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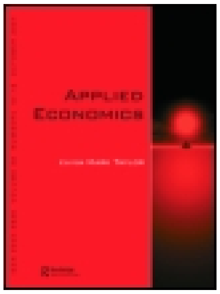

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Explaining personality pay gaps in the UK

Alita Nandi[a] & Cheti Nicoletti[b]

[a] Institute for Social and Economic Research (ISER), University of Essex, Colchester CO4 3SQ, UK

[b] Department of Economics and Related Studies, University of York, Heslington, York YO10 5DD, UK

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Explaining personality pay gaps in the UK

Alita Nandi[a,*] and Cheti Nicoletti[b]

[a]*Institute for Social and Economic Research (ISER), University of Essex, Colchester CO4 3SQ, UK*
[b]*Department of Economics and Related Studies, University of York, Heslington, York YO10 5DD, UK*

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Using the British Household Panel Survey we estimate the effect on pay of each of the Big Five personality traits for employed men living in the UK. We add to the existing literature by estimating the role of factors such as education and occupation in explaining personality pay gaps, by allowing the personality traits to affect wage differently across occupations, education levels and other workers characteristics, and by investigating personality pay gaps for high- and low-paid workers. We find that openness to experience is the most relevant personality trait in explaining wages, followed by neuroticism, agreeableness, extroversion and conscientiousness. Openness and extroversion are rewarded while agreeableness and neuroticism are penalized, but the openness pay gap is totally explained by differences in worker characteristics, particularly education and occupation.

Keywords: big five; decomposition; noncognitive skills; personality traits; wage gap

JEL Classification: J71; C21; J31

I. Introduction

There is a rapidly increasing literature that studies the effect of personality traits on earnings and the available empirical evidence shows that there is a significant effect (see Goldsmith *et al.*, 1997; Bowles *et al.*, 2001; Nyhus and Pons, 2005; Heckman *et al.*, 2006; Mueller and Plug, 2006; Cebi, 2007; Fortin, 2008; Heineck and Anger, 2010; Viinikainen *et al.*, 2010; Almlund *et al.*, 2011; Drago, 2011; Heineck, 2011; Cattan, 2012; Nyhus and Pons, 2012). We add to this literature by deepening our understanding of why people with different personality traits are paid differently. Building on existing research into the relationship between personality traits and potential determinants of pay (see Almlund *et al.*, 2011), we identify possible channels through which personality traits affect pay and estimate their contribution in explaining personality pay differences. More precisely we focus on evaluating the contribution of the following mediating factors: education, training, health, work experience, unemployment and occupational sorting. Our aim is to disentangle the part of the personality pay difference, which is explained by each of these mediating channels, and the residual difference, which is explained by a more direct effect of personality on pay through productivity or through other unobserved channels such as taste-based discrimination and wage bargaining.

Existing empirical studies usually estimate the effect of personality on pay by simply adding personality trait scores as additional explanatory variables in the pay equation (see, e.g., Nyhus and Pons, 2005; Mueller and Plug,

*Corresponding author. E-mail: anandi@essex.ac.uk

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2006; Heineck and Anger, 2010; Gensowski *et al.*, 2011; Heineck, 2011). This approach does not allow estimation of the contribution of different mediating factors in explaining pay differences. Additionally, this method assumes that personality traits are rewarded similarly across different occupations and levels of education as well as across different levels of pay. There is some sparse empirical evidence on the heterogeneous effect of personality on pay and on job performance (productivity). Psychologists find, for instance, positive associations between extraversion and job performance and between agreeableness and job performance for occupations that require social interaction or teamwork (e.g. Barrick and Mount, 1991; Mount and Barrick, 1998). In the economic literature the empirical evidence is thinner. Cattan (2012) finds that cognitive and personality traits have a heterogeneous effect on pay across occupations. In particular, she finds that self-confidence has a stronger positive effect for professionals, managers and sales/service workers than for other workers. On the contrary, checking for heterogeneity by education, Heckman *et al.* (2006) find that the personality pay premium/gap does not seem to differ across levels of education.

In our application we allow the effect of personality traits to vary by occupation, education, sector (private or public), firm size, work experience, health, past unemployment and training; we also allow the effect of personality traits to vary by the level of pay (quintiles); and we evaluate the contribution of different mediating factors in explaining the personality pay gaps by applying an Oaxaca–Blinder-type decomposition. To operationalize this we use individuals' Big Five personality trait scores (openness to experience, conscientiousness, extroversion, agreeableness and neuroticism) to classify them into two groups based on whether their personality score is above or below the median (e.g., high agreeable and low agreeable, high extrovert and low extrovert, etc.). We then compute the total effect of each personality trait on pay, i.e. the (mean or quintile) pay gap between people with high and low levels of the personality trait, and we decompose these pay gaps into two additive components: a component explained by differences in workers' characteristics (i.e. the mediating channels), and a residual unexplained component (also referred to as the counterfactual pay premium or gap). We decompose further the explained component to identify the contribution of each specific characteristic in explaining pay differences. To implement this decomposition analysis we adopt a novel method proposed by Firpo *et al.* (2007), which overcomes some of the shortcomings of the Oaxaca–Blinder method (see also Firpo *et al.*, 2011).

Using data for working-age men in paid employment from the British Household Panel Survey (BHPS), we find that there are significant differences in pay between high and low neurotic, high and low extrovert, and high and low agreeable workers, even after controlling for the observed mediating channels. On the contrary, the significant difference between high and low openness to experience disappears almost completely once we control for education and occupation. We also find that while the effect of personality traits is generally heterogeneous across occupations, it is similar across different levels of education.

The rest of the article is organized as follows. In Section II we review the literature on Big Five personality traits and in particular their estimated effects on pay as well as the possible theoretical explanations for these effects. We discuss the econometric method we use in Section III, the data we use in Section IV and present our main empirical results in Section V. In Section VI we show that these results are robust to a set of sensitivity analyses, which we carry out to address potential restrictive assumptions of our analysis: the assumptions of exogeneity of personality traits, of monotonicity of the pay-personality traits relationship, of absence of measurement error on personality traits and of a common support problem. Finally, we draw some conclusions in Section VII.

II. Background

Personality traits are generally defined as stable patterns of thought, feelings and behaviour (Borghans *et al.*, 2008). While these traits are relatively steady in adulthood (see Cobb-Clark and Schurer, 2012) they can be affected by parental background, environmental factors and interventions, during childhood and adolescence (Cunha *et al.*, 2006; Cunha and Heckman, 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 (versus closed to experience), conscientiousness (versus lack of direction), extraversion (versus introversion), agreeableness (versus antagonism) and neuroticism (versus emotional stability). This taxonomy has been extensively used among psychologists (see John and Srivastava, 1999), and analysing large sets of personality adjectives, Goldberg (1990) and Saucier and Goldberg (1996) find personality factor structures similar to the Big Five personality traits.

Recent studies that have examined the effect of Big Five personality traits on pay in the Netherlands, USA, Germany and UK (Nyhus and Pons, 2005; Mueller and Plug, 2006; Heineck and Anger, 2010; Heineck, 2011) find that agreeableness, openness to experience and neuroticism are significant in explaining pay even after controlling for other relevant explanatory variables; however, Viinikainen *et al.* (2010), investigating this issue for Finland, find that only extraversion matters. Some of these studies have acknowledged that part of the pay is explained by the occupational sorting by personality types (Mueller and Plug, 2006), but they have not tried to

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quantify how much of the personality pay differences is related to occupational sorting or to differences in other factors.

Besides personality pay differences, which can be explained by different observed mediating factors that researchers usually control for (typically occupation, education, training, health, work experience, unemployment and other job characteristics), there can be also a residual pay difference that may reflect

- differences in productivity: certain personality traits may enhance abilities required by specific tasks;
- differences in positive reciprocity (i.e. the attitude to compensate for kind actions): some personality traits are related to positive reciprocity and employers could be willing to pay a premium for a reciprocal worker who are more likely to be encouraged by incentives and promotions to increase their productivity (Bowles *et al.*, 2001; Dur *et al.*, 2010);
- differences in pay bargaining and workplace social networking abilities: these may be related to some personality traits and can ultimately affect pay (Mueller and Plug, 2006);
- differences in other unobserved characteristics that are potential determinants of pay and related to personality traits;
- taste-based discrimination: employers may prefer people with certain personality traits and be willing to pay more for working with such persons. The same argument applies to employees (colleagues) and customers. For example, customers may prefer to buy from sellers who are more agreeable and extrovert but only buy from those who are not (agreeable and extrovert) if they are 'compensated' with a lower price (see Altonji and Blank, 1999). So, we may find that agreeable workers are rewarded more in occupations that require a higher degree of interactions with colleagues or customers than disagreeable workers.

III. Econometric 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; Firpo *et al.*, 2007; Firpo *et al.*, 2011). In this article we consider: (i) the Blinder–Oaxaca decomposition (Blinder, 1973; Oaxaca, 1973), (ii) the generalization of this method proposed by Firpo *et al.* (2007), which we call the generalized Blinder–Oaxaca decomposition, and (iii) the combined weighting and regression method, which extends the generalized Blinder–Oaxaca decomposition to consider weights (Firpo *et al.*, 2007). We use these methods to decompose difference in mean and quantiles of log pay between comparison and reference groups. More precisely, for each of the Big Five personality traits our comparison and reference groups are people with high and low levels of the personality trait.

Let us represent the mean regression of the log pay as follows:

$$y_j = X_j\beta_j(\mu) + \varepsilon_j \tag{1}$$

where j takes value 1 for individuals belonging to the comparison group (group 1) and 0 for individuals 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 the mean regression coefficients and ε_j is an error term. Then, using the Blinder–Oaxaca approach, we can decompose the difference in mean log pay between the comparison and reference group as follows:

$$\begin{aligned}(\bar{y}_1 - \bar{y}_0) = {} & (\bar{X}_1 - \bar{X}_0)\beta_1(\mu) \\ & + (\bar{X}_0\beta_1(\mu) - \bar{X}_0\beta_0(\mu))\end{aligned} \tag{2}$$

where the first addend represents the composition effect and reflects mean differences in the characteristics, X, between the comparison and reference group, whereas the second addend is the residual or unexplained effect.

The composition effect can be further decomposed into additive parts representing the contribution of each explanatory variable to the pay difference:

$$(\bar{X}_1 - \bar{X}_0)\beta_1(\mu) = \sum_{k=1}^{K}\left(\bar{x}_{1,k} - \bar{x}_{0,k}\right)\beta_{1,k}(\mu) \tag{3}$$

where $\bar{x}_{j,k}$ is the *k-th* component of the vector of variables $\bar{X}_j$ and $\beta_{1,k}$ is the corresponding coefficient for the comparison group. The Blinder–Oaxaca approach is the only statistical method that allows estimating the separate contribution of each variable to explaining the mean pay gap; this is probably the reason why it is the most frequently used decomposition method in applied economics papers. Nevertheless, this decomposition approach 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 differs for the comparison and reference groups, it considers out of the sample predictions.

A solution to the first disadvantage has been recently provided by Firpo *et al.* (2007), who showed how to

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extend the Blinder–Oaxaca mean decomposition to other statistics using the re-centred influence function (*RIF*) approach (see Firpo *et al.*, 2009). We use this new method to decompose differences in quantiles of the pay. The *RIF* for the τ-quantile, q_τ, of a variable y is given by

$$RIF(y, q_\tau) = q_\tau + [\tau - d_\tau]/f_Y(q_\tau) \tag{4}$$

where $f_y(q_\tau)$ is the density distribution function of y computed at the quantile q_τ, and d_τ is a dummy variable taking value one if $y \leq q_\tau$ and zero otherwise. In our empirical application, we estimate $RIF(y,q_\tau)$ by replacing q_τ with its sample estimate and computing the density distribution using a nonparametric kernel estimation. The $RIF(y,q_\tau)$ satisfies the following properties:

(a) its mean is equal to the actual τ-quantile, $E_y[RIF(y, q_\tau)] = q_\tau$;
(b) the mean of its conditional expectation, $E_y[RIF(y, q_\tau)|X]$, is equal to the actual statistic q_τ, i.e. $E_x\{E_y[RIF(y,q_\tau)|X]\} = q_\tau$.

The conditional expectation $E_y[RIF(y,q_\tau)|X]$ is a function of X and it is what Firpo *et al.* (2009) define as the unconditional quantile regression. Assuming a linear relationship between $RIF(y,q_\tau)$ and X for both the comparison and reference groups, we can estimate $E_y[RIF(y_j,q_\tau)|X_j]$ using a linear regression:

$$RIF(y_j,q_\tau) = X_j\beta_j(q_\tau)+u_j \tag{5}$$

where j is, as before, the group indicator (0 or 1), X_j is a vector of K explanatory variables including the constant, $\beta_j(q_\tau)$ is the corresponding vector of coefficients for the τ-quantile and u_j is an error term. $\beta_j(q_\tau)$ is equal to the conditional quantile partial effect, i.e. the effect of an infinitesimal change in the covariates X_j on the conditional quantile and it is also equal to the unconditional quantile partial effect of the variables X_j, i.e. $E[dE[RIF(y_j,q_\tau)|X_j]/dX_j]$. Given the properties (a) and (b), it is easy to prove that the difference between the τ-quantile for group 1 and 0 is

$$\begin{aligned} q_{1\tau} - q_{0\tau} &= E_y[RIF(y_1, q_\tau)|X_1] \\ &\quad - E_y[RIF(y_0, q_\tau)|X_0] \\ &= \bar{X}_1\beta_1(q_\tau) - \bar{X}_0\beta_0(q_\tau) \end{aligned} \tag{6}$$

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

$$\begin{aligned} q_{1\tau} - q_{0\tau} = &\left(\bar{X}_1 - \bar{X}_0\right)\beta_1(v) \\ &+ \bar{X}_0(\beta_1(q_\tau) - \beta_0(q_\tau)) \end{aligned} \tag{7}$$

This decomposition is equivalent to the Blinder–Oaxaca method, with the only difference being that the dependent variable in the regression models is the *RIF* rather than *y*. We call the *RIF*-based decomposition the *generalized Blinder–Oaxaca*. Since *RIF* of the mean is equal to *y*, the *generalized Blinder–Oaxaca* includes the standard Blinder–Oaxaca decomposition as a special case.

The generalized Blinder–Oaxaca decomposition also allows us to produce a detailed decomposition to evaluate the contribution of each variable:

$$\begin{aligned} q_{1\tau} - q_{0\tau} = &\sum_{k=1}^{K} \left(\bar{x}_{1,k} - \bar{x}_{0,k}\right)\beta_{1,k}(q_\tau) \\ &+ \bar{X}_0(\beta_1(q_\tau) - \beta_0(q_\tau)) \end{aligned} \tag{8}$$

While the *generalized Blinder–Oaxaca method* does have the advantage of providing a decomposition of differences in statistics other than the mean, 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). These methods compute the counterfactual mean (or the counterfactual of any other statistic) for the comparison group, as if it had the same distribution of characteristics of the reference group, by considering the weighted mean of *y* using weights given by

$$w(X) = Pr(j = 0|X)/Pr(j = 1|X) \tag{9}$$

where $Pr(j = 0|X)$ and $Pr(j = 1|X)$ are the conditional probabilities of belonging to the reference and comparison groups. The difference between the observed mean log pay 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 (residual effect).

The probability $Pr(j = 1|X)$ can be estimated nonparametrically 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 for this reason we assume a logit model.

The main drawback of weighting methods is that they do not provide a detailed decomposition of the difference in mean, quantiles or any other statistic (i.e. a decomposition where the contribution of each single explanatory variable can be separated out).

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To compute counterfactual means, quantiles, variances and other summary statistics, it is possible to combine weights and generalized Blinder–Oaxaca methods. The combined method is based on the counterfactual estimation used by Firpo *et al.* (2007), i.e. the estimation of the *RIF*-regression for the comparison group:

$$RIF(y_1, v) = X_1\beta_1^{WR}(v) + u_1 \tag{10}$$

by using the above-described weights, $w(X)$. The superscript WR in $\beta_1{}^{WR}$ (v) stands for weighted regression, while v denotes the statistic of interest, which in our case is either the mean (μ) or a τ-quantile (q_τ). The estimation is consistent if either the weights (i.e. the logit model) are correctly estimated or the linear regression model is correctly specified. In summary, the combined weighting and regression based estimation method is double consistent (Robins and Rotnitzky, 1995). Using this weighted regression estimation we can compute the counterfactual statistic v for the comparison group, as if it had the same distribution of characteristics for the reference group, as $\bar{X}_o\beta_1^{WR}(v)$. Finally, we can decompose the pay gap between v_1 and v_0 into two additive components as follows:

$$\begin{aligned} v_1 - v_0 = {} & [\bar{X}_1\beta_1(v) - \bar{X}_o\beta_1^{WR}(v)] \\ & + [\bar{X}_o(\beta_1^{WR}(v) - \beta_0(v))] \end{aligned} \tag{11}$$

where the first addend between the square brackets represents the composition effect and the second addend represents the unexplained residual effect. We can further decompose the composition effect into two parts:

$$\begin{aligned} \bar{X}_1\beta_1(v) - \bar{X}_o\beta_1^{WR}(v) = {} & (\bar{X}_1 - \bar{X}_0)\beta_1(v) \\ & + \bar{X}_0\big(\beta_1(v) - \beta_1^{WR}(v)\big) \end{aligned} \tag{12}$$

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

As Firpo *et al.* (2007) note, the weighting approach requires the assumption of common support (i.e. the predicted probability of a high score for the personality trait must have a common range for people with high and low level of the score trait). In our application the support for the predicted probabilities is almost identical, and when we repeated the analysis on a restricted sample that enforced the common support restriction we obtained very similar results.

In our empirical application we use the generalized Blinder–Oaxaca decomposition to estimate compositional and residual effects but check for robustness of our results by also estimating these effects using the more robust combined weighting and regression approach. In all our estimation procedures we also consider weights to correct for the sampling design and for unit nonresponse (for details see Section IV).

IV. Data

We use data primarily from the 15th wave (i.e. year 2005) of the BHPS. In addition to the usual gross pay, we use other job-related information such as hours worked, occupation, firm size, part-time job, private or public sector job and some background information such as education, health condition, region of residence, potential work experience (i.e. by current age minus age when first left full-time education), past training and past unemployment experience. All variables are measured at the time of the interview in 2005, although some background information such as past training and past unemployment experience are based on information collected in earlier waves.

In the 15th wave, BHPS respondents were also asked a 15-item inventory for measuring their Big Five personality traits – openness to experience, conscientiousness, extraversion, agreeableness and neuroticism. They were asked to rate 15 statements (three for each trait) as to whether these were applicable to them on a 7-point scale (where 1 represents 'does not apply' and 7 'applies perfectly'). In Table 1 we report the questions asked in the BHPS to measure each of the Big Five personality traits and the personality facets or adjectives (as in John and Srivastava, 1999) related to each of them. We measure each personality trait as the average score of the responses to the three corresponding questions. We adopt the standard approach to assess measurement error problems by computing the standardized Cronbach's alpha reliability index. 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). Cronbach's alpha reliability indices of these measures are comparable to those for the 15-item inventory used in the GSOEP (Heineck and Anger, 2010; Heineck, 2011) and better than the 10-item inventory used by Gosling *et al.* (2003). The correlations between scores of these traits are quite low, providing support to the claim that these traits do in fact measure different facets of a person's personality.

Table 1. The Big Five personality traits: related facet-adjectives and the BHPS questions

Big Five traits	Personality facets, adjectives[a]	Respondent see himself herself as someone who
Openness to experience (openness)	Ideas (curious)	O1. is original, comes up with ideas
	Fantasy (imaginative)	O2. values artistic, aesthetic experiences
	Aesthetics (artistic)	O3. has an active imagination
	Actions (wide interests)	
	Feelings (excitable)	
	Values (unconventional)	
Conscientiousness	Competence (efficient)	C1. does a thorough job
	Order (organized)	C2. tends to be lazy (reversed score)
	Dutifulness (not careless)	C3. does things efficiently
	Achievement striving (thorough)	
	Self-discipline (not lazy)	
	Deliberation (not impulsive)	
Extraversion	Gregariousness (sociable)	E1. is talkative
	Assertiveness (forceful)Activity (energetic)	E2. is outgoing, sociableE3. is reserved (reversed score)
	Excitement-seeking (adventurous)	C3
	Positive emotions (enthusiastic)	
	Warmth (outgoing)	
Agreeableness	Trust (forgiving)	A1. is sometimes rude to others (reversed score)
	Straightforwardness (not demanding)	A2. has a forgiving nature
	Altruism (warm)	A3. is considerate and kind
	Compliance (not stubborn)	
	Modesty (not show-off)	
	Tender-mindedness (sympathetic)	
Neuroticism	Anxiety (tense)	N1. worries a lot
	Angry hostility (irritable)	N2. gets nervous easily
	Depression (not contented)	N3. is relaxed, handles stress well (reversed score)
	Self-consciousness (shy)	
	Impulsiveness (moody)	
	Vulnerability (not self-confident)	

Notes: [a]The list of adjectives associated with each of the big fives is taken from Table 4.1 in John and Srivastava (1999). The BHPS asks each respondent to rate the 15-items reported in the third column 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 corresponding three questions but changing the sign for items who are measuring an opposite personality concept.

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The main outcome of interest is the logarithm of hourly pay computed using the usual gross monthly pay 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 (for details on pay imputation see Taylor *et al.*, 2010).

We restrict the sample to men interviewed in 2005, 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. We exclude women from our analysis because of the issues of selection into labour participation and work interruptions, which typically affect women.

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 nonresponse using the cross-section weights for wave 15 provided in the publicly released BHPS dataset (for details on weighting procedure see Taylor *et al.*, 2010).

In Table 2 we report the mean and SE of the variables used in our analyses. We also report the mean, SD, first, second and third quartiles for each of the five personality traits in Table 3. We use the median score of each of these personality traits to distinguish between people with low and high levels of the trait. The largest SD and interquartile 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 than 50% of the people have values higher than 5.

V. Empirical Results

Relationship between pay and personality traits

In Table 4 we report differences in log pay for those with high and low levels of a personality trait (i.e. above and

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Table 2. Summary statistics

Variables	Mean	SE
Pay	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 30 hrs or more) in the last 3 years?	0.516	
Proportion of time unemployed since first interviewed	0.035	(0.002)
Number of observations	2688	

below the median) computed at the mean as well as at the 10th, 25th, 50th, 75th and 90th pay percentiles. These differences are approximately equal to the relative (rather than 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 on average paid less, whereas people with high openness and high extroversion tend to be paid more. Conscientiousness, however, is not associated with any statistically significant difference in pay. The largest difference in mean log pay is between high and low openness, 0.089, which corresponds to about £1.04 (or 10%) difference in hourly pay. Extroversion is also positively rewarded and implies on average an increase of about 5% (or 63 pence) in hourly pay. On the contrary, high agreeableness and neuroticism are penalized in the labour market with an average reduction in hourly pay of about 6% (or 72 pence).

These results seem in line with previous studies by Letcher and Niehoff (2004) and Mueller and Plug (2006), who consider a sample of Wisconsin high school graduates interviewed intermittently since they left high school in 1957 (Wisconsin Longitudinal Study), and with the studies by Heineck (2011) and Heineck and Anger (2010), who consider a UK household sample interviewed annually from 1991 and a German household sample interviewed annually from 1984 (the BHPS and the German Socio-Economic Panel). The results in Table 4 also 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 and highly introvert persons and a glass ceiling effect for individuals who are closed to experience.

Pay differences observed for people with diverse personalities could in part be explained by the fact that people with different personality characteristics sort out in different occupations, level of education, etc. Previous papers find for instance that conscientiousness and openness are

Table 3. Mean, SD, first, second and third quartiles of the Big Five personality traits

Big Five personality traits	Mean	SD	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. Difference in log pay at the mean and quantiles between workers with high level (greater than median) and low level (less than median) of the Big Five personality traits

	Difference in log pay at					
Big Five personality traits	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)

Notes: SEs are reported in the second row in parentheses.
Log pay differences that are statistically significant at the 10% and 5% levels are indicated with * and **, respectively.

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correlated with education (see Barrick and Mount, 1991; Raad and Schouwenburg, 1996) and that openness to experience, conscientiousness, agreeableness and neuroticism are correlated with men's occupational choice (see Cobb-Clark and Tan, 2011). This can explain part of the observed personality pay differences as confirmed by our decomposition results, which we present next.

Decomposition results

As a first step toward estimating the decompositions, for each of the Big Five personality traits, we estimate mean and unconditional quantile pay regressions separately for people with high and low levels of that trait (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 personality pay differences at the mean and at five different quantiles, into two main components: a component, called *composition effect*, which is explained by differences in the explanatory variables, and a *residual component*. This decomposition is computed using the generalized Blinder–Oaxaca method as described in Section III. We also provide a reliable detailed decomposition of the composition effects. For each of the personality traits we consider separate models, mean and quantile regressions, for people with high and low levels of the trait. These pay regressions include the following variables: 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 indicating whether the person has low or high level of the personality trait).

In Tables 5 and 6 we report the results for the decomposition of the log pay gap at the mean and at different quantiles. In the second and third columns of these tables we report the composition and residual effects estimated using the generalized Blinder–Oaxaca decomposition. We also report whether the total, explained and unexplained pay gaps are statistically significant at the 1%, 5% and 10% levels of significance.

Table 5. Decompositions of mean log pay differences using Generalized Blinder–Oaxaca Method

Big Five personality traits	Mean log pay difference	Composition effect	Residual effect
Openness	0.089**	0.071**	0.018
Conscientiousness	−0.008	−0.009	0.001
Extroversion	0.053**	0.013	0.040
Agreeableness	−0.055**	0.001	−0.056
Neuroticism	−0.062**	0.001	−0.063**

Note: * and ** indicate statistical significance at the 10% and 5% levels, respectively.

Looking at the decomposition results for the mean differences (see Table 5) we find that differences for openness and conscientiousness are almost completely due to differences in the personal and job characteristics as evidenced by almost zero residual effects. The opposite is true for pay differentials between low and high levels of agreeableness, extroversion and neuroticism.

In Table 7 we present the results of the generalized Blinder–Oaxaca detailed decomposition 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). The pay advantage for persons with high openness to experience is explained mainly by occupation and education, whereas the pay disadvantage for high conscientious people, although not statistically significant,

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Table 6. Decomposition of percentile pay differences using the Generalized Blinder–Oaxaca method

Big Five personality traits	Log pay difference	Composition effect	Residual effect
Openness to experience			
10th percentile	0.079*	0.105**	−0.026
25th percentile	0.076**	0.050**	0.026
50th percentile	0.087**	0.107**	−0.021
75th percentile	0.076**	0.079	−0.003
90th percentile	0.124**	0.091**	0.033
Conscientiousness			
10th percentile	−0.040	0.052	−0.092
25th percentile	0.003	−0.011	0.014
50th percentile	−0.002	−0.003	0.001
75th percentile	0.013	−0.028	0.041
90th percentile	0.024	−0.038	0.062
Extroversion			
10th percentile	0.125**	0.036	0.089**
25th percentile	0.085**	0.020	0.065**
50th percentile	0.052*	0.013	0.039
75th percentile	0.012	−0.013	0.025
90th percentile	0.022	−0.036	0.058
Agreeableness			
10th percentile	−0.102**	−0.006	−0.096**
25th percentile	−0.056*	−0.000	−0.056*
50th percentile	−0.045	0.016	−0.061**
75th percentile	−0.065*	0.005	−0.070**
90th percentile	−0.060	0.022	−0.082
Neuroticism			
10th percentile	−0.071*	0.005	−0.076*
25th percentile	−0.089**	−0.009	−0.080**
50th percentile	−0.075**	−0.007	−0.068**
75th percentile	−0.028	0.018	−0.046
90th percentile	−0.060	−0.001	−0.059

Note: * and ** indicate statistical significance at the 10% and 5% levels, respectively.

seems to be explained by education, occupation, region and other job characteristics (in particular part-time).

Looking at the log pay gaps at different quantiles (see Table 6), we find a similar story. Differences in pay percentiles between people with high and low openness to experience are mainly explained by differences in characteristics but differences in percentiles for agreeable, extrovert and neurotic people are not. Conscientiousness is not associated with any significant difference in pay percentiles and these small pay differences are not explained by characteristics either.

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 other hand, the sticky floor effect observed for highly neurotic people and highly introvert workers persists even after controlling for mediating factors.

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 6), the pay gap increases at the higher end of the pay 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 pay 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

Table 7. Generalized Blinder–Oaxaca detailed decomposition of mean log pay differences of the Big Five personality traits

Detailed decomposition	Openness to experience	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

Notes: The effect of composite variables that subsume a set of univariate variables is 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 8. Generalized Blinder–Oaxaca detailed decomposition of percentile log 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 quantile difference	0.079	0.076	0.087	0.076	0.124

Notes: The effect of composite variables that subsume a set of univariate variables is 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.

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(decreases) for the workers at the top (bottom) of the pay 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 workers with high and low openness to experience (see second and last columns in Table 6). We report these detailed decomposition results in Table 8. We find that educational level and type of occupation are the key factors explaining the differences in pay between high and low openness to experience. 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 are 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 and the hiring process depend on the level of openness to experience.

Heterogeneous effect of personality traits

In this section we assess whether and to what extent personality traits are rewarded differently across different occupations, education and levels of the other covariates. The decomposition results presented in the last section are based on estimation of separate pay regressions for low and high levels of each personality trait. So, these regressions allow us to test whether there is a heterogeneous effect of personality traits by education, occupation, work experience and each of the other covariates. In the first two columns of Table 9 we report the estimated coefficients of the regressions for the subgroups of workers with low levels of openness to experience. In the next column we report the difference in the regression coefficients for workers with high and low levels of openness to experience computed using the Blinder–Oaxaca decomposition (see formulas (8) in Section III). We also report a *t*-test for whether this difference is zero (i.e. for the equality of regression coefficients for high and low levels of the trait) in the last column. In Tables 10–13, we report corresponding statistics for the other personality traits: conscientiousness, extroversion, agreeableness and neuroticism. The corresponding difference in the coefficients computed using the combined weighting and regression method (see formulas (11) in Section III) provides qualitatively similar results and so are not reported here.

For openness to experience the only variables with a significant difference in coefficients are the dummy variables for managerial occupations and for high level of extroversion (see Table 9). It seems that openness is more rewarded for managers and senior officials, but less rewarded for extrovert people.

Conscientiousness is more rewarded for managers and senior officials and it is very little rewarded for elementary occupations and for process, plant and machine operatives (see Table 10). Generally people with health issues, which limit their amount of work, and part-time workers are paid less, but if they have a high level of conscientiousness this penalty is smaller.

Extroversion is on average rewarded positively and there do not seem to be significant differences in the rewards across different types of occupations (see Table 11). On the contrary, there are significant differences across regions. Furthermore, an extrovert person suffers a pay penalty if he/she is highly neurotic or highly open to experience. Finally, the wage profile by experience is flatter for extrovert people.

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Table 9. (Log) pay regression coefficients for low levels of openness to experience and their difference with the corresponding coefficients for high levels of openness to experience

Explanatory variables	(Log) pay regression coefficient for low levels of openness to experience	SE	Difference in (log) pay regression coefficient between high and low levels of openness to experience	SE
Education (Omitted: None)				
No qualification	−0.147**	0.045	0.018	0.080
Vocational education	−0.046	0.044	−0.084	0.076
GCSE or O-level	−0.064*	0.036	0.059	0.056
College or university degree	0.215**	0.045	−0.066	0.063
Experience	0.034**	0.005	0.004	0.008
Experience square	−0.001**	0.000	0.000	0.000
Part-time	−0.058	0.090	0.058	0.127
Temporary job	−0.161	0.140	0.156	0.157
Small firm size	−0.181**	0.045	−0.036	0.071
Public sector	−0.022	0.039	0.070	0.054
Health problems or disabilities	−0.019	0.029	−0.041	0.046
Health limits work	−0.082	0.052	0.073	0.089
Training	−0.031	0.028	0.069	0.043
Unemployment	−0.637**	0.126	0.025	0.211
Occupation (Omitted: Skilled Trades)				
Managers and senior officials	0.251**	0.046	0.109*	0.063
Professionals	0.272**	0.061	−0.011	0.086
Associate professionals	0.136**	0.051	0.055	0.071
Administrative and secretarial	−0.058	0.088	0.015	0.103
Personal service	−0.104	0.076	0.004	0.163
Sales and customer service	−0.144*	0.082	−0.041	0.137
Process, plant and machine operatives	−0.072*	0.043	0.083	0.064
Elementary occupations	−0.193**	0.044	−0.013	0.068
Region (Omitted: London)				
Rest of South-East	−0.063	0.064	0.043	0.101
South-West	−0.157**	0.068	0.073	0.107
Anglia & Midlands	−0.189**	0.061	0.059	0.099
North West	−0.176**	0.071	−0.055	0.117
Rest of the North	−0.193**	0.062	−0.019	0.100
Wales	−0.261**	0.062	0.095	0.100
Scotland	−0.250**	0.066	0.070	0.100
Northern Ireland	−0.213**	0.059	−0.005	0.096
Personality traits				
High extroversion	0.088**	0.028	−0.090**	0.042
High neuroticism	−0.032	0.027	−0.056	0.044
High conscientiousness	−0.025	0.032	0.066	0.047
High agreeableness	−0.038	0.032	−0.052	0.045
Constant	2.262**	0.089	−0.132	0.135

Note: * and ** indicate statistical significance at the 10% and 5% levels, respectively.

There is a negative effect on pay for working in small firms but this effect reduces to less than half for agreeable workers. The effect of past training seems to be positive for agreeable and negative for disagreeable workers. There aren't statistically significant differences in the agreeableness reward across occupations, but it would seem that agreeableness is positively rewarded for occupations that require managerial skills (managers, senior officials and professionals) and in occupations that involve contacts with other colleagues (secretarial and administrative occupations) or with customers (sales and customer service), but negatively rewarded for blue collars (elementary occupations and for process, plant and machine operatives). Finally, agreeable workers seem to have a flatter pay profile by work experience.

Neuroticism is penalized in all occupations but especially so for occupations in personal service, sales and customer service. Finally, extrovert workers who are also neurotic are paid less.

VI. Some Sensitivity Analyses

In this section we consider robustness checks and some sensitivity analyses to address some possible limitations

Table 10. (Log) pay regression coefficients for low levels of conscientiousness and their difference with the corresponding coefficients for high levels of conscientiousness

Explanatory variables	(Log) pay regression coefficient for low levels of conscientious-ness	SE	Difference in (log) pay regression coefficient between high and low levels of conscientious-ness	SE
Education (Omitted: None)				
No qualification	−0.167**	0.047	0.059	0.080
Vocational education	−0.111**	0.046	0.096	0.071
GCSE or O-level	−0.062*	0.035	0.046	0.055
College or university degree	0.194**	0.040	−0.027	0.065
Experience	0.035**	0.005	0.002	0.008
Experience square	−0.001**	0.000	0.000	0.000
Part-time	−0.097	0.067	0.232*	0.134
Temporary job	−0.090	0.073	−0.023	0.164
Small firm size	−0.141**	0.042	−0.108	0.069
Public sector	0.003	0.032	0.014	0.055
Health problems or disabilities	−0.007	0.025	−0.073	0.047
Health limits work	−0.114**	0.049	0.155*	0.086
Training	−0.010	0.025	0.032	0.044
Unemployment	−0.631**	0.115	0.038	0.226
Occupation (Omitted: Skilled Trades)				
Managers and senior officials	0.238**	0.043	0.111*	0.066
Professionals	0.221**	0.052	0.074	0.090
Associate professionals	0.109**	0.045	0.093	0.074
Administrative and secretarial	−0.063	0.047	−0.010	0.142
Personal service	−0.176**	0.078	0.134	0.125
Sales and customer service	−0.230**	0.082	0.158	0.133
Process, plant and machine operatives	−0.053	0.039	0.021	0.065
Elementary occupations	−0.208**	0.042	0.020	0.067
Region (Omitted: London)				
Rest of South-East	−0.098*	0.051	0.149	0.117
South-West	−0.202**	0.061	0.189	0.123
Anglia & Midlands	−0.214**	0.053	0.127	0.113
North West	−0.230**	0.060	0.059	0.135
Rest of the North	−0.250**	0.054	0.125	0.114
Wales	−0.260**	0.053	0.102	0.113
Scotland	−0.265**	0.050	0.110	0.119
Northern Ireland	−0.244**	0.050	0.089	0.110
Personality traits				
High extroversion	0.043*	0.026	0.008	0.044
High neuroticism	−0.044*	0.024	−0.008	0.047
High conscientiousness	−0.024	0.028	0.064	0.043
High agreeableness	−0.050	0.031	−0.005	0.046
Constant	2.278**	0.076	−0.205	0.162

Note: * and ** indicate statistical significance at the 10% and 5% levels, respectively.

of our analysis: (i) robustness check of generalized Blinder–Oaxaca method, (ii) endogeneity (reverse causality) of personality traits, (iii) nonmonotonicity of the pay–personality traits relationship, (iv) measurement error on personality traits, (v) common support problem and (vi) reference group issue.

Combined weighting and regression-based method

As explained in Section III, composition effects estimated using combined weighting and regression-based methods are more robust than the ones estimated using the generalized Blinder–Oaxaca method, which we have used. As the detailed decompositions can only be estimated using the latter, we were constrained to using that method. So, we also decompose the personality pay differences at the mean and 5 quantiles using the more robust combined weighting and regression-based methods. The weights for this method are based on logit models estimated to explain the probability of having high levels of a personality trait rather than low. The explanatory variables used in the logit models are the same as those used in the mean and unconditional quantile regression pay models. The results are reported in Tables 14 and 15. We find that the composition effects using both methods are similar, showing that our results are robust.

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Table 11. (Log) pay regression coefficients for low levels of extroversion and their difference with the corresponding coefficients for high levels of extroversion

Explanatory variables	(Log) pay regression coefficient for low levels of extroversion	SE	Difference in (log) pay regression coefficient between high and low levels of extroversion	SE
Education (Omitted: None)				
No qualification	−0.156**	0.048	−0.008	0.076
Vocational education	−0.059	0.041	−0.019	0.072
GCSE or O-level	−0.042	0.041	−0.024	0.055
College or university degree	0.185**	0.041	−0.026	0.063
Experience	0.046**	0.005	−0.022**	0.008
Experience square	−0.001**	0.000	0.000**	0.000
Part-time	−0.112	0.075	0.160	0.123
Temporary job	−0.068	0.117	−0.075	0.144
Small firm size	−0.220**	0.046	0.071	0.072
Public sector	0.038	0.035	−0.071	0.053
Health problems or disabilities	−0.055*	0.031	0.031	0.043
Health limits work	−0.049	0.052	−0.002	0.087
Training	−0.014	0.029	0.018	0.043
Unemployment	−0.777**	0.142	0.275	0.188
Occupation (Omitted: Skilled Trades)				
Managers and senior officials	0.278**	0.045	0.046	0.064
Professionals	0.269**	0.057	−0.070	0.090
Associate professionals	0.121**	0.047	0.060	0.071
Administrative and secretarial	−0.105	0.072	0.165	0.112
Personal service	−0.137*	0.070	0.052	0.126
Sales and customer service	−0.195*	0.109	0.055	0.142
Process, plant and machine operatives	−0.065	0.045	0.054	0.064
Elementary occupations	−0.217**	0.044	0.067	0.067
Region (Omitted: London)				
Rest of South-East	0.052	0.072	−0.197**	0.095
South-West	0.018	0.077	−0.317**	0.104
Anglia & Midlands	−0.006	0.070	−0.358**	0.093
North West	−0.105	0.084	−0.198*	0.112
Rest of the North	−0.086	0.071	−0.262**	0.094
Wales	−0.044	0.071	−0.394**	0.096
Scotland	−0.061	0.068	−0.356**	0.096
Northern Ireland	−0.070	0.067	−0.322**	0.090
Personality traits				
High neuroticism	−0.017	0.027	−0.106**	0.047
High openness	0.036	0.029	−0.068*	0.041
High conscientiousness	−0.025	0.032	0.052	0.047
High agreeableness	−0.046	0.032	−0.028	0.045
Constant	1.987**	0.094	0.528**	0.129

Note: * and ** indicate statistical significance at the 10% and 5% levels, respectively.

Endogeneity and reverse causality issues

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

Previous papers on the relationship between the Big Five personality traits and pay (see, e.g., Mueller and Plug, 2006; Viinikainen *et al.*, 2010) 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 focused 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

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Table 12. (Log) pay regression coefficients for low levels of agreeableness and their difference with the corresponding coefficients for high levels of agreeableness

Explanatory variables	(Log) pay regression coefficient for low levels of agreeableness	SE	Difference in (log) pay regression coefficient between high and low levels of agreeableness	SE
Education (Omitted: None)				
No qualification	−0.182**	0.048	0.103	0.080
Vocational education	−0.078*	0.044	0.062	0.075
GCSE or O-level	−0.058*	0.034	0.047	0.058
College or university degree	0.171**	0.037	0.013	0.067
Experience	0.041**	0.005	−0.018**	0.008
Experience square	−0.001**	0.000	0.000**	0.000
Part-time	0.004	0.070	−0.093	0.131
Temporary job	−0.119	0.104	0.069	0.158
Small firm size	−0.229**	0.043	0.135*	0.071
Public sector	0.022	0.032	−0.083	0.056
Health problems or disabilities	−0.060**	0.028	0.064	0.044
Health limits work	−0.027	0.051	−0.101	0.080
Training	−0.027	0.027	0.084*	0.045
Unemployment	−0.679**	0.116	−0.047	0.243
Occupation (Omitted: Skilled Trades)				
Managers and senior officials	0.271**	0.039	0.078	0.069
Professionals	0.236**	0.055	0.087	0.086
Associate professionals	0.177**	0.045	−0.056	0.076
Administrative and secretarial	−0.075	0.069	0.130	0.104
Personal service	−0.107	0.072	0.018	0.130
Sales and customer service	−0.208**	0.080	0.225	0.156
Process, plant and machine operatives	−0.023	0.039	−0.061	0.070
Elementary occupations	−0.174**	0.041	−0.065	0.070
Region (Omitted: London)				
Rest of South-East	−0.016	0.062	−0.105	0.110
South-West	−0.127*	0.068	0.021	0.112
Anglia & Midlands	−0.167**	0.063	−0.007	0.102
North West	−0.177**	0.073	−0.057	0.116
Rest of the North	−0.172**	0.064	−0.086	0.103
Wales	−0.230**	0.064	0.024	0.103
Scotland	−0.228**	0.064	0.023	0.103
Northern Ireland	−0.211**	0.060	−0.018	0.102
Personality traits				
High extroversion	0.059**	0.027	−0.044	0.044
High neuroticism	−0.045*	0.026	−0.023	0.045
High openness	0.018	0.026	−0.042	0.043
High conscientiousness	−0.003	0.030	0.007	0.046
Constant	2.148**	0.085	0.119	0.146

Note: * and ** indicate statistical significance at the 10% and 5% levels, respectively.

this endogeneity issue. Some of them have tried to take account explicitly of the issue either by using instrumental variable estimation or by using a latent factor model approach. For example, Osborne-Groves (2005) estimate the effect of personality on pay 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 the 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). However, in our pay regressions we have controlled for variables that could be related to changes in the personality traits and to pay and hence could have contributed to the reverse causality. In particular, we have considered variables that represent the person's past labour 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, and hence controlling for

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Table 13. (Log) pay regression coefficients for low levels of neuroticism and their difference with the corresponding coefficients for high levels of neuroticism

Explanatory variables	(Log) pay regression coefficient for low levels of neuroticism	SE	Difference in (log) pay regression coefficient between high and low levels of neuroticism	SE
Education (Omitted: None)				
No qualification	−0.160**	0.046	0.046	0.082
Vocational education	−0.071	0.043	0.004	0.072
GCSE or O-level	−0.051	0.035	0.013	0.057
College or university degree	0.193**	0.039	−0.046	0.067
Experience	0.034**	0.005	0.006	0.008
Experience square	−0.001**	0.000	0.000	0.000
Part-time	0.001	0.079	−0.083	0.122
Temporary job	−0.142	0.111	0.143	0.140
Small firm size	−0.183**	0.044	−0.046	0.077
Public sector	0.011	0.034	−0.021	0.052
Health problems or disabilities	−0.031	0.028	−0.021	0.047
Health limits work	−0.006	0.059	−0.099	0.082
Training	0.003	0.028	−0.016	0.044
Unemployment	−0.613**	0.126	−0.086	0.208
Occupation (Omitted: Skilled Trades)				
Managers and senior officials	0.306**	0.040	−0.037	0.071
Professionals	0.256**	0.055	−0.006	0.091
Associate professionals	0.150**	0.047	−0.005	0.073
Administrative and secretarial	−0.029	0.086	−0.063	0.106
Personal service	−0.032	0.076	−0.246*	0.133
Sales and customer service	−0.096	0.080	−0.208	0.147
Process, plant and machine operatives	−0.044	0.041	−0.003	0.069
Elementary occupations	−0.215**	0.042	0.059	0.070
Region (Omitted: London)				
Rest of South-East	−0.015	0.066	−0.102	0.092
South-West	−0.090	0.071	−0.119	0.100
Anglia & Midlands	−0.149**	0.065	−0.064	0.087
North West	−0.176**	0.073	−0.109	0.116
Rest of the North	−0.198**	0.064	−0.040	0.095
Wales	−0.191**	0.065	−0.083	0.091
Scotland	−0.214**	0.066	−0.044	0.088
Northern Ireland	−0.202**	0.063	−0.046	0.084
Personality traits				
High extroversion	0.080**	0.026	−0.110**	0.048
High openness	0.011	0.026	−0.015	0.044
High conscientiousness	0.005	0.029	−0.024	0.050
High agreeableness	−0.055*	0.028	−0.011	0.047
Constant	2.169**	0.091	0.051	0.128

Note: * and ** indicate statistical significance at the 10% and 5% levels, respectively.

Table 14. Decompositions of mean log pay differences using Combined Weighting and Regression Method

Big Five personality traits	Mean log pay difference	Composition effect	Residual effect
Openness	0.089**	0.080	0.009
Conscientiousness	−0.008	−0.005	−0.003
Extroversion	0.053**	0.016	0.037
Agreeableness	−0.055**	0.008	−0.063
Neuroticism	−0.062**	0.001	−0.063

Note: Log pay differences that are statistically significant at the 10% and 5% levels are indicated with * and **, respectively.

them should reduce the reverse causality problem. We also do an additional sensitivity check by restricting our sample to people aged 30 years or more, i.e. to an age range when personality traits are more stable (see, e.g., Costa and McCrae, 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.

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Table 15. Decomposition of percentile pay differences using Combined Weighting and Regression Method

Big Five personality traits	Log pay difference	Composition effect	Residual effect
Openness to experience			
10th percentile	0.079*	0.081	−0.002
25th percentile	0.076**	0.039	0.037
50th percentile	0.087**	0.105	−0.018
75th percentile	0.076**	0.079	−0.003
90th percentile	0.124**	0.113	0.011
Conscientiousness			
10th percentile	−0.041	0.035	−0.076
25th percentile	0.003	−0.008	0.012
50th percentile	−0.002	−0.004	0.002
75th percentile	0.013	−0.028	0.041
90th percentile	0.024	−0.013	0.037
Extroversion			
10th percentile	0.125**	0.039	0.086
25th percentile	0.085**	0.013	0.072
50th percentile	0.052*	0.012	0.040
75th percentile	0.012	−0.014	0.026
90th percentile	0.022	−0.025	0.047
Agreeableness			
10th percentile	−0.101**	−0.008	−0.093
25th percentile	−0.056	0.003	−0.059
50th percentile	−0.044	0.025	−0.069
75th percentile	−0.065*	0.027	−0.092
90th percentile	−0.061	0.023	−0.084
Neuroticism			
10th percentile	−0.071	0.019	−0.090
25th percentile	−0.088**	−0.009	−0.079
50th percentile	−0.075**	−0.013	−0.062
75th percentile	−0.028	0.009	−0.037
90th percentile	−0.060	−0.002	−0.058

Note: Log pay differences that are statistically significant at the 10% and 5% levels are indicated with * and **, respectively.

Nonmonotonicity issue

To verify whether the relationship between pay 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 percentiles and above the 75th percentile, respectively. In Table 16, 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 pay and the personality level is monotonic for each of the five 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.

Measurement error issues

We are also concerned with measurement error issues because personality traits are difficult to measure. Osborne-Groves (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 pay 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 pay 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 issue

To take account of the common support issue we repeat our analysis by restricting the sample to the people with common support for the predicted probability of having high rather than low levels of the personality trait studied. We find that there are only few cases with no common support and the decomposition analysis results do not change at all.

Reference group issue

A very common problem with Oaxaca–Blinder type decompositions is that the decomposition may be sensitive to the group that is taken as the base or reference group. In Section III we had discussed decompositions by taking group 0 as the reference group:

$$(\bar{y}_1 - \bar{y}_0) = (\bar{X}_1 - \bar{X}_0)\beta_1(\mu) + \bar{X}_0(\beta_1(\mu) - \beta_0(\mu)) \tag{13}$$

If we take group 1 as the reference group the decomposition will be

$$(\bar{y}_0 - \bar{y}_1) = (\bar{X}_0 - \bar{X}_1)\beta_0(\mu) + (\beta_0(\mu) - \beta_1(\mu)) \tag{14}$$

which can be rewritten as

$$(\bar{y}_0 - \bar{y}_1) = -(\bar{X}_1 - \bar{X}_0)\beta_0(\mu) - \bar{X}_1(\beta_1(\mu) - \beta_0(\mu)) \tag{15}$$

Table 16. Differences in log pay at the mean and quantiles between extreme and medium levels of Big Five personality traits

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

Notes: SDs are reported in the second row in parentheses.
Log pay differences that are statistically significant at the 10% and 5% levels are indicated with * and **, respectively.

Table 17. Changing the reference group: decompositions of mean log pay differences using the Generalized Blinder–Oaxaca Method

Big Five personality traits	Mean log pay difference	Composition effect	Residual effect
Openness	−0.089**	−0.096**	0.007
Conscientiousness	0.008	0.009	−0.001
Extroversion	−0.053**	−0.004	−0.049**
Agreeableness	0.055**	−0.005	0.060**
Neuroticism	0.062**	0.011	0.051**

Note: * and ** indicate statistical significance at the 10% and 5% levels, respectively.

The difference between the composition effect in Equations 13 and 15 (in addition to reversal of sign) is that in Equation 13 the difference in characteristics is indexed or weighted by the coefficients of the group 1 coefficients and that in Equation 15 by group 0 coefficients. In Tables 17 and 18 we report the composition and residual effects (and their SE) where we take those with more than a median value of a personality trait as the reference group. Comparing these tables to Tables 5 and 6 where we had taken the group with less than median value of a personality trait as the reference group, we find that in both cases,

- mean log pay difference for openness to experience is almost completely explained by differences in composition while that is not the case for extraversion, agreeableness and neuroticism;
- the glass ceiling effect for those who are closed to experience and the sticky floor effect for high agreeable are explained by differences in characteristics;
- the sticky floor effect for high neurotic and introvert persists even after controlling for characteristics, but by changing the reference group the pattern is broken at the 10th percentile (residual effect at the 10th percentile is lower than that at the 25th percentile).

VI. Conclusions

In this article we estimate the total effect of personality traits on pays, i.e. personality pay gaps for each of the Big Five personality traits, and we decompose these pay gaps into their indirect effect that operates through educational,

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Table 18. Changing the reference group: decomposition of percentile pay differences using the Generalized Blinder–Oaxaca method

Big Five personality traits	Log pay difference	Composition effect	Residual effect
Openness to experience			
10th percentile	−0.079*	−0.033**	−0.046
25th percentile	−0.076**	−0.101**	0.025
50th percentile	−0.087**	−0.090**	0.003
75th percentile	−0.076**	−0.119**	0.043
90th percentile	−0.124**	−0.103**	−0.021
Conscientiousness			
10th percentile	0.040	−0.014	0.054
25th percentile	−0.003	−0.019	0.016
50th percentile	0.002	0.010	−0.008
75th percentile	−0.013	0.045	−0.058**
90th percentile	−0.024	0.022	−0.046
Extroversion			
10th percentile	−0.125**	−0.008	−0.117**
25th percentile	−0.085**	−0.020	−0.065**
50th percentile	−0.052*	0.001	−0.053**
75th percentile	−0.012	0.004	−0.016
90th percentile	−0.022	0.007	−0.029
Agreeableness			
10th percentile	0.102**	−0.002	0.104**
25th percentile	0.056*	−0.010	0.066**
50th percentile	0.045	−0.007	0.052*
75th percentile	0.065**	−0.010	0.075**
90th percentile	0.060	−0.021	0.081*
Neuroticism			
10th percentile	0.071*	0.033	0.038
25th percentile	0.089**	0.027	0.062**
50th percentile	0.075**	0.016	0.059**
75th percentile	0.028	0.010	0.018
90th percentile	0.060	0.010	0.050

Note: * and ** indicate statistical significance at the 10% and 5% levels, respectively.

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occupational choices and other personal and job characteristics, and a residual (unexplained) effect. We implement this analysis using the generalized Oaxaca–Blinder decomposition and the more robust combined weighting and regression-based approach proposed by Firpo *et al.* (2011). These decomposition approaches allow us to analyse 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, education and other job and personal characteristics.

Our main results can be summarized in the following points. First, the personality trait associated with the largest pay gap is openness to experience and it is followed by neuroticism, agreeableness, extroversion and conscientiousness. While openness to experience and extroversion are rewarded in the labour market, agreeableness, neuroticism and conscientiousness are penalized (although conscientiousness pay gap is not statistically significant). Second, the pay gaps associated with openness to experience and conscientiousness are explained mainly by differences in characteristics, whereas pay gaps associated with extroversion, neuroticism and agreeableness remain mainly unexplained. Third, 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. In case of agreeableness and closeness to experience, however, the sticky floor and glass ceiling effects disappear once we control for differences in personal and job characteristics.

Looking at the heterogeneity of the effect of personality traits, we find some evidence of differences in the pay reward or penalty associated with personality traits across occupations but not across education. Conscientiousness and agreeableness are rewarded positively for managers and senior officials but are not at all rewarded for elementary occupations and for process, plant and machine operatives. There is a pay penalty associated with neuroticism for all occupations, but especially so for occupations in personal service, sales and customer service. It seems that openness is more rewarded for managers and senior officials. Finally, there seems also to be an interaction effect between personality traits. Openness and extroversion have generally a positive effect on pay, but neuroticism combined with extroversion and openness combined with extroversion lead to a negative effect on pay.

As we find that pay gaps (at the mean and quantiles) associated with extroversion, agreeableness and neuroticism are significantly different from zero but are hardly explained by the observed mediating channels, we cannot provide any empirical evidence for why these differences persist. Here we reiterate some of the possible explanations for this unexplained difference as put forth by economic theory.

In the case of agreeableness, the positive pay premium generally observed for occupations that require managerial skills or that involve contacts with other people may be explained by an increase in productivity, but what perhaps could explain the pay penalty observed for blue collars (elementary occupations and for process, plant and machine operatives) is that being less agreeable (more antagonist) could be related to better skills in pay bargaining. The residual pay disadvantage for neuroticism could in part be explained by reduced productivity (but we control for health problems and disabilities and for workers who report to have health issues that limit the amount of work he/she can do) and in part by social desirability or taste-based discrimination. Extreme level of neuroticism can be related to mental illness. An attempt to identify the effect of productivity and taste-based discrimination related to mental health conditions in the UK is presented in Longhi *et al.* (2012), who find that workers with mental health problems have a productivity reduction but also suffer a small pay penalty probably associated with discrimination, especially if they work in well-paid jobs. Finally, extroversion could improve workplace social networking, which could in turn increase productivity or the chances of career advancements. But it is difficult to speculate further on possible explanations for the unexplained pay gaps.

In the face of such strong empirical evidence of large unexplained pay gaps associated with extroversion, agreeableness and neuroticism, further empirical research assisted by richer data of these 'unobserved' factors postulated by economic theory is required.

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