

Explaining personality pay gaps in the UK

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Non-technical summary

Several empirical studies emphasize the relevance of personality traits on wages. There are various reasons why personality traits can be important in explaining wages. First, employers, co-workers and potential customers may prefer workers with some personality traits rather than others; and these preferences may entail lower wages for people with less preferred personality traits. Second personality may have an effect on job performance and productivity. Third, people with different personality traits may sort out into occupations with different levels of wages.

Previous studies do not attempt to assess the different reasons explaining pay differences across personality traits. In this paper, by using the Big-Five trait taxonomy (openness to experience, conscientiousness, extroversion, agreeableness, and neuroticism), we classify people into different personality groups based on the level of each personality trait. We then decompose the pay gap between these groups into a part explained by differences in workers' characteristics and a residual part. While the first part is explained by the sorting out of people with diverse personality traits in different occupations, levels of education, work experience, types of job, etc.; the residual part reflects differences in productivity or in preferences of employers, co-workers or customers.

Also contrary to previous studies, we allow the personality traits to be paid differently across occupations, educational levels and other job characteristics. Finally, most studies estimate the relationship between personality traits and wages for the average paid worker and assume that it is the same for the high and low paid worker. Here we relax that assumption and estimate this relationship separately at different points of the wage distribution.

For our empirical analysis we use data from the British Household Panel Survey. The pay differences in order of size are for openness to experience, neuroticism, agreeableness and extroversion. People who are little open to experience are paid less and this disadvantage is totally explained by differences in their characteristics (especially education and occupation). On the contrary, the pay gap for highly neurotic, extrovert or agreeable workers is not explained by characteristics and it is probably related to differences in taste-based discrimination or productivity or both.

Explaining personality pay gaps in the UK

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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.

JEL: J71; C21; J31

Keywords: Big-Five trait, decomposition, wage

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1. Introduction

In recent years there has been an increasing number of economic papers looking at the relationship between earnings and personality traits (see for example Goldsmith *et al.* 1997, Bowles *et al.*, 2001; Mueller and Plug 2006, Cebi 2007, Heckman *et al.* 2008, Fortin 2008) 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 personality traits, but who are otherwise identical, could be considered unfair. In this paper we estimate the counterfactual pay gap between workers with different personality traits which we would observe if they were equal in terms of characteristics which are rewarded in the labor market.

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 we decompose the pay gap between these groups into two additive components: a component explained by differences in workers' characteristics and a residual unexplained component. We decompose further the explained component to identify the contribution of each specific characteristic in explaining pay differences (detailed decomposition). The residual component provides an estimation of the counterfactual pay gap between workers with different personality traits but otherwise identical.

In theory this estimated 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 workers' characteristics related to productivity. By using the British Household Panel Survey we control for a large set of characteristics such as level of education, occupation, work experience, previous unemployment, training, and other personal and job characteristics, which allow us to reduce the omitted variables problem.

To implement the decomposition analysis we adopt a method proposed by Firpo et al (2007), which uses weights to equalize the distribution of the characteristics between personality groups, and recentered influence functions to provide a detailed decomposition as in the Oaxaca-Blinder approach (Blinder, 1973; Oaxaca, 1973). Our analysis provides for the first time a detailed decomposition of the personality pay gap at the mean and at different quantiles.

We find that the high agreeable and high neurotic people are on average paid less. The opposite is true for openness and extroversion. Conscientiousness is the only trait that does not provide any statistically significant pay reward or penalty. Taking a look at the entire distribution we find that pay differences for conscientiousness is invariant across the distribution. On the other hand there appears to be a sticky floor effect for highly neurotic, highly agreeable and highly introvert people and a glass ceiling effect for people who are not open to experience.

Further investigation reveals that the differences for openness and conscientiousness are almost completely related to a composition effect (explained mostly by education and occupation) but not so for agreeableness, extroversion and neuroticism. Results at the different quantiles are quite similar. The glass ceiling effect for those who are not open to experience and the sticky floor effect for highly agreeable workers are eliminated once we account for the differences in characteristics. However, the sticky floor effect for highly neurotic and highly introvert workers cannot be explained by differences in characteristics. We also perform some sensitivity analysis to control for problems of endogeneity, measurement error, common support issues and to check for monotonicity in the relationship between wages and personality traits. Our results are robust to these issues.

In the next section we better motivate our work by referring to the previous literature in this area. We then follow by describing the decomposition method and the data used in our empirical application, the results of which are discussed at the end of the paper before we conclude.

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 traits¹ 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, 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 is not based on 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

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.

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 be willing to pay these persons more even if they 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.

In this paper we provide for the first time a decomposition of differences in pay between people with high and low of each of the Big Five personality traits into two additive components: a component explained by differences in occupation, work experience, level of education, and other job and personal observed characteristics relevant to determine wages, and a residual unexplained component which may reflect differences in unobserved productivity and non-productivity related characteristics. Our main objective is to identify the contribution of each of the observed wage determinants in explaining pay differential across personality traits and compare these with the residual (due “solely” to differences in personality traits).

Another contribution that we make here is that we look at the effect of personality over the entire wage distribution and not just at the means. Existing studies, do not usually consider that the effect of personality traits on wages may differ at different points of the wage distribution.

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 is a set of personal and job characteristics. For each of the Five-Big personality traits our comparison (reference) group is defined by people with high (low) levels of such 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 observed for the reference group. The difference between the observed mean log wage for the comparison group and its counterfactual mean 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 wage regression by,

$$y^j = \beta^j x^j + \varepsilon^j$$

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), β^j is the corresponding vector of 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 $(\beta^1 \bar{x}^1 - \beta^1 \bar{x}^0)$ and $(\beta^1 \bar{x}^0 - \beta^0 \bar{x}^0)$, 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:

$$\beta^1 \bar{x}^1 - \beta^1 \bar{x}^0 = \sum_{k=1}^K \beta_k^1 (\bar{x}_k^1 - \bar{x}_k^0)$$

where \bar{x}_k^j 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 in explaining pay gaps and for this reason it is still largely used in applied economic 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 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 is a function of y and v , $RIF(y, v)$, which satisfies the following properties:

- its mean is equal to the actual statistic v , $E_y[RIF(y, v)] = v$;
- the mean of its conditional expectation given x , $E_y[RIF(y, v)|x]$, is equal to the actual statistic v , i.e. $E_x\{E_y[RIF(y, v)|x]\} = v$.²

Given these properties and assuming a linear relationship between $RIF(y, v)$ and x , it is easy to generalize the Blinder-Oaxaca method to decompose differences in quantiles or other statistics. It is just a question of applying the Blinder-Oaxaca method using the *RIF*-regression rather than the y -regression, *i.e.*, replacing the dependent variable y (log wage) with the $RIF(y, v)$.

The *RIF*-regression can be used to provide an approximation of the composition effect that is of the marginal effect of a change of the distribution of x from the comparison group to the reference group distribution. Firpo et al (2009) prove that the

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

composition effect estimated using the RIF-regression is equal to the marginal effect plus a remainder which goes to 0 for infinitesimal changes in the distribution of x or in the special case where the ν statistics is the mean.

In our application we focus on quantiles and mean. The *RIF* of a τ -quantile is given by

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

where q_τ is the τ -quantile, $I(\cdot)$ is the indicator function taking value 1 if the event between parenthesis is true and 0 otherwise, and $f(\cdot)$ is the density distribution of y computed at the τ -quantile. In our empirical application 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.

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.

We call the *RIF* based decomposition the generalized Blinder-Oaxaca or regression based method. This method can be applied to decompose differences in mean, quantiles, variance and other statistics (see Firpo *et. al.* 2009) and can be used to produce a detailed decomposition to evaluate the contribution of each variable in explaining pay differences. Nevertheless, the generalized method provides only an approximation of the composition effect when the change in the distribution of x from the comparison to the reference group is large, and it 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 equalize the distribution of the variables x between the two groups compared. A counterfactual statistic for the comparison group, assuming the same distribution of x 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 categorical and 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 Rosebaum 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 y (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 weighted linear regression of the *RIF* for the comparison group by using the above described weights. The estimation is consistent if either the weights (i.e. the logit model) are correctly estimated or the linear regression model is correctly specified.³ The counterfactual statistics are computed as in the Blinder-Oaxaca decomposition but considering the coefficients estimated using the weighted regression (*RIF*) model instead of the simple mean regression model. Given the counterfactual, we can again decompose the pay gap into two additive parts: the composition effect given by the difference between the comparison group and its counterfactual statistics; and the residual

³ In summary, the combined weighting and regression based estimation method is double consistent (Robins and Rotnitzky 1995).

unexplained part given by the difference between the counterfactual and the reference group statistics. We can further decompose the composition effect into two parts: (1) the composition effect based on the generalized Blinder-Oaxaca approach; (2) the difference between the composition effect in the generalized Oaxaca and in the combined weighting and regression based approach. The first part can be further decomposed into additive components reflecting the contribution of each explanatory variable as in the generalized Blinder-Oaxaca decomposition; whereas the second part measures the deviation of the Blinder-Oaxaca composition effect from the more robust estimation obtained using the combined weighting and regression approach and thus the reliability of the detailed decomposition.

In our empirical application we apply both the generalized Blinder-Oaxaca decomposition and the more robust weighting and regression based approach. In all our 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 Study (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).⁴ All adult co-residents of these original sample members are also eligible for interview.

We use data primarily from the wave 15 (2005) of the BHPS as the Big Five personality traits were measured in that wave. We restrict the sample to men interviewed in wave 15 who were between the ages of 24 and 64 years, currently living in the UK and

⁴ All children born to members of this original sample also become part of that sample and become eligible for interview when they turn 16.

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.⁵

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 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 three measured items. We adopt the standard approach to assess measurement error problems by computing the standardized Cronbach's alpha reliability index.⁶ 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 Household Panel survey and

⁵ 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.

⁶ 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).

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 Srivastava 1999 or Mueller and Plug 2006).

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 reports the mean, standard deviation, first, second and third quartiles for each of the five personality traits. 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 takes values from 1 to 7. The largest standard deviation and inter-quartile range (which are measures of variability) are observed for neuroticism, followed by extroversion and openness. For conscientiousness and agreeableness there is less variability and more the 50% of the people have values higher than 5.

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 |

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.⁷ We find that the average log hourly wage for those with high and low levels (above and below the median) of a personality trait are significantly different for all traits except conscientiousness.⁸ 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).

⁷ 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.

⁸ Test results on significance of the pay differences are reported in Table 5.1 in Section 5.

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

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

Wage

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, 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 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 (*experience*).

Respondents are also asked to report whether they have any health problems or disabilities.⁹ 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*).

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*).

⁹ 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 .

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*).

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

Table 4.4: Summary statistics

| Variables | Mean | s.d. |
|--|--------|-------|
| Wage | 13.277 | 0.147 |
| Work experience | 25.007 | 0.220 |
| Current occupation (3 digit code) | | |
| Managers and senior officials | 0.193 | 0.008 |
| Professional | 0.131 | 0.007 |
| Associate professional and technical | 0.145 | 0.007 |
| Administrative and secretarial | 0.062 | 0.005 |
| Skilled trades | 0.166 | 0.007 |
| Personal service | 0.021 | 0.003 |
| Sales and customer service | 0.025 | 0.003 |
| Process, plant and machine operatives | 0.152 | 0.007 |
| Elementary occupations | 0.105 | 0.006 |
| Current job is temporary | 0.027 | 0.003 |
| Working part-time | 0.033 | 0.004 |
| Working in a private firm | 0.776 | 0.008 |
| Size of the firm is less than 10 | 1.830 | 0.007 |
| Region of current residence | | |
| London | 0.085 | 0.005 |
| Rest of South-East | 0.193 | 0.008 |
| South-West | 0.095 | 0.006 |
| Anglia & Midlands | 0.222 | 0.008 |
| North West | 0.110 | 0.006 |
| Rest of the North | 0.142 | 0.007 |
| Wales | 0.044 | 0.004 |
| Scotland | 0.089 | 0.006 |
| Northern Ireland | 0.021 | 0.003 |
| Highest educational qualification received: | | |
| None | 0.072 | 0.005 |
| Vocational or technical education | 0.049 | 0.004 |
| GCSE or O-level | 0.145 | 0.007 |
| A-level or other higher education but below college degree | 0.529 | 0.010 |
| College or university degree | 0.205 | 0.008 |

Table 4.4: Summary statistics (continued)

| Variables | Mean | s.d. |
|---|-------|-------|
| Any health problems or disability? | 0.467 | 0.010 |
| The extent to which health limits the amount of work | | |
| A lot | 0.011 | 0.002 |
| Somewhat | 0.018 | 0.003 |
| Just a little | 0.031 | 0.003 |
| Not at all | 0.941 | 0.005 |
| Received any training (of 30hrs or more) in the last 3 years? | 0.516 | 0.010 |
| Proportion of time unemployed since first interviewed | 0.035 | 0.002 |

5. Decomposition analysis results

In this section we present the results of the pay gap decomposition. 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. In 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 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. Notice that neuroticism for people at the top of the earning distribution could be associated with very demanding and stressful jobs which are better paid; whereas openness could be an important personality characteristic more likely to be required for high paid jobs but not for low paid jobs. To investigate better this and other potential explanations for the pay differential we use the decomposition analysis.

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

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

As a first step towards estimating the decompositions, we estimate mean or 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 (see second and third columns in Tables 5.2 and 5.4). These are computed using the combined weighting and regression based method defined in Section 2. We use logit models to predict the probability of having high rather than low levels of each type of personality trait and to compute the weights to be used in this method. In the last column of Tables 5.2 and 5.4

we also report 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 and in the logit models used to compute the weights we control for the following variables: education, occupation, potential work experience and its square, other job characteristics (part-time, temporary job, public sector and firm size), health dummies for bad health and for health problems limiting amount of work, past training and past unemployment experience, personality trait (dummies for low and high level of each personality trait except the one analyzed) and region.¹⁰

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.

Table 5.2. Decompositions of mean pay differences

| Personality | Mean Difference | Combined weighting and regression method | | Generalized Blinder- Oaxaca |
|-------------------|--------------------|---|-----------------|--------------------------------|
| | | 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 |

Previous results have found that conscientiousness and openness are correlated with education (see Barrick and Mount 1991, and Raad and Schouwenburg 1996) and this can explain why the pay differences for conscientious and open people are almost completely explained by the composition effect. That is the case here as well. In our logit

¹⁰ A more detailed description of these variables is provided in Section 4.

model used to predict the probability of openness to experience, we find that it is positively related to college or university degree, and negatively related to no educational qualification and elementary occupations. Similarly for conscientiousness, we find that high conscientiousness is positively related to long work experience and having a GCSE or O level. It is also negatively related to part-time jobs and administrative-secretarial and sales or customer services occupations.

Even if the composition effect is a very small proportion of the total effect for extroversion, agreeableness and neuroticism, it does not imply necessarily that these personality traits are independent of all our explanatory variables. It could also be the case that these three personality traits are either associated with variables which are not very significant in explaining wages, or with a set of variables of which some are positively and others are negatively related to pay. 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.

In Table 5.3 we present the results of the generalized Blinder-Oaxaca detailed decomposition¹¹ 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 composite effect for these cases is a 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 more in particular by the dummies for no educational qualification and college or university degree) and

¹¹ Notice that the generalized Blinder-Oaxaca decomposition for mean differences is identical to the standard Oaxaca decomposition (see Section 3 for more details).

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).

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 |

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

Table 5.4. Decomposition of percentile pay differences

| Personality | Difference | Combined Weighting and Regression Method | | Generalized |
|-----------------------------|------------|--|-----------------|-----------------------------------|
| | | Composition effect | Residual Effect | Blinder-Oaxaca 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 |

In case of agreeableness, once we control for the person's personal and job characteristics, the pay gap increases at the higher end of the wage distribution but decreases at the 10th 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 composite effects estimated by 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.

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

| | 10 th percentile | 25 th percentile | 50 th percentile | 75 th percentile | 90 th 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 |
| <i>Generalized Blinder- Oaxaca Composition effect</i> | <i>0.083</i> | <i>0.049</i> | <i>0.118</i> | <i>0.079</i> | <i>0.100</i> |
| <i>Residual effect</i> | <i>-0.004</i> | <i>0.027</i> | <i>-0.031</i> | <i>-0.003</i> | <i>0.024</i> |
| <i>Total pay difference</i> | <i>0.079</i> | <i>0.076</i> | <i>0.087</i> | <i>0.076</i> | <i>0.124</i> |

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.

Summarizing, 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 that antagonism (the opposite of agreeableness) 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 major problem 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 residual unexplained pay gaps.

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 replicate 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 or above the 75th percentile. 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 case 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.¹²

¹² 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.

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

| Personality | Mean | Differences in | | | | |
|--------------------------|-----------|-----------------|-----------------|-----------------|-----------------|-----------------|
| | | 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.

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, for example 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 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). In 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 needs to be very cautious.

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 be relevant only for individuals with observed 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% (95%) and 110% (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 exist when using weights. To avoid the last problem we replicate 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 Five-Big 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 make a person more socially acceptable, increase her social networks and finally lead to better mental health and well-being.

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.

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