.2 and 5.4 we report the composition and residual effect estimated using the combined method and in the fourth column the composition effect estimated using the generalized Blinder-Oaxaca decomposition. As already explained in Section 2, while the generalized Blinder-Oaxaca decomposition provides an estimation of the composition effect which could be biased; the decomposition based on combined weighting and regression based method provides a more robust estimation but does not allow us to estimate detailed decompositions. However, where we find that the composition effects estimated using the two types of decomposition are similar, we can use the generalized Blinder-Oaxaca method to provide a reliable detailed decomposition.

In the log wage equations we control for the same variables as in the logit model (described earlier).

Looking at the decomposition results for the mean differences (see Table 5.2) we find that differences for openness and conscientiousness are almost completely related to a composition effect; whereas differences in the personal and job characteristics do not explain the pay differentials between low and high levels of agreeableness, extroversion and neuroticism.

In Table 5.3 we present the results of the generalized Blinder-Oaxaca detailed decomposition[12] to evaluate the contribution of different variables to the mean pay difference. It is meaningful to discuss these results for the mean difference between people with high and low openness to experience and conscientiousness because the composition effect for these cases is large (90% and 60% of the total difference). Additionally, in these two cases the Blinder-Oaxaca approach provides an accurate estimate of the composition effect because it is close to the more robust estimate provided by the combined weighting and regression based approach. The pay advantage for high open to experience persons is explained mainly by education (and in particular by the dummies for no educational qualification and college or university degree) and occupation (especially professional, associate professional and technical, and elementary occupations); whereas the pay disadvantage for high conscientious people, although not statistically significant, seems to be explained by education, occupation, region and other job characteristics (in particular part-time).

Looking at the pay gaps at different quantiles (see Table 5.4), we find a similar story. Differences in pay percentiles between people with high and low openness to experience is mainly explained by differences in characteristics but differences in percentiles for agreeable, extrovert and neurotic people are not. Conscientiousness does not imply any significant difference in pay percentiles and these small pay differences are not explained by characteristics either.

Notice that the apparent glass ceiling effect for workers who are more closed to experience disappears once we control for the composition effect. This implies that the bigger pay advantage of openness to experience observed at the top percentiles is related to the fact that people with low and high openness to experience have different job and personal characteristics. On the contrary, the sticky floor effect observed for highly neurotic people and highly introvert workers persist even after controlling for the composition effect. This seems to suggest that emotional stability and extroversion are personality traits better rewarded in low paid occupations (such as plant and machine

[12] Notice that the generalized Blinder-Oaxaca decomposition for mean differences is identical to the standard Oaxaca decomposition (see Section 3 for more details).

operatives and elementary occupations) as confirmed by the estimated coefficients in our wage regressions.

In case of agreeableness, once we control for the person's personal and job characteristics (moving from the first to the third column in Table 5.4), the pay gap increases at the higher end of the wage distribution but decreases at the 10^{th} percentile, thus equalizing the pay gap across the whole distribution. In that sense the sticky floor disappears. Since we find that agreeableness is associated with both no educational qualification as well as with college or degree education, an explanation for this result is that at the high (low) end of the wage distribution, workers are better (worse) educated which masks (accentuates) the pay penalty for agreeableness. So, once we control for education the pay penalty for agreeableness increases (decreases) for the workers at the top (bottom) of the pays distribution.

To better assess possible determinants of these pay percentile differences, we consider the detailed decomposition but only for the cases where there is a substantial composition effect and where the estimates of this effect using the two methods are close to each other. This seems to hold for the decomposition of the pay differences between high and low openness to experience (see second and last column in the first panel of Table 5.4). We report the detailed decomposition results for these cases in Table 5.5.

We find that educational level and type of occupation are the main variables explaining the differences in pay between high and low openness to experience (see Table 5.5). More precisely, at the bottom quantiles the differences are explained mainly by the dummies for no educational qualification and low paid occupations such as elementary occupations, while at the top quantile the difference is explained mainly by the dummies for college or degree, professional, associate professional and technical occupations. In other words, pay differences for openness to experience is almost completely explained by the sorting out of people with specific personality levels into specific levels of education and occupations. This may reflect that occupational and educational choices are related to the level of openness or a personality-based discrimination in the hiring process especially against people with low openness and in some occupations.

Summary and some reflections

It seems that the most relevant personality traits in explaining differences in pay are openness, agreeableness, neuroticism and extroversion. While pay advantages associated to openness are explained mainly by differences in characteristics; the pay differences associated with extroversion, neuroticism and agreeableness are not. Finally, the pay gap for openness and agreeableness does not change significantly across the wage distribution, at least after controlling for the composition effect; whereas there seems to be a sticky floor effect for introversion and neuroticism.

As we see, for extroversion, agreeableness and neuroticism the pay difference (at the mean and quantiles) is significantly different from zero and mostly unexplained by characteristics. By its very definition, there are no empirical explanations for the residual difference. Here we reiterate some of the possible explanations for this unexplained difference as put forth by economic theory. In the case of agreeableness, what perhaps could explain the residual pay gap is being less agreeable (more antagonist) could be related to better skills in the wage bargaining. On the contrary, the pay disadvantage for neuroticism could be related to a reduced productivity. In our wage equations we take account of the possible reduced productivity by considering dummies for bad health and presence of health problems which limit amount of work, which are indeed correlated with neuroticism. However, the residual unexplained pay difference is still negative and this could in part be related to taste based discrimination. Notice that the unexplained pay disadvantage for neuroticism is bigger at the bottom than at the top of the distribution perhaps indicating that neuroticism is a more prejudiced trait for low paid occupations such as blue-collar. Finally, extroversion could improve workplace social networking which could in turns increase productivity or the chances of career advancements.

But it is obviously difficult to speculate further on possible explanations for the unexplained pay gaps. The only safe conclusion we can make is that the unexplained pay gaps can be related to unobserved differences in productivity and/or to some sort of discrimination.

6. Some sensitivity analyses

In this section we consider some sensitivity analyses to address some possible limits of our analysis: (i) non-monotonicity of the wage-personality traits relationship (ii) endogeneity (reverse causality) of personality traits, (iii) measurement error of personality traits and (iv) common support problem.

Non-monotonicity issue

To verify whether the relationship between wage and personality traits is monotonic, we repeat our analysis by considering extremely low, medium and extremely high levels of each personality trait, which correspond to scores below the 25th percentile, between the 25th and 75th percentile and above the 75th percentile, respectively. In Table 6.1, we report the pay difference in mean and at different quantiles between workers with extremely high and medium levels as well as between workers with medium and extremely low levels of each personality score. We cannot reject the assumption that the relationship between wage and the personality level is monotonic for each of the personality traits. This is because in the majority of cases the pay differences between extremely high and medium levels have the same sign as the differences between medium and extremely low levels of each personality trait, and in the cases where the sign changes the pay differences are not statistically different from zero. For this reason we decided to concentrate our attention on the pay differences between people with personality levels above and below the median.[13]

Endogeneity and reverse causality issues

Another potential limitation of our analysis is the endogeneity of the personality traits with respect to pay. Decomposition analyses are usually applied to explain differences in pay between two sub-groups of the population identified by an exogenous variable such as characteristics fixed at birth, say gender. In our case, the personality traits are exogenous for the part explained by genetic endowments, predetermined for the part explained by the family background characteristics, but they are potentially endogenous

[13] Results on decomposition comparing people with personality score extremely low, medium and extremely high are in line with the ones reported here and are available upon request from the authors.

for the part explained by the type of labor market experience. This endogeneity problem is more precisely a reverse causality problem which occurs for example when a successful career implies a change in personality traits.

Previous papers on the relationship between the Big Five personality traits and wage (see for example Muller and Plug 2006 and Viinikainen *et. al.* 2007) recognize the potential reverse causality issue and suggest that its magnitude should be small given that personality traits are found to be quite stable over time and especially after the age of 30. Other researchers who have focus on the Rosenberg self-esteem scale or the Rotter locus control scale (which refers to the extent to which individuals believe that they can control events that affect them) have also recognized the endogeneity issue. Some of them have tried to take account explicitly of the issue by either using instrumental variable estimation or by using a latent factor model approach. For example, Osborne-Grove (2005) estimate the effect of personality on wage using as main instrument for the personality score (the Rotter locus control scale) the same personality score measured early in life. Goldsmith *et. al.* (1997) use as instrumental variable for self-esteem its prediction based on a number of presumably exogenous variables. Heckman *et al.* (2006) take account of endogeneity by estimating a factor model to identify two factors representing latent cognitive and personality abilities.

We do not have adequate instruments for our Big Five personality traits and we do not have enough multiple measures for each personality trait to make it possible to consider a latent factor model approach as in Heckman *et al.* (2006). As a consequence, we decided to adopt a different strategy. We restrict our sample to people aged 30 years or more *i.e.*, to an age range when personality traits are more stable (see for example Costas and McCare 1988, Rantanen *et. al.* 2007). This should help in reducing the reverse causality bias and we find that our decomposition results do not change. However, this does not imply that our results are free of any endogeneity bias and interpretation of the personality effect as a causal effect should be made with caution.

Note, however, that in our wage regressions we have controlled for variables which could be related to changes in the personality traits and hence could have contributed to the reverse causality. In particular, we have considered variables that represent the person's past labor market experience (including past unemployment and training) and dummies for the presence of health problems. We find that these variables affect personality traits, especially neuroticism, hence controlling for them should reduce the reverse causality problem.

Measurement error issue

We are also concerned with measurement error issues because personality traits are difficult to measure. Osborne-Grove (2005) and Mueller and Plug (2006) try to correct for the potential measurement error bias by assuming a classical measurement error model, and inflating the otherwise attenuated effect of the personality skills in the wage regression. This type of procedure is not applicable in our study because our personality trait effect is not given by an estimated coefficient in the wage equation.

Since we use our personality trait score to divide the population of workers into two groups with scores above and below the median, it is possible that measurement errors are relevant only for individuals with scores close to the median. For this reason, we test how sensitive our results are to the exclusion of individuals whose personality scores are between 90% and 110% (and also between 95% and 105%) of the median. We find that our results hardly change when we drop these individuals.

Common support problem

One of the main problems when considering the Blinder-Oaxaca or generalized Blinder-Oaxaca decomposition is the fact that the explanatory variables could have different supports for the two groups to be compared and this implies that counterfactual statistics are computed using out of the sample prediction (see Barsky *et. al.* 2002). A similar problem, but less troublesome one, exists when using weights. To avoid the last problem we repeat our analysis by restricting our sample to the people with common support for the predicted probability of having high rather than low level of the personality trait studied on each occasion. We find that there are only few cases with no common support and the decomposition analysis results do not change at all.

6. Conclusions

In this paper we estimate the total effect of personality traits on wages and we decompose it into its indirect effect which operates through educational, occupational choices and other personal and job characteristics, and a residual effect. We implement this analysis by using the generalized Oaxaca-Blinder decomposition and the combined weighting and regression based approach proposed by Firpo *et. al*. (2007). These decomposition approaches allow us to analyze the total effect of each of the Big Five personality traits at the mean as well as at different quantiles and allow the reward of each personality trait to vary across occupations, and other job and personal characteristics.

Our main results can be summarized in the following three points. First, it seems that the most relevant personality trait in explaining differences in pay is openness followed by neuroticism, agreeableness and extroversion. Second, there is a glass ceiling effect for people who are closed to experience and there is a sticky floor effect for introvert, high agreeable and neurotic people. These sticky floor effects are more relevant in low paid occupations such as blue-collar occupations. In case of agreeableness however, this sticky floor effect disappears once we control for personal and job characteristics. Third, pay advantages associated with openness to experience are explained mainly by differences in characteristics; whereas pay advantages associated with extroversion and pay penalties linked to neuroticism and agreeableness remain unexplained. These unexplained differences could be associated with unobserved diversity in skills enhancing productivity, career advancements or wage increases, and with taste based wage discrimination.

The results clearly show that neuroticism and agreeableness are penalized in the labor market while openness to experience and extroversion are rewarded. We would however be cautious in making any policy prescriptions about encouraging the development of certain personality traits based on these results alone as these rewards and penalties pertain only to the labor market and not to other meaningful aspects of life. For example, while agreeableness is penalized in the labor market, it may be highly rewarded in family and personal relationships.

Furthermore, rewards and penalties related to personality could be considered unfair if not justified by differences in productivity. In our analysis we have been able to identify the part of the personality pay gaps explained by differences in workers' characteristics and the residual gap which would persist even if workers with different personality traits were otherwise identical. However, we are not able to disentangle the reasons behind the residual pay gap which could be related to unobserved productivity differences but also to taste based discrimination on the part of the consumer, coworker or employer.

References

Altonji, Joseph G. and Rebecca Blank. 1999 "Race and Gender in the Labor Market" in O. Ashenfelter and D. Card, (eds), *Handbook of Labor Economics* Elsevier Science B.V. Volume 3c: 3144-3259.

Antecol, H., Jong, A., Steinberger M. (2008) The sexual orientation wage gap: the role of occupational sorting and human capital. *Industrial and Labor Relations Review.* 61 (4):518-543.

Barrick, Murray R. and Michael K. Mount. 1991. "The big five personality dimensions and job performance: a meta-analysis." *Personnel Psychology*. 44:1-26.

Barsky, R., J. Bound, K. Charles and J. Lupton. 2002 "Accounting for the Black-White wealth gap: a nonparametric approach." *Journal of the American Statistical Association*. 97(459):663-673.

Benet-Martinez, V. & O. P. John. (1998). "*Los Cinco Grandes* across cultures and ethnic groups: Multitrait multimethod analyses of the Big Five in Spanish and English." *Journal of Personality and Social Psychology*. 75:729-750.

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

Borghans, Lex, Angela Lee Duckworth, James J. Heckman and Bas ter Weel. 2008. "The Economics and Psychology of Personality Traits." *The Journal of Human Resources*. 43 (4):972-1059.

Bowles, S., H. Gintis, M. Osborne. 2001. "Incentive-Enhancing Preferences: Personality, Behavior, and Earnings" *American Economic Review*. 91 (2): 155-158.

Cebi, M. 2007. "Locus of control and human capital investment revisited." *Journal of Human Resources.* 42 (4):919–932.

Chiswick, B. R,. Le, A. T, and. Miller P. W. (2008) How immigrants fare across the earnings distribution in Australia and the United States. *Industrial and Labor Relations Review*. 61, (3):353-372.

Costa Jr., P.T., McCrae, R.R., 1988. Personality in adulthood: a six-year longitudinal study of self-reports and spouse ratings on the NEO Personality Inventory. *Journal of Personality and Social Psychology.* 54:853–863.

Cronbach, Lee J. 1951. "Coefficient Alpha and the Internal Structure of Tests." *Psychometrika*.16 (3):297–334.

Cunha, Flavio, James J. Heckman, Lance Lochner and Dimitriy V. Masterov. 2006. "Interpreting the Evidence on Life Cycle Skill Formation" Chapter 12 in *Handbook of the Economics of Education*, (Eds) E. Hanushek and F. Welch, North Holland

Cunha, Flavio and James J. Heckman. 2008. "Formulating, Identifying and Estimating the Technology of Cognitive and Noncognitive Skill Formation." *The Journal of Human Resources*. 43 (4):738-782.

DiNardo, John, Nicole M. Fortin and Thomas Lemieux. 1996. "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach." *Econometrica*. 64 (5):1001-1044.

Filer, R.K., 1986. "The role of personality and tastes in determining occupational structure." *Industrial and Labor Relations Review* 39 (3): 412–424.

Firpo, Sergio, Nicole Fortin and Thomas Lemeiux. 2007. "Decomposing Wage Distributions using Recentered Influence Function Regressions" http://www.econ.ubc.ca/nfortin/ffl1_nber2.pdf

——. 2009. "Unconditional quantile regressions." *Econometrica*. Forthcoming.

Fortin, Nicole M. 2008. "The Gender Wage Gap among Young Adults in the United States: The Importance of Money versus People." *The Journal of Human Resources*. 43 (4):884-918

Goldberg, Lewis R. 1990. "An Alternative "Description of Personality": The Big-Five Factor Structure." *Journal of Personality and Social Psychology*. 59(6):216-1229.

Goldsmith, A.H., J. R. Veum, W. Darity. 1997. "The impact of psychological and human capital and wages." *Economic Inquiry*. 35 (4):815–829.

Gosling, S. D., P. J. Rentfrow and W. B. Swann. 2003. "A very brief measure of the Big-Five personality domains." *Journal of Research in Personality*. 37:04-528.

Heckman, James. J., L. Malofeeva, R. Pinto and P. Savelyev. 2008. "The Effect of the Perry Preschool Program on Cognitive and Noncognitive Skills: Beyond Treatment Effects," Unpublished manuscript, University of Chicago, Department of Economics.

Heckman, James J., Jora Stixrud, and Sergio Urzua. 2006. "The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior." *Journal of Labor Economics*. 24(3):411-482.

Heineck, Guido. 2007. "Does it pay to be nice? Personality and earnings in the UK" *LASER Discussion Papers*. Paper No. 3. 29pages

——. and Silke Anger. 2009. "The Returns to Cognitive Abilities and Personality Traits in Germany" *Labour Economics*. In press.

Hirano, K., G. Imbens and G. Ridder. 2003. "Efficient estimation of average treatment effects using the estimated propensity score." *Econometrica*. 71:1307-1338.

Jackson, M., 2006. Personality traits and occupational attainment. *European Sociological Review*. 22 (2):187–199.

John, O. P. and S. Srivastava. 1999. "The Big Five trait taxonomy: History, measurement, and theoretical perspectives." In O. P. John & L. A. Pervin (Eds.), *Handbook of Personality: Theory and Research*. New York: Guilford Press.

Krueger, Alan B. and David Schkade. 2008. “Sorting in the Labor Market Do Gregarious Workers Flock to Interactive Jobs?.” *The Journal of Human Resources*. 43 (4):860-883

Lemieux, Thomas. 2002. “Decomposing changes in wage distributions: a unified approach.” *The Canadian Journal of Economics*. 35(4):646-688 .

Letcher, Dr. Lloyd, Jr. and Dr. Brian Niehoff. 2004. “Psychological capital and wages: a behavioural economic approach.” http://www.midwestacademy.org/Proceedings/2004/papers/Letcher,Niehoff.doc.

Rantanen, J., Metsäpelto, R-L, Feldt, T., Pulkkinen, L., & Kokko, K. (2007). Long-term stability and change in the Big Five in adulthood. *Scandinavian Journal of Psychology*, 48: 511-518.

Mount, Michael K. and Murray R. Barrick. 1998. “Five reasons why the "big five" article has been frequently cited.” *Personnel Psychology*. 51:849-857.

Mueller, Gerrit and Erik J.S. Plug. 2006. “Estimating the Effect of Personality on Male and Female Earnings” *Industrial Labor Relations Review*. 60(1):1-22.

Nyhus, Ellen K. and Empar Pons. 2005. “The effects of personality on earnings.” *Journal of Economic Psychology*. 26:363–384

Oaxaca, Ronald. 1973. “Male-Female wage differentials in urban labor markets.” *International Economic Review*. 14(3):693-709.

Osborne-Groves, Melissa. 2005. “How important is your personality? Labor market returns to personality for women in the US and UK.” *Journal of Economic Psychology*. 26:827–841

——. 2005. “Personality and the intergenerational transmission of economic status.” Chapter 7 in Bowles, Samuel, Herbert Gintis and Melissa Groves, Melissa Osborne. (Eds.) *Unequal Chances: Family Background and Economic Success*. Princeton, NJ: Princeton University Press.

Raad, Boele de and Henri C. Schouwenburg. 1996. “Personality in learning and education: a review.” *European Journal of Personality*. 10:303-336.

Rosenbaum P. and D., R. 1983. “The central role of the propensity score in observational studies for causal effects.” *Biometrika.* 70(1):41-55.

Saldago, Jesus. F. 1997. “The five factor model of personality and job performance in the European Community.” *Journal of Applied Psychology*. 82(1):30-43.

Saucier, G. and L. R. Goldberg 1996. “The language of personality: Lexical perspectives on the five-factor model.” in J. S. Wiggins (Ed.), *The five-factor model of personality: Theoretical perspectives*. 21-50. New York, NY, US: Guilford Press.

Viinikainen, Jutta, Katja Kokko, Lea Pulkkinen and Jaakko Pehkonen . “Personality traits and earnings: evidence from Finland.”
http://www.eale.nl/conference2007/programme/Papers%20Friday%2011.00-13.00/add45048.pdf

Wooldridge, J. M. 2002. “Inverse probability weighted M-Estimators for sample selection, attrition, and stratification.” *Portuguese Economic Journal.* 1:117-139.

——. 2007. “Inverse probability weighted M-Estimation for general missing data problems.” *Journal of Econometrics.* 141(2):1281-1301.

Table 4.1 The Big Five personality traits: related facet-adjectives and the BHPS questions

Big Five traits	Personality facets, adjectives	Respondent see himself herself as someone who
Openness to experience (openness)	Ideas (curious) Fantasy (imaginative) Aesthetics (artistic) Actions (wide interests) Feelings (excitable) Values (unconventional)	O1. is original, comes up with ideas O2. values artistic, aesthetic experiences O3. has an active imagination
Conscientiousness	Competence (efficient) Order (organized) Dutifulness (not careless) Achievement striving (thorough) Self-discipline (not lazy) Deliberation (not impulsive)	C1. does a thorough job C2. tends to be lazy (reversed score) C3. does things efficiently
Extraversion	Gregariousness (sociable) Assertiveness (forceful) Activity (energetic) Excitement-seeking (adventurous) Positive emotions (enthusiastic) Warmth (outgoing)	E1. is talkative E2. is outgoing, sociable E3. is reserved (reversed score)
Agreeableness	Trust (forgiving) Straightforwardness (not demanding) Altruism (warm) Compliance (not stubborn) Modesty (not show-off) Tender-mindedness (sympathetic)	A1. is sometime rude to others (reversed score) A2. has a forgiving nature A3. is considerate and kind
Neuroticism	Anxiety (tense) Angry hostility (irritable) Depression (not contented) Self-consciousness (shy) Impulsiveness (moody) Vulnerability (not self-confident)	N1. worries a lot N2. gets nervous easily N3. is relaxed, handles stress well (reversed score)

Table 4.2. Mean, standard deviation, first, second and third quartiles for each of the five personality traits.

	Mean	s.d.	25th percentile	Median	75th percentile
Openness	4.59	1.05	4.00	4.67	5.33
Conscientiousness	5.30	0.98	4.67	5.33	6.00
Extroversion	4.36	1.10	3.67	4.33	5.00
Agreeableness	5.21	0.98	4.67	5.33	6.00
Neuroticism	3.31	1.16	2.33	3.33	4.00

Table 4.3: Mean and quantiles of wage by personality group

.	Log wage					
	Mean	10th percentile	25th percentile	50th percentile	75th percentile	90th percentile
High openness	2.512	1.919	2.177	2.516	2.817	3.138
	(0.019)	(0.033)	(0.021)	(0.024)	(0.027)	(0.038)
Low openness	2.424	1.841	2.101	2.429	2.741	3.014
	(0.017)	(0.033)	(0.022)	(0.019)	(0.020)	(0.024)
High	2.456	1.852	2.143	2.459	2.770	3.080
conscientiousness	(0.020)	(0.039)	(0.022)	(0.020)	(0.024)	(0.034)
	2.464	1.893	2.139	2.461	2.757	3.056
Low conscientiousness	(0.016)	(0.031)	(0.020)	(0.018)	(0.021)	(0.030)
High extroversion	2.490	1.946	2.180	2.488	2.771	3.083
	(0.018)	(0.023)	(0.020)	(0.022)	(0.024)	(0.036)
Low extroversion	2.437	1.821	2.095	2.436	2.759	3.061
	(0.017)	(0.031)	(0.022)	(0.019)	(0.021)	(0.030)
High agreeableness	2.422	1.805	2.101	2.426	2.726	3.021
	(0.021)	(0.041)	(0.030)	(0.027)	(0.029)	(0.034)
Low agreeableness	2.477	1.905	2.158	2.471	2.791	3.081
	(0.015)	(0.027)	(0.016)	(0.017)	(0.021)	(0.028)
High neuroticism	2.419	1.831	2.081	2.409	2.752	3.018
	(0.021)	(0.041)	(0.029)	(0.026)	(0.026)	(0.031)
Low neuroticism	2.481	1.903	2.170	2.484	2.781	3.078
	(0.016)	(0.028)	(0.016)	(0.018)	(0.021)	(0.028)

Note: Standard errors are reported in the second row and in parenthesis for each personality group.

Table 4.4: Summary statistics

Variables	Mean	
Wage	13.277	(0.147)
Work experience	25.007	(0.220)
Current occupation (3 digit code)		
Managers and senior officials	0.193	
Professional	0.131	
Associate professional and technical	0.145	
Administrative and secretarial	0.062	
Skilled trades	0.166	
Personal service	0.021	
Sales and customer service	0.025	
Process, plant and machine operatives	0.152	
Elementary occupations	0.105	
Current job is temporary	0.027	
Working part-time	0.033	
Working in a private firm	0.776	
Size of the firm is less than 10	0.170	
Region of current residence		
London	0.085	
Rest of South-East	0.193	
South-West	0.095	
Anglia & Midlands	0.222	
North West	0.110	
Rest of the North	0.142	
Wales	0.044	
Scotland	0.089	
Northern Ireland	0.021	
Highest educational qualification received:		
None	0.072	
Vocational or technical education	0.049	
GCSE or O-level	0.145	
A-level or other higher education but below college degree	0.529	
College or university degree	0.205	
Any health problems or disability?	0.467	
The extent to which health limits the amount of work		
A lot	0.011	
Somewhat	0.018	
Just a little	0.031	
Not at all	0.941	
Received any training (of 30hrs or more) in the last 3 years?	0.516	
Proportion of time unemployed since first interviewed	0.035	(0.002)

Note: Standard errors are in parenthesis.

Table 5.1. Difference in wages at the mean and quantiles between workers with high level (greater than median) and low level (less than median) of each personality trait

	Differences in					
Personality	Mean	10th percentile	25th percentile	50th percentile	75th percentile	90th percentile
Openness	0.089 **	0.079 *	0.076 **	0.087 **	0.076 **	0.124 **
	(0.025)	(0.047)	(0.030)	(0.031)	(0.034)	(0.045)
Conscientiousness	-0.008	-0.041	0.003	-0.002	0.013	0.024
	(0.025)	(0.049)	(0.029)	(0.028)	(0.032)	(0.046)
Extroversion	0.053 **	0.125 **	0.085 **	0.052 *	0.012	0.022
	(0.025)	(0.039)	(0.030)	(0.029)	(0.032)	(0.047)
Agreeableness	-0.055 **	-0.101 **	-0.056	-0.044	-0.065 *	-0.061
	(0.026)	(0.049)	(0.034)	(0.031)	(0.035)	(0.044)
Neuroticism	-0.062 **	-0.071	-0.088 **	-0.075 **	-0.028	-0.060
	(0.026)	(0.050)	(0.033)	(0.032)	(0.033)	(0.042)

Note: Standard errors are reported in the second row in parentheses for each personality group.
* and ** indicate statistical significance at 10% and 5%.

Table 5.2. Decompositions of mean pay differences

	Mean	Combined weighting and regression method		Generalized Blinder-Oaxaca
Personality	Difference	Composition effect	Residual effect	Composition effect
Openness	0.089**	0.080	0.009	0.071
Conscientiousness	-0.008	-0.005	-0.003	-0.009
Extroversion	0.053**	0.016	0.037	0.013
Agreeableness	-0.055**	0.008	-0.063	0.001
Neuroticism	-0.062**	0.001	-0.063	0.001

Table 5.3. Generalized Blinder-Oaxaca detailed decomposition of mean pay differences

Detailed decomposition	Openness	Conscientiousness	Extroversion	Agreeableness	Neuroticism
Education	0.031	-0.009	-0.007	0.003	0.007
Occupation	0.052	-0.009	0.009	-0.005	-0.003
Other job characteristics	-0.003	-0.009	0.007	0.001	0.001
Health	0.002	-0.001	0.002	0.002	-0.008
Past training/ unemployment	0.003	0.006	0.000	0.004	-0.006
Personality traits	-0.003	0.006	0.010	0.003	0.012
Region	-0.004	-0.009	-0.006	-0.009	-0.001
Work experience	-0.006	0.015	-0.002	0.003	-0.001
Generalized Blinder-Oaxaca Composition effect	***0.071***	***-0.009***	***0.013***	***0.001***	***0.001***
Residual effect	***0.018***	***0.002***	***0.040***	***-0.057***	***-0.063***
Total mean difference	***0.089***	***-0.008***	***0.053***	***-0.055***	***-0.062***

Note: The effect of composite variables which subsume a set of univariate variables are computed by summing the effect of each of the univariate variables. Other job characteristics include dummies for part-time, temporary job, public sector and firm size; health includes dummies for bad health and for health problems limiting amount of work,

Table 5.4. Decomposition of percentile pay differences

			Combined Weighting and Regression Method		Generalized Blinder-Oaxaca
Personality	Difference		Composition effect	Residual Effect	Composition effect
Openness to experience					
10^{th} percentile	0.079	*	0.081	-0.002	0.083
25^{th} percentile	0.076	**	0.039	0.037	0.049
50^{th} percentile	0.087	**	0.105	-0.018	0.118
75^{th} percentile	0.076	**	0.079	-0.003	0.079
90^{th} percentile	0.124	**	0.113	0.011	0.100
Conscientiousness					
10^{th} percentile	-0.041		0.035	-0.076	0.043
25^{th} percentile	0.003		-0.008	0.012	-0.011
50^{th} percentile	-0.002		-0.004	0.002	-0.003
75^{th} percentile	0.013		-0.028	0.041	-0.030
90^{th} percentile	0.024		-0.013	0.037	-0.042
Extroversion					
10^{th} percentile	0.125	**	0.039	0.086	0.033
25^{th} percentile	0.085	**	0.013	0.072	0.021
50^{th} percentile	0.052	*	0.012	0.040	0.013
75^{th} percentile	0.012		-0.014	0.026	-0.013
90^{th} percentile	0.022		-0.025	0.047	-0.033
Agreeableness					
10^{th} percentile	-0.101	**	-0.008	-0.093	-0.009
25^{th} percentile	-0.056		0.003	-0.059	-0.001
50^{th} percentile	-0.044		0.025	-0.069	0.016
75^{th} percentile	-0.065	*	0.027	-0.092	0.005
90^{th} percentile	-0.061		0.023	-0.084	0.018
Neuroticism					
10^{th} percentile	-0.071		0.019	-0.090	0.006
25^{th} percentile	-0.088	**	-0.009	-0.079	-0.009
50^{th} percentile	-0.075	**	-0.013	-0.062	-0.008
75^{th} percentile	-0.028		0.009	-0.037	0.018
90^{th} percentile	-0.060		-0.002	-0.058	-0.001

Table 5.5. Generalized Blinder-Oaxaca detailed decomposition of percentile pay differences between people with high and low levels of openness to experience

	10th percentile	25th percentile	50th percentile	75th percentile	90th percentile
Education	0.042	0.012	0.037	0.045	0.057
Occupation	0.045	0.058	0.071	0.058	0.060
Type of job	-0.008	-0.003	0.002	-0.001	-0.005
Health	0.002	0.001	0.000	0.001	0.003
Past training / unemployment	0.005	0.002	0.003	0.002	0.000
Personality traits	-0.002	-0.010	0.011	-0.014	0.002
Region	-0.005	0.000	-0.003	-0.005	-0.007
Work experience	0.005	-0.011	-0.002	-0.007	-0.011
Generalized Blinder-Oaxaca Composition effect	***0.083***	***0.049***	***0.118***	***0.079***	***0.100***
Residual effect	***-0.004***	***0.027***	***-0.031***	***-0.003***	***0.024***
Total pay difference	***0.079***	***0.076***	***0.087***	***0.076***	***0.124***

Note: The effect of composite variables which subsume a set of univariate variables are computed by summing the effect of each of the univariate variables. Other job characteristics include dummies for part-time, temporary job, public sector and firm size; health includes dummies for bad health and for health problems limiting amount of work.

Table 6.1 Difference in mean and quantiles between extreme and medium levels for each personality trait

Personality	Differences in: Mean	10th percentile	25th percentile	50th percentile	75th percentile	90th percentile
Openness						
Extremely high	0.046	-0.050	0.036	0.066 *	0.023	0.080
Vs medium	(0.032)	(0.063)	(0.028)	(0.038)	(0.041)	(0.059)
Medium Vs	0.042	0.073	0.036	0.060	0.065 *	0.072
Extremely low	(0.031)	(0.058)	(0.038)	(0.043)	(0.035)	(0.057)
Conscientiousness						
Extremely high	-0.069 **	-0.066	-0.021	-0.067 *	-0.106 **	-0.061
Vs medium	(0.035)	(0.061)	(0.035)	(0.039)	(0.038)	(0.059)
Medium Vs	0.009	-0.046	0.002	0.012	0.025	0.057
Extremely low	(0.028)	(0.048)	(0.034)	(0.032)	(0.038)	(0.049)
Extroversion						
Extremely high	0.047	0.016	0.050	0.025	0.039	0.092
Vs medium	(0.035)	(0.057)	(0.034)	(0.042)	(0.046)	(0.068)
Medium Vs	0.017	0.096 *	0.042	0.030	-0.051	-0.014
Extremely low	(0.028)	(0.057)	(0.033)	(0.031)	(0.036)	(0.049)
Agreeableness						
Extremely high	-0.093 **	-0.098 **	-0.092 **	-0.119 **	-0.102 **	-0.092
Vs medium	(0.033)	(0.048)	(0.041)	(0.044)	(0.041)	(0.067)
Medium Vs	-0.019	-0.021	-0.009	0.009	-0.024	-0.070
Extremely low	(0.028)	(0.050)	(0.032)	(0.031)	(0.038)	(0.048)
Neuroticism						
Extremely high	-0.049	-0.039	-0.081 *	-0.089 *	0.022	0.035
Vs medium	(0.041)	(0.073)	(0.048)	(0.048)	(0.066)	(0.079)
Medium Vs	-0.038	-0.041	-0.046	0.003	-0.032	-0.020
Extremely low	(0.027)	(0.050)	(0.030)	(0.031)	(0.033)	(0.041)

Note: Standard errors are reported in the second row in parentheses for each personality group.
* and ** indicate statistical significance at 10% and 5% level.