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The Returns to Personality Traits across the Wage Distribution☆

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Abstract

This paper investigates variation in the wage effects of non-cognitive skills across the wage distribution. I expect (i) increasing explanatory power and (ii) increasing magnitudes of the effects of non-cognitive skills on wages across the wage distribution. I test these hypotheses using unconditional quantile regressions with data from Germany, the UK and Australia. To test the joint explanatory contribution of multiple variables within a quantile-regression framework, I propose a new statistic that quantifies the rise in explanatory power generated by additional explanatory variables. The findings support both hypotheses and provide further evidence for the importance of non-cognitive skills in the labor market.

Keywords: non-cognitive skills, personality traits, unconditional quantile regression
JEL: C21, J24, J31

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1. Introduction

Non-cognitive skills[1] are important predictors for various indicators of labor market success (Heckman and Rubinstein, 2001; Heckman et al., 2006), including wages (e.g. Braakmann, 2009; Heineck and Anger, 2010; Heineck, 2011; Mueller and Plug, 2006). Typically, studies focus on identifying effects at the mean of the wage distribution. However, investigations at the mean could neglect heterogeneous effects of non-cognitive skills on wages and would thus lead to an incomplete understanding of the connection between these two variables. Nevertheless, to my knowledge, heterogenous wage effects of non-cognitive skills for low- and high-wage employees have not yet been investigated. In this paper, I fill this blind spot in the literature by analyzing the interplay between personality traits and wages across the wage distribution.

One can easily imagine non-cognitive skills to have heterogeneous wage effects for workers at different points in the wage distribution for multiple reasons. The wages of low-paying jobs are limited by minimum wages in many countries which could also reduce the wage effect of personality traits in these jobs. Minimum wages could reduce the overall wage dispersion in low-wage jobs. In this case, there could simply be no room left for further individual bargaining in which personality traits could play a role. Additionally, low-paying jobs likely consist of tasks in which non-cognitive skills are not as important for performance as in high-paying jobs. For example, it is unlikely that low-paid fruit pickers benefit monetarily from being extravert. In contrast, high-paid employees with leadership responsibilities could certainly profit from extraversion, e.g. by motivating their employees or being more likely to attract new customers. In such cases, estimating the average effect of personality traits on wages ignores heterogeneous effects and would thus draw an incomplete picture of the interplay between personality and wages.

In this article, I investigate variation in the effects of personality traits on wages. I introduce a framework of wage determination that encompasses human capital endowments as well as non-cognitive skills. Previous studies (Mueller and Plug, 2006; Nandi and Nicoletti, 2014) name some potential channels, including productivity and wage bargaining, through which non-cognitive skills affect wages. However, they do not incorporate these considerations into a formal model. I propose a static model of wage determination in which wages consist of a minimum wage rate, productivity pay, and a bargaining premium. Non-cognitive skills could affect productivity and wage bargaining in my model. I assume the share of both pay components of

[1]Like Heineck and Anger (2010) and Heckman and Kautz (2012), I use the terms personality traits and non-cognitive skills interchangeable. My definition follows Heckman and Kautz (2012): “Personality traits are manifested through thoughts, feelings, and behaviors, and therefore, must be inferred from measures of performance on ’tasks,’ broadly defined.

overall wages to increase from low- to high-wage employees. Thus, I hypothesize that (i) the importance as well as (ii) the magnitude of the effects of non-cognitive skills on wages increase across the wage distribution.

I subsequently test these hypotheses with longitudinal survey data from the German Socio-Economic Panel Study (SOEP), the UK Household Longitudinal Study (also known as: Understanding Society, UKHLS) and the Household, Income and Labour Dynamics in Australia (HILDA) survey. I apply unconditional quantile regressions (UQR) to estimate marginal effects of covariates at different points of the wage distribution. Because non-cognitive skills are a set of multiple variables, I develop a statistical test to quantify the joint relative increase in explanatory power after including an arbitrary number of additional regressors in the estimations. I refer to this statistic as δR^2.

I contribute to the literature in a number of ways. First, this is the first study to offer a theoretical framework that predicts variation in the returns to non-cognitive skills across the wage distribution and its empirical testing. Second, the empirical analyses for three countries with different scales of non-cognitive skills makes it possible to draw conclusions about the generalizability of the results as well as to compare different scales used to survey non-cognitive skills. Third, the statistic δR^2 developed in this paper can also be used in other applications and thus provides researchers with a new method of comparing the joint explanatory power of multiple regressors between any percentiles of interest within an UQR-framework.

My findings indicate that the importance of personality traits in the wage determination process increases in Germany, the UK and Australia. Additionally, the effects of certain personality traits (especially agreeableness, neuroticism and risk taking) increase across the wage distribution. These results hold for full-time employees, males and females. Furthermore, the results are unchanged when investigating non-linear effects in all countries and hold in several robustness checks.

This paper is organized as follows: Section 2 develops a theoretical model of wage determination under uncertainty and derives testable hypotheses. Section 3 presents the basic concepts of personality traits and gives an overview of previous findings. Section 4 describes the data. Section 5 presents the econometric approaches. Section 6 presents and discusses the results of the estimations. Section 7 concludes.

2. Theoretical Considerations

2.1. A simple static model of wage determination under uncertainty

My starting point is a framework comparable to Lazear (2000) and Bandiera et al. (2005) where firms use at least partially performance-based pay schemes with a guaranteed minimum wages to maximize worker effort and thus productivity. I extend this model by a flexible rent-sharing parameter as suggested by Card et al. (2016). Consider the following wage determination model:

$$w_i = \tilde{W}_i + r_i \tag{1}$$

where w_i is the individual hourly wage. $\tilde{W}_i$ are minimum wages either set by law, labor market institutions, or individual preferences. The employer has to pay $\tilde{W}_i$ in order to sustain employment (it can also be referred to as the outside option), r_i is an individual rent-sharing parameter. Because $\tilde{W}_i$ is determined exogenously, it can be written as:

$$\tilde{W}_i = \alpha + X'_{1i}\beta + \varepsilon_i \tag{2}$$

where α is an exogenously set minimum, X'_i is an individual-specific set of covariates like occupation that is associated with wages, e.g. through collective agreements, and ε_i is an individual-specific error term.

The rent-sharing parameter r_i gives the share of the firms' surplus from employment that can be split between employer and employee and is obtained by the employee. Theoretically, r_i can be as large as the gap between $\tilde{W}_i$ and actual (potentially unobserved) worker productivity w_i^{prod} [2], but never exceed $w_i^{prod} - w_i$ in the long run because this would mean that the employment of i yields a net loss for the firm. A typical example for such rent-sharing is performance pay in which individuals are paid piece rates based on their productivity. This has the advantage to incentivize workers' effort and can thus be rational for firms (Lazear, 2000). However, these models require perfect or at least constant information on worker productivity, which can be an unrealistic assumption. Thus, I introduce a parameter $c_k \, \epsilon [0,1]$ that indicates the degree of certainty on productivity for job k. Consequently, I break down the rent-sharing parameter into two components:

$$r_i = c_k p_i + (1 - c_k) b_i \tag{3}$$

where p_i is the individual productivity above $\tilde{W}_i$ and b_i is a bargaining share. The certainty on productivity c_k can range from 0 to 1 and weighs productivity and bargaining shares in the rent-sharing parameter. p_i can be written as:

[2] For clarification: $w_i^{prod} = \tilde{W}_i + p_i$, where p_i is the true productivity above $\tilde{W}_i$. I will discuss p_i in detail later on.

$$p_i = X'_{2i}\gamma + X'_{3i}\delta + \nu_i \tag{4}$$

X'_{2i} is an individual-specific set of human capital variables (like education) and X'_{3i} are other individual-specific characteristics that affect productivity, like non-cognitive skills. ν_i is an idiosyncratic error. Similarly, I can write the bargaining share as:

$$b_i = X'_{3i}\zeta + X'_{4i}\theta + \upsilon_i \tag{5}$$

where X'_{3i} are covariates that affect bargaining power as well as productivity (e.g. motivation) and X'_{4i} is a vector of covariates determining bargaining power only; υ_i again is an idiosyncratic error.

Based on (2) to (5) we obtain:

$$w_i = \alpha + X'_{1i}\beta + \varepsilon_i + c_k(X'_{2i}\gamma + X'_{3i}\delta + \nu_i) + (1 - c_k)(X'_{3i}\zeta + X'_{4i}\theta + \upsilon_i) \tag{6}$$

By decreasing certainty on productivity, the variables X'_{4i} gain weight in the wage-equation and should thus play a more pronounced role when certainty on productivity is low. In contrast, when certainty is high (e.g., in the case of a fruit picker), c_k equals 1 and wages are solely based on the minimum wage $\tilde{W}_i$ and worker productivity p_i. Firms would want to estimate c_k rather conservatively to prevent w_i from exceeding w_i^{prod}. However, firms are usually better informed about individual productivity compared to their employees (in terms of the surplus from employment), because they know the overall mean productivity $\overline{w^{prod}}$ and can use this knowledge to their advantage. Firms would want to convince employees that w_i^{prod} is relatively low to keep a larger share of the surplus from employment, thus keeping $(1 - c_k)b_i$ small.

2.2. *Wage determination across the wage distribution*

As described Section 2.1, jobs differ in the degree of the certainty on individual productivity. Arguably, higher-paying jobs are related to more noisy measurements of productivity.[3] There are other examples for mostly low-wage jobs with simple measures of productivity, like the number of delivered packages for postmen or the time to process everyday tasks for a secretary. In contrast, there are many examples for high-paid jobs that do not have simple measures for productivity like managerial positions, researchers, etc..

[3]This presumption is further discussed in Appendix A.

Thus, I assume that high-paying positions are related to a lower degree of certainty c_k of productivity.

Additionally, the gap between $\tilde{W}_i$ and actual worker's productivity w_i^{prod} most likely increases in high-paying positions, where minimum wages or collective agreements hardly cover a large share of pay. I illustrate the theoretical considerations with an example (see Table 1): consider three wage categories, "low"," medium" and "high". Each category exhibits a different amount of certainty, with $c_k = 1$ for low-paying jobs, $c_k = 0.7$ for medium-paying jobs and $c_k = 0.3$ for high-paying jobs.[4] Similarly, the relative share of $\tilde{W}_i$ of w_i^{prod} is assumed to arbitrarily decrease between the jobs from 0.9 (low-paying) to 0.5 (high-paying). Thus, the maximum amount of r_i increases from 0.1 to 0.5. With rising pay the importance of productivity pay shares increases and so does uncertainty on productivity. As a consequence, b_i gains importance with rising wage levels. In this example, the low-paid employee has no room for wage negotiations, while up to 35% of the high-paying position's pay can be achieved through bargaining.

To summarize, my wage determination model suggests that wages are determined by three parameters: (i) minimum wages set either by labor market institutions or the individual's reservation wage, (ii) productivity bonuses and (iii) a bargaining premium. As an additional component, I propose c_k as a parameter of productivity certainty. I assume that c_k decreases from low- to high-paying jobs. Certainty is very high in low-paying jobs that consist of low-skilled tasks such as fruit picking. In contrast, c_k should decline for jobs with complex tasks in which productivity is difficult to measure. Employers want to maximize profits, they estimate c_k rather conservatively and have likely equal or better knowledge of c_k than the worker herself. Thus, there may be a gap between the true, but potentially unobserved productivity w_i^{prod} and $\tilde{W}_i + cp_i$. This gap, an individual specific surplus, can be shared between employer and employee. The employee's share is b_i, which is the individual bargaining premium. Firms will pay a maximum of $b_i = w_i^{prod} - (c_k p_i + \tilde{W})$ in a competitive labor market. Because c_k rises and the relative share of $\tilde{W}_i$ declines with rising pay levels, the relative shares of productivity pay p_i and the bargaining premium b_i increase in the same manner.

2.3. Non-cognitive skills and wage determination

My theoretical model suggests that employees can directly increase their pay by adjusting two parameters: (i) productivity p_i and (ii) the bargaining premium b_i. Additionally, wages could indirectly be increased by increasing $\tilde{W}_i$, e.g., by picking jobs that have minimum wages or rather high base wages within an occupation.

[4] These degrees of certainty are chosen arbitrary. The only assumption needed for my argument is that certainty decreases with higher-paying jobs.

This section discusses how non-cognitive skills fit into the model.

I start with theoretical considerations of the effect of personality traits on productivity p_i. Traits like orderliness or motivation could positively affect productivity, because they could lead to less mistakes in work routines. In the example of an assembly line worker, higher degrees of motivation could be related to less faulty parts in the manufacturing process. This could have a direct impact on wages if there is a wage penalty for damaged parts or through less output of functional parts.

Personality traits could also affect the bargaining premium b_i. Employers have an incentive to minimize this premium without decreasing productivity. If individual i is uncertain of his or her exact productivity, personality traits could affect the behavior to maximize b_i. For example, individuals who do not handle stress well are likely to perform worse in wage negotiations than comparable employees who are stress resistant. In the same manner, these individuals are potentially less likely to opt out of employment at the current employer and search for another job because they could underestimate their bargaining power and additionally underestimate their potential pay at another employer.

Non-cognitive skills can also influence wages indirectly. For example, personality traits affect occupational choice (John and Thomsen, 2014) which itself affects wages (for example in raising $\tilde{W}_i$ through minimum wages in specific occupations set by collective agreements). In the same manner, personality could affect educational attainment or the tendency to perform overtime work, which then affects wages. Thus, non-cognitive skills could have both mediating (through other variables) or direct effects on wages.

Taking these considerations into account, I define the vectors from (6) such that the empirical model is:

$$\begin{aligned} w_i =& minwage + job_i'\beta + female_i\phi + c_k(humcap_i'\gamma + ncs_{1i}'\delta) + (1-c_k)(ncs_{1i}'\zeta + ncs_{2i}'\theta) \\ &+ \varepsilon_i + c_k\nu_i + (1-c_k)\upsilon_i \end{aligned} \tag{7}$$

where *minwage* indicates the minimum wage (exogenously set either by law, costs of living, etc.), *job* is a set of employment characteristics that for example contains occupation, industry or union membership. *female* is a variable that indicates the individual's gender, which could affect wages for example through taste-based (Becker, 1971) or statistical (Phelps, 1972) discrimination. *humcap* is a set of human capital controls like education and employment experience, ncs_1 is a set of non-cognitive skills that affects productivity as well as bargaining outcomes (e.g. conscientiousness) and ncs_2 is a set of non-cognitive skills that affects bargaining only (e.g., extraversion could affect bargaining but not necessarily productivity).[5]

Overall, the implications for the connection between non-cognitive skills and wages derived from theory can be split into two hypotheses. The first one is:

H1: The importance of personality traits in the wage determination process is larger for high- compared to low-wage employees.

In other words, I expect the share of explained variance by personality traits to be higher for high-compared to low-wage employees, conditional on control variables. However, this does not necessarily imply an increase in the magnitudes of the effects of personality traits on wages[6]. This leads to my second hypothesis:

H2: The effect of personality traits on wages is larger for high- compared to low-wage employees.

These hypotheses should hold in all market-based economies despite slight differences in institutional settings. To show the generalizability of these results, I test the hypotheses for various countries.

3. Personality Traits & Previous Findings

3.1. The Big Five

The five factor model of personality (McCrae and Costa, 2008) is widely used in sociology (Jackson, 2005), political science (Mondak et al., 2010), psychology (Ashton et al., 2009), and economics (Bartling et al., 2009; Bruttel and Fischbacher, 2013). The model consists of five personality dimensions: (i) neuroticism is related to emotionality and self-doubt (Judge et al., 1999); (ii) extraversion indicates outgoingness and social orientation (Judge et al., 1999); (iii) openness to experience is related to creativity as well as nonconformity and autonomy (Judge et al., 1999); (iv) conscientiousness measures the degree of self-control and achievement

[5]In the case of the SOEP (with which I conduct the main part of my analysis) *minwage* contains the constant as well as a dummy variable for East Germany, *job* contains dummy variables for full-time employment, public sector employment, establishment size, industry and occupation. *humcap* contains work experience, tenure and schooling. Additionally, I control for marriage and children because they could work as a proxy for human capital investments. ncs_1 contains neuroticism, openness to experience, conscientiousness, locus of control and risk taking. ncs_2 contains extraversion, agreeableness and reciprocity (positive and negative). Potentially, some items from ncs_1 only affect productivity but not bargaining and some items from ncs_2 could also affect productivity. However, because I cannot separately estimate effects on productivity or bargaining, but only the overall effect of personality on wages, this separation is technically not important for the empirical analysis.

[6]For example, the coefficient size of a respective trait could stay be identical for high- low-wage employees, but the effect could be statistically significant for high-wage employees only. In this case, the importance of the respective item in the wage determination process is higher for high- compared to low-wage employees, but the effect would not increase.

orientation (Judge et al., 1999); (v) agreeableness is connected to cooperative behavior and gentleness (Judge et al., 1999).

In my theoretical model, neuroticism, openness to experience and conscientiousness might affect productivity, while extraversion, agreeableness and neuroticism could affect the bargaining share. For example, conscientious workers are likely to make fewer mistakes than their less-conscientious counterparts. In contrast, agreeableness might affect the bargaining share because agreeable individuals could perform worse in face-to-face negotiations.

The wage effects of the big five are investigated by Braakmann (2009), Heineck and Anger (2010), Nyhus and Pons (2012) and Mueller and Plug (2006). These studies generally find that neuroticism is negatively correlated with male (Mueller and Plug, 2006; Nyhus and Pons, 2005) and female wages (Nyhus and Pons, 2005). Openness to experience is positively related to wages of males (Nyhus and Pons, 2012; Mueller and Plug, 2006) and females (Mueller and Plug, 2006; Heineck and Anger, 2010). Conscientiousness is positively related to female (Mueller and Plug, 2006) and male wages (Heineck and Anger, 2010). Agreeableness is negatively related to male (Mueller and Plug, 2006; Heineck and Anger, 2010) and female wages (Nyhus and Pons, 2012; Heineck and Anger, 2010). Extraversion is not correlated with wages in most studies (Nyhus and Pons, 2005, 2012; Mueller and Plug, 2006).

Mueller and Plug (2006), Heineck and Anger (2010) and Heineck (2011) suggest to estimate non-linear effects, because the labor market may not always reward specific traits in a linear form. For example, employees could be too extraverted or too introverted when employers may prefer moderately extraverted employees.

Studies investigating the effect of the big five across the distribution of wages are scarce. Nandi and Nicoletti (2014) investigate the effect of the big five for British men with the BHPS and find increasing returns to openness to experience, declining returns to extraversion and equal returns to neuroticism and agreeableness across the distribution of wages. Brenzel and Laible (2016) investigate the returns to the big five for Germany and find no changes in the returns to the big five across the distribution of wages. However, both studies are limited by small samples which leads to imprecise estimations at the tails of the wage distribution.

3.2. Other personality traits

Locus of control measures individuals' perception of their influence on events in their lives (Rotter, 1966). The concept differentiates between internal locus of control and external locus of control. An internal locus of control indicates high perceived individual control over events in life, while an external locus of control indicates low perceived individual control over events in life.

In the theoretical model, locus of control could affect productivity and bargaining premiums. Individuals with an external locus of control could be less motivated to do thorough work because they think that achievement is more dependent on luck than own abilities. Additionally, this thinking could relate to bad performances in individual bargaining situations. Empirical studies find a negative correlation between an external locus of control and wages (Braakmann, 2009; Heineck and Anger, 2010).

Reciprocity refers to behavior towards others. Positive reciprocity refers to the degree to which individuals return favors; negative reciprocity refers to behaviors such as revenge (Fehr and Gächter, 2000). Both could affect bargaining shares: e.g., individuals who return favors could be rewarded for their pro-social behavior in negotiation situations. Empirically, positive reciprocity is positively related to male and female wages, while negative reciprocity is positively related to male wages, only (Heineck and Anger, 2010). I presume that reciprocity affects the bargaining share

Risk taking or risk aversion could affect both productivity and bargaining premiums and may have adverse wage effects. For example, risk aversion may be rewarded and related to productivity in some jobs (e.g., in research departments), but penalized in others (e.g., in insurance companies). Risk taking could also be related to the initiation of wage negotiations or the performance in these situations. Semykina and Linz (2007) find positive wage effects for risk taking. Braakmann (2009) uses a simple self-assessed scale for risk taking to show a negative wage correlation for women in some cases. Besides the direct correlation with wages, risk aversion could have an indirect influence on wages through competitive behavior (Bartling et al., 2009); the selection into competitive pay schemes can lead to higher wages (Niederle and Vesterlund, 2007).

4. Data

4.1. General Description

I use data from Germany, the UK, and Australia to test my hypotheses. For Germany, I use the Socio-Economic Panel (SOEP) from 1991 to 2013 (Wagner and Frick, 2007). The analysis with this sample uses 135,135 observations for 17,349 individuals. The dependent variable is the natural logarithm of the gross hourly wage, which is calculated from monthly gross wages and weekly working hours. Control variables are gender, migratory background, region, age, age squared, married, children under 16 in the household, public sector employment, labor market experience (full-time, part-time, unemployment) in years, tenure, full-time employment, the survey year and the number of employees in the firm.

For the UK, I use the UK Household Longitudinal Study (UKHLS) from 2009 to 2015 . It contains 68,614 person-year observations for 17,169 individuals that are used in the analysis. The UKHLS allows to control for a large set of covariates: educational degree, public sector employment, firm size, full-time employment, age, age squared, married, children under 16 in the household, overtime and the survey year.

For Australia, I use the first 15 waves of the Household, Income and Labor Dynamics in Australia (HILDA) panel study (Wooden and Watson, 2007). My final sample contains 49,514 person-year observations for 10,007 respondents. Control variables are educational degree, firm size, full-time employment, age, age squared, tenure, married, children under 15 in the household, temporary employment, migratory status, union membership, casual employment and the survey year. All samples are restricted to employees aged between 19 and 65 and are full- or part-time employed.[7]

In contrast to comparable studies (Heineck and Anger, 2010), I use occupation and industry indicators as control variables in my main analysis, because I am only interested in the direct wage effects of personality traits. Without taking occupation and industry into account, one cannot estimate the pure wage effect of personality traits, because respondents with specific characteristics could self-select into specific high- or low-paying occupations.

4.2. Measures of Personality

While the three data sets are fairly similar, the manner in which they survey personality traits is different. The SOEP surveys the largest amount of character traits, i.e., the big five, locus of control, reciprocity (positive and negative) and risk aversion. All items are surveyed in several years (see Table 2 for an overview of the personality traits in the SOEP). While risk taking is surveyed on an 11-point scale, the other personality traits are questioned with multiple items on 7 point scales, each. Reciprocity is surveyed with three items, locus of control[8] with eight items[9] and the big five with three items each. The distribution of all character traits divided by one standard deviation is pictured in Figure 1 for Germany. In line with the previous literature

[7]Tables C1 to C3 give an overview over the covariates included in the three samples.

[8]Locus of control was measured as external locus of control. Thus, a higher score on this construct refers to less perceived influence on events in one's live.

[9]Heineck and Anger (2010) only use the external locus of control items from the SOEP due to low scale reliability of the internal locus of control scale. I combine both scales into one sum score which increases the scale realiability from 0.57 to 0.60 compared to only the external locus of control scale. Additionally, the HILDA does not make this distinction. Thus, comparability benefits from this approach.

(Braakmann, 2009; Heineck and Anger, 2010), I construct additive indices for each trait. The Cronbach's α (Cronbach, 1951) values vary between 0.49 and 0.82, which is consistent with previous findings (Heineck and Anger, 2010).

The UKHLS, which serves here mostly as a check for robustness for the SOEP results contains the SOEP's scale for the big five. However, the data were only surveyed in one wave (wave 3, Figure C shows the distribution for men and women respectively). The reliability ratios values vary between 0.54 to 0.71, as can be seen in Table 2.

The HILDA contains more sophisticated measures for the big five (in three waves) and locus of control (in four waves). In contrast to the other two data sets, the HILDA uses a 28-item scale for the big five (Losoncz, 2009) and a seven item scale for locus of control (their distribution by gender is displayed in Figure C). The internal consistency scores range from 0.74 to 0.84, which are better values than in the other data sets (an overview of the item sets and their respective reliability ratios provides Losoncz, 2009).

Overall, using multiple data sets and personality scales yields several advantages: the scales in the SOEP and UKHLS are widely used and well-established, but have a relatively low internal consistency. The traits surveyed with the Australian HILDA are more sophisticated than the short scales from the SOEP and UKHLS and should be more reliable in general. If the European and Australian results are similar, this would show that (i) the short scales are nevertheless reasonable instruments of measurement and (ii) the results seem to be generizable, as implied by theory.

Unfortunately, not every SOEP-, UKHLS-, or HILDA-wave contains the necessary measures. To use the data effectively, gaps due to missing questions in the survey are filled by imputing the previous valid response. For example, the 2012 questionnaire of the SOEP does not include the big five items. Thus, I insert the values from 2010. This method of imputation follows Heineck and Anger (2010).

Personality traits can change with age (Soto et al., 2011). To tackle this problem, I follow Heineck and Anger (2010); Heineck (2011) and Nyhus and Pons (2012) who regressed the personality traits in their analyses on age and age squared and used the residuals of these regressions for the analysis. Studies show (Cobb-Clark and Schurer, 2012, 2013) that personality traits are mostly stable for at least four years and mostly stable around the age of 30 (Costa and McCrae, 1994). With a mean age of 40-42 years in all data sets, the personality traits should mostly be stable. As constant factors, such as genetic determination and family background account for large variation in personality traits (Eysenck, 1990; Riemann et al., 1997; Anger and Schnitzlein, 2017), I expect within-individual variation across time in non-cognitive skills to be a minor problem.

Reverse causality is a point of concern. Success in the job or other events could lead to character traits that are positively related to wages and vice versa (Specht et al., 2011). However, this does not seem to pose a large problem in the data, because the character traits are mostly stable within individuals. For example, Cobb-Clark and Schurer (2013) estimate the effect of positive and negative life events on locus of control with panel data and find no significant effects in adult life. Elkins et al. (2017) also show that personality traits are relatively stable, but that health problems, especially in adolescence, can lead to an increase in (external) locus of control. To tackle this problem, I will additionally conduct my estimations with a sample that excludes respondents below age 30 and above age 55 to reduce the potential influence of health problems in adolescence and old age.

5. Econometric Strategy

5.1. Identification Strategy and Model Sensitivity

I am interested in the direct effect of non-cognitive skills on wages and the interplay between personality and wages. Figure 2 graphically illustrates the connection between causes and outcomes in a directed acyclical graph (DAG) as suggested by Pearl (2009).

Personality traits can affect human capital endowments like education or employment characteristics like occupation or industry. However, these are not the effects of interest. Thus, I account for them in the empirical model by controlling for these relationships. All shaded areas and dotted lines in Figure 2 are such controls. The mechanisms relevant for the hypotheses are marked with solid lines. This is important when discussing the results, because I solely investigate direct effects and not the overall effect of personality on wages.

It is insightful to investigate effects of personality traits for different subgroups. Personality traits could have heterogeneous effects for part- and full-time employees. Jobs with more complex tasks (with lower certainty regarding productivity) could be more often full-time. Part time employment in contrast could mostly encompass jobs with lower task complexity. Thus, I expect non-cognitive skills to have a larger impact on the wages of full-time workers compared to their part-time counterparts. The literature (Heineck and Anger, 2010; Nandi and Nicoletti, 2014) implies that the returns to personality traits differ between men and women. Dependent on the employer, an extravert woman could be treated differently than an extravert man. Thus, I will also run separate regressions by gender. Mueller and Plug (2006) and Heineck and Anger (2010) point out that it could also be the case that a “normal“ degree of extraversion, agreeableness or any other trait has no wage effect, but that extremely high or low degrees of certain traits could be rewarded or punished. As they expect non-linear effects, I consider non-linearities in the estimations.

Despite the longitudinal structure of the data, I do not use fixed effects models in my analysis for several reasons. First, the personality traits in the surveys are not collected on a regular basis and have large gaps within individuals over time. Second, there is little variance within individuals over time. Non-cognitive skills are mostly stable over time and therefore, their effects are usually eliminated by fixed effects on the respondent level. Thus, it is questionable whether personality effects can be identified in fixed effects models. Additionally, because personality traits are likely exogenous, including them should have similar consequences to using fixed effects, because ruling out differences in relatively time-constant characteristics is an argument for using fixed effects models.

5.2. Unconditional Quantile Regression (UQR)

I use unconditional quantile regressions (UQR, Firpo et al., 2009) to estimate the effect of personality traits on wages at different points of the wage distribution. In contrast to the conditional quantile regression (CQR, Koenker and Bassett, 1978), the UQR uses the unconditional distribution to determine the quantiles of interest. Because the hypotheses aim at comparing overall low- to high-wage employees, it is necessary to use a method based on the unconditional wage distribution.

The UQR performs an OLS-regression on the recentered influence function (RIF) of a specific quantile τ of interest. One can construct the influence function of this quantile with:

$$IF(Y, Q_\tau) = \frac{\tau - \mathbb{1}\{Y < Q_\tau\}}{f_y(Q_\tau)} \tag{8}$$

where $\mathbb{1}\{Y < Q_\tau\}$ is an indicator function to weight the quantile, f_y is the density function of the marginal distribution at Q_τ. The RIF-concept extends this approach by adding the quantile of choice Q_τ to the influence function:

$$RIF(Y, Q_\tau) = Q_\tau + \frac{\tau - \mathbb{1}\{Y < Q_\tau\}}{f_y(Q_\tau)} \tag{9}$$

Thus, I estimate coefficients covariates at points of the unconditional distribution of wages (Y) via RIF-OLS. I use cluster-bootstrapped standard errors that account for clustering on the respondent level with 400 repetitions as suggested by Cameron and Miller (2015) to acknowledge the panel structure of the data.

5.3. Testing Hypotheses

To test hypothesis H1, which assumes a larger importance of personality traits in the wage determination process for high-wage employees, I have to test the joint explanatory contribution of multiple regressors at different quantiles and the mean of the dependent variable. Intuitively, it may seem suitable to compare the R^2 values of a regression with and without controlling for personality traits and simply compute their difference (which I will refer to as ΔR^2). This way, one could easily compare the absolute explanatory contribution of the measures for non-cognitive skills. This approach would work for a mean regression (classical OLS) as well as unconditional quantile regressions via RIF-OLS because both methods make it possible to compute R^2.

However, this comparison suffers from a large disadvantage: OLS maximizes R^2 by definition by minimizing the residual sum of squares. In contrast, the R^2-values of RIF-OLS will likely be smaller because the share of explained variance in the dependent variable is smaller in a regression e.g. to the 10th percentile compared to the mean. Consequentially, ΔR^2 is likely to be larger in the mean regression compared to quantile regressions because of the overall smaller share of explained variance in an UQR-setting. However, a possibility to rule out the disadvantage the UQR has by construction in this setting is to compare relative changes in R^2, similar to likelihood-ratio tests in maximum-likelihood estimations

Thus, to test the explanatory power of the joint personality traits, I propose δR^2 as a statistic to quantify the relative change in explained variance at a quantile of interest. I compare the R^2-values of a model that controls for personality items to a standard Mincer-like wage equation that contains all regressors except the personality variables, resulting in the following equation:

$$\delta R^2(\tau) = 100(\frac{R^2_{unrestricted}(\tau)}{R^2_{restricted}(\tau)} - 1) \tag{10}$$

where $R^2_{unrestricted}(\tau)$ is the R^2 from an estimation that controls for personality items and all other control variables at a quantile τ of interest and $R^2_{restricted}(\tau)$ is the R^2 from an estimation with the same dependent variable and quantile of interest, but without controlling for personality traits. The quotient yields results that are per definition ≥ 1, as R^2 is strictly increasing with additional variables. Subtracting 1 from this equation and multiplying the result by 100 yields the percentage change in the explained variance resulting from adding, in this case, personality items in the wage estimations. This way, I obtain the relative gain in explanatory power in a way that is comparable between different quantiles of interest. If the importance of the personality items were identical across the wage distribution, δR^2 would be identical at all quantiles of interest because the relative gain in explanatory power by including personality traits is identical at every quantile of Y. As an illustration, every table with regression results contains the $R^2_{unrestricted}(\tau)$ value of the current model, the $R^2_{restricted}(\tau)$ value of the same model without personality variables, the $\Delta R^2(\tau)$, which simply is $R^2_{unrestricted}(\tau) - R^2_{restricted}(\tau)$ and the change in the explained variance, $\delta R^2(\tau)$. For further clarification, appendix B gives a more detailed overview of the statistic and tests its properties with simulated data.

To test the statistical significance of the differences in δR^2, I bootstrap the R^2 value of every estimation with 400 repetitions and conduct t-tests between the different δR^2 values at each quantile investigated. The standard error of each δR^2 is reported. To test hypothesis H1, which predicts a rising importance of personality traits in the wage determination process across the wage distribution, I test if δR^2 at the 90th percentile is significantly larger than δR^2 at the mean, median and 10th percentile.[10]

Hypothesis H2 which assumes increasing effects of personality traits across the distribution of wages is simply tested by comparing coefficients of the respective traits. I test if the coefficient of a personality item is significantly (on the 10 percent level) larger at the 90th compared to the estimate of the coefficient at the 10th percentile. If this condition is met by the coefficient of at least one personality item, the finding supports the hypothesis. Additionally, hypothesis H2 is rejected if the effects of one or more traits are significantly smaller at the 90th compared to the 10th percentile, median or mean of wages.[11]

6. Results

6.1. Full sample

Not every data set contains the same variables and thus the same controls. To ensure comparability, I estimated models with the same set of controls available for all countries (Table C4 shows the results). However, because the overall results do not differ between regression with comparable controls and regressions with the full set of controls for each country, I show and discuss the specifications with all available control variables for the respective countries in my results to get the most precise estimates possible with the data.

The results for the UQRs and OLS are presented in Table 13. For Germany, the OLS-results are generally consistent with previous findings obtained via the EIV-method (Heineck and Anger, 2010; Mueller and Plug, 2006). High scores in locus of control and agreeableness are negatively related to wages while positive

[10] I will also show δR^2 across the full wage distribution for all countries. However, because bootstrapping δR^2 is relatively time consuming, I only estimate significance tests for these percentiles.

[11] Again, I will as well show the coefficients of the personality traits across the wage distribution.

reciprocity and risk taking are related to higher wages.

However, I am especially interested in the importance of personality traits across the wage distribution. The coefficients of risk taking, agreeableness, neuroticism and positive reciprocity increase in both magnitude and statistical significance across the distribution of wages. Looking at the overall change in explanatory power displayed in δR^2, I can confirm my presumption: δR^2 increases across the distribution of wages and is maximal at the 90th percentile. Thus, I cannot reject hypothesis H1 in the German sample. Additionally, the differences between the coefficients of agreeableness, neuroticism, positive reciprocity and risk taking between the 90th and 10th percentile are significantly different and increase across the wage distribution. This supports hypothesis H2.

Next, I investigate the results for the UK. The results for the personality traits included in this sample largely mirror the results for the big five in Germany. As in the German sample, δR^2 is largest at the 90th percentile. Again, I cannot reject hypothesis H1, even with fewer personality traits in the estimations. The magnitude of the effects of neuroticism and agreeablenes increases significantly across the distribution of wages, which supports hypothesis H2. Table 3 also shows the results for Australia. Despite using other scales for the respective personality items, the results are fairly similar to those for Germany and the UK. Again, the coefficients of agreeableness, conscientiousness and locus of control increase significantly, as well as δR^2. Thus, the results again support hypotheses H1 and H2.

Overall, the results concerning hypothesis H1 are displayed in Figure 3. As can be seen, δR^2 increases across the wage distribution in all countries thus supporting H1. Additionally, Figures 4 to 6 show the coefficients of personality traits for each country from the 5th to the 95th percentile of wages. Overall, the coefficients stay fairly constant across the wage distribution with the exemptions mentioned before. However, the coefficients never decrease significantly. Thus, these findings support H2.

6.2. Employment status subsamples

The returns to personality traits could differ between full- and part-time employees, as discussed in Section 5.1. The importance of personality traits across wages increases for full-time employees in all countries, as seen in Tables 4, 5 and 6. The drivers are essentially the same traits as in the full sample. δR^2 rises across the distribution of wages. Thus, H1 cannot be rejected in these samples. Additionally, the effects of agreeableness, risk taking, neuroticism (UK and Australia only), openness to experience (UK only) and locus of control (Australia only) increase across the distribution of wages for full-time employees, which supports hypothesis

H2.

However, the effects disappear in the part-time samples in Germany and the UK in which, except locus of control, personality traits seem to be rather unrelated to wages. In all countries, the importance as well as the effects of personality traits do not seem to increase across the wage distribution. Thus, H1 and H2 have to be rejected in all three countries.

6.3. Male and female subsamples

The estimations for the male and female subsamples in Germany are displayed in Table 7.[12] Generally, the importance of non-cognitive skills in the female subsample is much smaller than in the male subsample except at the 90th percentile, where δR^2 is practically equal in both samples. This can indicate two things: (i) personality is important in high-wage jobs independent of gender and (ii) personality is more important for men than for women in average- or low-paying jobs. This could be an indirect result of discrimination of women if they are not rewarded as much for bargaining behavior etc.. Jointly, the importance of personality traits increases across the distribution of wages as displayed in δR^2. Thus, one cannot reject hypothesis H1 for gender-specific estimations in Germany.

Comparing the effects of personality traits across the wage distribution reveals several differences between the genders. While the effects of agreeableness and neuroticism show a large increase in magnitude and statistical significance for women compared the men, the effects for males are statistically significant, but the changes across quantiles are not statistically significant. Neuroticism increases in its negative sign and gains significance for women, the effects for neuroticism and agreeableness for males are U-shaped. The effect of risk taking, in contrast, increases positively both in magnitude and statistical significance for men only. Nevertheless, both subsamples support hypothesis H2.

The estimates for the UK displayed in Table 8 are comparable. However, unlike in the estimations for Germany, the differences between δR^2 at the same percentile between men and women are smaller compared to the differences in Germany. Interestingly, the effect of extraversion increases significantly for women, but not for men. Nevertheless, the findings support both H1 and H2.

The estimations for Australia in Table 9 show increasing effects for locus of control, agreeableness for

[12] Surprisingly, I find different effects for openness for men and women compared to Heineck and Anger (2010). One explanation could be that I control for occupation and industry and thus rule out selection effects of personality traits on the choice of occupation, because openness significantly affects occupational choice (John and Thomsen, 2014) that could be indirectly related to wages. However, the effects of positive reciprocity, external locus of control, agreeableness and neuroticism are comparable to the literature.

both genders and an increasing effect of conscientiousness for females only. The results show relatively small differences between men and women. Both estimations show significant increases in δR^2 across the distributions of wages, thus further supporting hypothesis H1 and H2.

6.4. *Non-linearities*

Mueller and Plug (2006) and Heineck and Anger (2010) also report non-linear effects in the impact of personality traits on wages. In this case, they argue that extremely high or low values in personality traits should affect wages, while average degrees of the respective traits are not rewarded nor punished. I advance their approach by estimating non-linear effects at different points of the distribution of wages by estimating regressions with dummies that indicate being in the top or bottom 25% of a respective trait.

Table 10 reports the results for Germany. As expected, the estimation shows non-linear effects in some cases, largely in line with Heineck and Anger (2010) in coefficient size and direction. Low scores in neuroticism, locus of control and agreeableness are related to higher wages at most points, while high scores in locus of control and agreeableness are punished. Overall, the effects of agreeableness, neuroticism, negative reciprocity and risk taking increase across the distribution of wages. The effect of locus of control, however seems to decrease for individuals with a high external locus of control, but to increase for employees with an internal locus of control. δR^2 as well as ΔR^2 both rise across the distribution of wages and compared to the mean. Thus, the findings support hypothesis H1 as well as hypothesis H2.

The estimations with the UKHLS in Table 11 draw a similar picture. High degrees of agreeableness are especially punished at the 90th percentile of wages, while a low score in neuroticism is increasingly rewarded across the distribution of wages. Unlike in Germany, but in line with Heineck (2011) both high and low degrees of conscientiousness lead to a wage penalty. Overall, as in the German case, δR^2 increases across the distribution of wages.

The Australian sample shows very similar results in Table 12. Again, locus of control and agreeableness are the traits most closely related to wages. The effects increase across the distribution of wages. Thus, this approach further supports hypothesis H1 and H2 in all countries.

6.5. *Robustness*

The measurements of personality traits likely suffers from measurement error. This would lead to attenuation bias and thus a bias of the respective coefficients towards 0 (Cobb-Clark and Schurer, 2013). To account for this problem, Heineck and Anger (2010) and Mueller and Plug (2006) use an errors-in-variables

(EIV) approach to correct for attenuation bias by using the Cronbach's α values as measures for the reliability of the constructs[13]. However, this method makes strong assumptions and does not allow for systematic correlations between measurement errors in the respective variables with each other or with the error term. Thus, I use this approach only as a test for robustness. Table 13 and Figures C3 to C5 show the results for the full samples. As expected, the coefficients for most personality traits increase in magnitude as well as statistical significance. The results can be seen as upper bounds of the effects of personality traits on wages. However, due to the strong assumptions the EIV-approach makes, they have to be interpreted with caution. Nevertheless, the EIV approach comes to the same conclusions as estimations without the correction. This indicates the robustness of the results.

As an additional robustness check, I computed a model which only includes the 2005 SOEP-wave. 2005 is the only year in which all personality items were surveyed, except risk taking, which was surveyed in 2004 and 2006.[14] Thus, investigating the 2005-wave only should largely be free of errors due to the imputation. The results are largely consistent with my previous findings, as I cannot reject hypothesis H1 in this sample.

I also estimate specifications for each country that do not control for occupation and industry, because the access to certain jobs could also be restricted by discrimination. Thus, controlling for both variables could lead to a downward bias of the effects of non-cognitive skills. However, the results do not differ significantly from the full models concerning hypotheses H1 and H2.

Because Elkins et al. (2017) suggest that locus of control could be affected by health problems which mostly target older individuals, and Cobb-Clark and Schurer (2013) suggest that locus of control is less stable for young and old individuals, I restricted the samples to employees aged 30 to 55. However, the results do not differ significantly in either the SOEP, UKHLS or HILDA.

To fully exploit the nature of the data sets, I estimated random effects panel estimations (without the EIV-correction) and found similar results (in this case, I computed δR^2 for the overall R^2 of the RE-estimations). Additionally, following Heineck and Anger (2010), I adjusted for sample selection with the Heckman (1979)-approach using dummy variables for the highest education achieved by a parent as instruments[15]. This procedure does not significantly alter the coefficients of the personality items in any estimation. I additionally

[13] Mueller and Plug (2006) give a comprehensive introduction to the procedure in their appendix.

[14] Wave 3 is the equivalent in the UKHLS. All personality traits were surveyed in this wave only. However, I do not explicitly discuss the estimation for this model, because the findings are, again, very in line with the SOEP.

[15] I use two dummy variables: one that indicates if the father achieved college-level education and one for the mother, because these are available in all data sets. However, the results are robust to using comparable instruments, such as the socio-economic status of one parent.

estimated models only containing the big five (which are surveyed in all countries) and restricted the sample to observations from 2009 on to ensure comparability. However, the results did not change significantly for any country.

Overall, the effects as well as the importance of personality traits on wages both increase in all countries regardless of the method used and across different subsamples, the only exception being the part-time employee subsamples in all countries. Figures 7 to 9 show the δR^2 values for different subsamples for the three countries.[16]

7. Conclusion

In recent years, labor economists began to direct their attention towards the importance of non-cognitive skills for labor market outcomes. Along with classical human capital endowments like education, non-cognitive skills play an important role for various labor market outcomes (Heckman and Kautz, 2012).

This article contributes to this literature in several ways. I derive a framework of wage determination and hypothesize that personality traits are of greater importance for the wages of high-wage compared to low-wage employees. Additionally, I expect the effects of personality traits on wages to be larger for high- compared to low-wage employees. I test the resulting hypotheses with survey data from Germany, the UK and Australia, which include various items for non-cognitive skills. To measure the importance of personality traits in wage regressions, I propose the new statistic δR^2 that quantifies the rise in explanatory power by adding personality traits to an extended Mincer-type wage equation.

My findings indicate that personality traits are more important for high-wage employees in full-time employment compared to their low-wage counterparts in the wage determination process in all three countries. The effects of personality traits on wages in terms of magnitude as well increase in all countries with the exception of the part-time sub samples. The results suggest that especially agreeableness, risk taking, locus of control and neuroticism have a larger impact on wages for high- compared to low-wage employees.

Overall, the findings thus generally confirm the notion that non-cognitive skills are important determinants of wages (Heckman and Kautz, 2012). Additionally, I shed light on heterogeneous effects for different pay levels that have, to my knowledge, not been investigated previously. Given the evidence on the effect of personality traits on labor market outcomes, it could be in the interest of schools to bolster non-cognitive

[16]The δR^2-values for all specifications including robustness-checks are plotted from Figure 7 to 9 for all countries.

skills in addition to the classical curricula, as suggested by Heckman et al. (2010).

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Tables

Table 1: Illustrative example to the theory

Pay level	c_k	$\tilde{W}_i/w_i^{prod}$	$r_i(max) = w_i^{prod} - \tilde{W}_i$	$max[(c_k p_i)/w_i^{prod}]$	$max[((1-c_k)b_i)/w_i^{prod}]$
Low	1.0	0.9	0.1	0.10	0.00
Medium	0.7	0.7	0.3	0.21	0.09
High	0.3	0.5	0.5	0.15	0.35

Table 2: Non-cognitive skills in the SOEP & UKHLS

Dimension	Items	Surveyed in SOEP	α SOEP	α UKHLS
Neuroticism	I worry a lot I get nervous easily I handle stress well (reversed)	2005, 2009, 2013	0.63	0.71
Openness to experience	I am original, comes up with new ideas I value artistic expression I have an active imagination	2005, 2009, 2013	0.59	0.63
Extraversion	I am communicative I am sociable I am reserved (reversed)	2005, 2009, 2013	0.64	0.66
Conscientiousness	I do a thorough job I do thing effectively/efficiently I tend to be lazy (reversed)	2005, 2009, 2013	0.57	0.54
Agreeableness	I am sometimes too coarse with others (reversed) I have a forgiving nature I friendly with others	2005, 2009, 2013	0.49	0.59
Locus of control	What you achieve depends on luck Others make the crucial decisions in my life Possibilities are defined by social conditions Little control over my life Abilities are more important than effort How Life Proceeds Depends On Me You Have To Work Hard For Success In Case Of Difficulties Doubts About Own Abilities	2005, 2010	0.60	
Positive Reciprocity	Return favors Help those who help me Help those who have helped me in the past	2005, 2010	0.62	
Negative Reciprocity	Get revenge for severe injustices Cause similar problems to those who cause me problems Insult those who insult me	2005, 2010	0.82	
Risk taking	Personal willingness to take risks	2004, 2006, 2008-2013		

Notes: Years surveyed is only shown for the SOEP because the big five were only surveyed once in the UKHLS (Wave 3). Source: SOEP 1991-2013; UKHLS 2009-2015.

Table 3: Results of UQR & least square regressions

	Germany (SOEP, N=135,135)				United Kingdom (UKHLS, N=68,614)				Australia (HILDA, N=49,514)			
	OLS	10^{th} Percentile	50^{th} Percentile	90^{th} Percentile	OLS	10^{th} Percentile	50^{th} Percentile	90^{th} Percentile	OLS	10^{th} Percentile	50^{th} Percentile	90^{th} Percentile
Extraversion	-0.001	-0.004	0.000	-0.002	0.007^{+}	0.004	0.012^{**}	-0.002	-0.001	-0.005	-0.002	0.001
	(0.003)	(0.006)	(0.003)	(0.006)	(0.003)	(0.003)	(0.004)	(0.008)	(0.003)	(0.004)	(0.003)	(0.006)
Agreeableness	-0.017^{***}	-0.007	-0.017^{***}	-0.026^{***}	-0.021^{***}	-0.007^{+}	-0.020^{***}	-0.035^{***}	-0.025^{***}	-0.012^{*}	-0.020^{***}	-0.039^{***}
	(0.003)	(0.006)	(0.003)	(0.006)	(0.003)	(0.004)	(0.005)	(0.007)	(0.003)	(0.005)	(0.003)	(0.007)
Conscientiousness	0.003	0.012^{*}	-0.003	0.006	0.013^{***}	0.013^{***}	0.010^{*}	0.017^{*}	0.015^{***}	0.007^{+}	0.012^{***}	0.019^{**}
	(0.003)	(0.006)	(0.003)	(0.007)	(0.003)	(0.004)	(0.004)	(0.007)	(0.003)	(0.004)	(0.003)	(0.006)
Neuroticism	-0.007^{**}	-0.005	-0.004	-0.015^{**}	-0.028^{***}	-0.014^{***}	-0.023^{***}	-0.032^{***}	0.003	0.000	0.000	0.009
	(0.003)	(0.006)	(0.003)	(0.006)	(0.003)	(0.003)	(0.005)	(0.007)	(0.003)	(0.004)	(0.003)	(0.007)
Openness	0.000	-0.010	0.001	0.000	-0.003	-0.010^{*}	-0.003	0.013^{+}	0.001	-0.008^{+}	0.000	0.001
	(0.003)	(0.006)	(0.003)	(0.006)	(0.003)	(0.004)	(0.004)	(0.008)	(0.003)	(0.004)	(0.003)	(0.007)
Locus of control	-0.034^{***}	-0.035^{***}	-0.022^{***}	-0.041^{***}					-0.033^{***}	-0.020^{***}	-0.034^{***}	-0.044^{***}
	(0.003)	(0.006)	(0.003)	(0.005)					(0.003)	(0.004)	(0.003)	(0.006)
Positive reciprocity	0.007^{**}	0.006	0.006^{*}	0.017^{**}								
	(0.003)	(0.005)	(0.003)	(0.006)								
Negative reciprocity	0.000	-0.001	-0.001	0.000								
	(0.003)	(0.007)	(0.003)	(0.005)								
Risk taking	0.009^{***}	-0.012^{*}	0.012^{***}	0.023^{***}								
	(0.002)	(0.006)	(0.002)	(0.005)								
R^2	0.581	0.273	0.453	0.268	0.385	0.163	0.379	0.175	0.507	0.179	0.399	0.218
$R^2_{restricted}$	0.577	0.272	0.450	0.265	0.382	0.162	0.377	0.174	0.501	0.177	0.395	0.214
ΔR^2	0.004	0.001	0.002	0.003	0.003	0.001	0.002	0.002	0.006	0.001	0.004	0.004
δR^2	0.714^{***}	0.393^{***}	0.505^{***}	1.243^{***}	0.860^{***}	0.588^{***}	0.494^{***}	1.131^{***}	1.265^{***}	0.740^{***}	1.063^{***}	1.864^{***}
	(0.005)	(0.005)	(0.004)	(0.012)	(0.007)	(0.009)	(0.005)	(0.016)	(0.009)	(0.011)	(0.008)	(0.018)

Notes: Standard errors (in parentheses) and R^2-values are derived from bootstrapping with 400 replications. The dependent variable is the natural logarithm of the hourly wage. Significance levels: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Sources: SOEP v30 1991-2013, UKHLS 2009-2015, HILDA 2001-2015.

Table 4: Results of UQR & least square regressions by employment status (SOEP)

	Full time (N=100,252)				Part time (N=34,883)			
	OLS	10^{th} Percentile	50^{th} Percentile	90^{th} Percentile	OLS	10^{th} Percentile	50^{th} Percentile	90^{th} Percentile
Extraversion	-0.002^{+}	-0.005	0.001	0.001	0.001	0.002	0.001	0.007
	(0.001)	(0.005)	(0.003)	(0.007)	(0.003)	(0.011)	(0.007)	(0.009)
Agreeableness	-0.020^{***}	-0.014^{*}	-0.018^{***}	-0.030^{***}	-0.007^{*}	-0.009	0.004	-0.005
	(0.001)	(0.006)	(0.003)	(0.006)	(0.003)	(0.011)	(0.007)	(0.009)
Conscientiousness	-0.002^{+}	-0.004	-0.005	0.010	0.000	-0.005	0.004	-0.006
	(0.001)	(0.005)	(0.003)	(0.006)	(0.003)	(0.012)	(0.007)	(0.009)
Neuroticism	-0.013^{***}	-0.017^{**}	-0.005^{+}	-0.015^{*}	0.005^{+}	0.006	0.013^{*}	0.001
	(0.001)	(0.005)	(0.003)	(0.006)	(0.003)	(0.010)	(0.006)	(0.009)
Openness	0.003^{*}	0.007	0.001	0.005	0.004	0.003	0.002	-0.007
	(0.001)	(0.006)	(0.003)	(0.006)	(0.003)	(0.011)	(0.007)	(0.009)
Locus of control	-0.031^{***}	-0.029^{***}	-0.024^{***}	-0.038^{***}	-0.037^{***}	-0.057^{***}	-0.027^{***}	-0.021^{*}
	(0.001)	(0.006)	(0.004)	(0.006)	(0.003)	(0.012)	(0.007)	(0.009)
Positive reciprocity	0.011^{***}	0.012^{*}	0.007^{*}	0.018^{**}	-0.002	-0.002	-0.015^{*}	-0.005
	(0.001)	(0.005)	(0.003)	(0.006)	(0.003)	(0.010)	(0.006)	(0.009)
Negative reciprocity	-0.001	-0.002	0.003	-0.001	-0.004	-0.012	-0.005	-0.001
	(0.001)	(0.005)	(0.003)	(0.005)	(0.003)	(0.012)	(0.007)	(0.009)
Risk taking	0.015^{***}	-0.001	0.014^{***}	0.025^{***}	-0.002	-0.016	0.004	0.004
	(0.001)	(0.005)	(0.003)	(0.006)	(0.003)	(0.010)	(0.006)	(0.007)
R^2	0.578	0.250	0.439	0.253	0.561	0.302	0.428	0.324
$R^2_{restricted}$	0.561	0.248	0.435	0.248	0.558	0.300	0.426	0.324
ΔR^2	0.006	0.002	0.004	0.004	0.003	0.002	0.002	0.001
δR^2	1.158^{***}	0.716^{***}	0.824^{***}	1.801^{***}	0.480^{***}	0.601^{***}	0.437^{***}	0.310^{***}
	(0.008)	(0.008)	(0.007)	(0.017)	(0.006)	(0.010)	(0.007)	(0.006)

Notes: Standard errors (in parentheses) and R^2-values are derived from bootstrapping with 400 replications. The dependent variable is the natural logarithm of the hourly wage. Significance levels: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Source: SOEP v30 1991-2013.

Table 5: Results of UQR & least square regressions by employment status (UKHLS)

	Full time (N=51,815)				Part time (N=16,799)			
	OLS	10^{th} Percentile	50^{th} Percentile	90^{th} Percentile	OLS	10^{th} Percentile	50^{th} Percentile	90^{th} Percentile
Agreeableness	-0.024^{***}	-0.010^{*}	-0.024^{***}	-0.037^{***}	-0.010^{*}	-0.005	-0.015^{+}	-0.023
	(0.002)	(0.004)	(0.004)	(0.008)	(0.005)	(0.006)	(0.008)	(0.015)
Conscientiousness	0.013^{***}	0.017^{***}	0.006	0.020^{*}	0.012^{*}	0.009	0.014^{+}	0.014
	(0.002)	(0.005)	(0.005)	(0.008)	(0.005)	(0.006)	(0.007)	(0.014)
Extraversion	0.008^{***}	0.009^{*}	0.010^{*}	-0.004	0.005	0.000	0.007	0.005
	(0.002)	(0.005)	(0.004)	(0.008)	(0.005)	(0.005)	(0.007)	(0.015)
Neuroticism	-0.026^{***}	-0.010^{*}	-0.019^{***}	-0.024^{**}	-0.033^{***}	-0.016^{**}	-0.030^{***}	-0.050^{***}
	(0.002)	(0.005)	(0.005)	(0.008)	(0.005)	(0.005)	(0.007)	(0.014)
Openness	-0.007^{**}	-0.010^{*}	-0.005	0.014^{+}	0.001	-0.009^{+}	0.004	0.007
	(0.002)	(0.005)	(0.005)	(0.008)	(0.005)	(0.005)	(0.008)	(0.015)
R^2	0.411	0.186	0.377	0.184	0.300	0.096	0.301	0.181
$R^2_{restricted}$	0.407	0.185	0.375	0.182	0.296	0.095	0.298	0.179
ΔR^2	0.004	0.001	0.002	0.002	0.003	0.002	0.003	0.002
δR^2	0.921^{***}	0.607^{***}	0.554^{***}	1.140^{***}	1.107^{***}	1.588^{***}	1.039^{***}	1.167^{***}
	(0.009)	(0.009)	(0.007)	(0.018)	(0.018)	(0.039)	(0.019)	(0.027)

Notes: Standard errors (in parentheses) and R^2-values are derived from bootstrapping with 400 replications. The dependent variable is the natural logarithm of the hourly wage. Significance levels: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Source: UKHLS 2009-2015.

Table 6: Results of UQR & least square regressions by employment status (HILDA)

	Full time (N=37,444)				Part time (N=12,070)			
	OLS	10^{th} Percentile	50^{th} Percentile	90^{th} Percentile	OLS	10^{th} Percentile	50^{th} Percentile	90^{th} Percentile
Extraversion	-0.001	-0.006	-0.002	0.002	-0.004	-0.015^{*}	-0.005	-0.008
	(0.002)	(0.005)	(0.004)	(0.007)	(0.003)	(0.007)	(0.005)	(0.011)
Agreeableness	-0.025^{***}	-0.013^{*}	-0.023^{***}	-0.039^{***}	-0.022^{***}	-0.009	-0.017^{**}	-0.031^{**}
	(0.002)	(0.006)	(0.004)	(0.009)	(0.004)	(0.010)	(0.006)	(0.012)
Conscientiousness	0.016^{***}	0.010^{*}	0.016^{***}	0.018^{*}	0.012^{***}	0.008	0.000	0.031^{***}
	(0.002)	(0.005)	(0.004)	(0.007)	(0.003)	(0.008)	(0.005)	(0.009)
Neuroticism	0.004^{*}	-0.002	0.002	0.014^{+}	0.000	0.007	-0.003	-0.002
	(0.002)	(0.005)	(0.004)	(0.008)	(0.003)	(0.008)	(0.005)	(0.009)
Openness	0.001	-0.011^{*}	0.002	0.007	0.004	0.006	0.007	-0.012
	(0.002)	(0.005)	(0.005)	(0.008)	(0.003)	(0.008)	(0.005)	(0.010)
Locus of control	-0.036^{***}	-0.026^{***}	-0.036^{***}	-0.047^{***}	-0.024^{***}	-0.018^{*}	-0.028^{***}	-0.022^{*}
	(0.002)	(0.005)	(0.004)	(0.007)	(0.004)	(0.009)	(0.005)	(0.010)
R^2	0.504	0.193	0.389	0.209	0.481	0.143	0.392	0.251
$R^2_{restricted}$	0.495	0.190	0.383	0.203	0.477	0.142	0.389	0.248
ΔR^2	0.009	0.002	0.006	0.006	0.005	0.002	0.004	0.004
δR^2	1.843^{***}	1.148^{***}	1.650^{***}	2.828^{***}	1.022^{***}	1.258^{***}	0.915^{***}	1.497^{***}
	(0.013)	(0.016)	(0.013)	(0.029)	(0.019)	(0.041)	(0.019)	(0.037)

Notes: Standard errors (in parentheses) and R^2-values are derived from bootstrapping with 400 replications. The dependent variable is the natural logarithm of the hourly wage. Significance levels: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Source: HILDA 2001-2015.

Table 7: Results of UQR & least square regressions by gender (SOEP)

	Females (N=63,069)				Males (N=72,066)			
	OLS	10^{th} Percentile	50^{th} Percentile	90^{th} Percentile	OLS	10^{th} Percentile	50^{th} Percentile	90^{th} Percentile
Extraversion	-0.001	-0.004	-0.003	0.002	-0.001	-0.001	-0.001	0.006
	(0.002)	(0.011)	(0.004)	(0.008)	(0.002)	(0.008)	(0.004)	(0.007)
Agreeableness	-0.009^{***}	0.009	-0.006	-0.031^{***}	-0.025^{***}	-0.027^{***}	-0.019^{***}	-0.025^{***}
	(0.002)	(0.010)	(0.004)	(0.007)	(0.002)	(0.007)	(0.004)	(0.006)
Conscientiousness	0.006^{**}	0.005	0.001	0.005	-0.004^{*}	-0.001	-0.008^{*}	0.004
	(0.002)	(0.010)	(0.004)	(0.007)	(0.002)	(0.007)	(0.004)	(0.007)
Neuroticism	-0.005^{**}	-0.006	0.004	-0.020^{**}	-0.013^{***}	-0.016^{*}	-0.006	-0.013^{+}
	(0.002)	(0.009)	(0.004)	(0.007)	(0.002)	(0.008)	(0.004)	(0.007)
Openness	-0.005^{**}	-0.017^{+}	0.002	-0.009	0.009^{***}	0.011	0.004	0.012^{+}
	(0.002)	(0.009)	(0.004)	(0.007)	(0.002)	(0.008)	(0.004)	(0.007)
Locus of control	-0.025^{***}	-0.027^{**}	-0.019^{***}	-0.033^{***}	-0.038^{***}	-0.036^{***}	-0.029^{***}	-0.036^{***}
	(0.002)	(0.010)	(0.004)	(0.008)	(0.002)	(0.008)	(0.004)	(0.007)
Positive reciprocity	0.002	-0.004	-0.001	0.000	0.012^{***}	0.021^{**}	0.006	0.019^{**}
	(0.002)	(0.009)	(0.004)	(0.007)	(0.002)	(0.007)	(0.004)	(0.006)
Negative reciprocity	-0.002	-0.002	-0.008^{+}	0.008	0.001	-0.003	0.007^{+}	-0.004
	(0.002)	(0.010)	(0.004)	(0.006)	(0.002)	(0.007)	(0.004)	(0.006)
Risk taking	0.001	-0.018^{*}	0.002	0.019^{**}	0.014^{***}	-0.001	0.015^{***}	0.029^{***}
	(0.002)	(0.009)	(0.004)	(0.007)	(0.002)	(0.007)	(0.004)	(0.006)
R^2	0.538	0.221	0.439	0.284	0.610	0.366	0.451	0.256
$R^2_{restricted}$	0.536	0.219	0.437	0.280	0.603	0.364	0.447	0.251
ΔR^2	0.002	0.001	0.001	0.004	0.007	0.002	0.004	0.005
δR^2	0.449^{***}	0.515^{***}	0.321^{***}	1.294^{***}	1.132^{***}	0.444^{***}	0.921^{***}	2.134^{***}
	(0.005)	(0.009)	(0.005)	(0.015)	(0.007)	(0.006)	(0.008)	(0.020)

Notes: Standard errors (in parentheses) and R^2-values are derived from bootstrapping with 400 replications. The dependent variable is the natural logarithm of the hourly wage. Significance levels: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Source: SOEP v30 1991-2013.

Table 8: Results of UQR & least square regressions by gender (UKHLS)

	Females (N=39,549)				Males (N=29,065)			
	OLS	10^{th} Percentile	50^{th} Percentile	90^{th} Percentile	OLS	10^{th} Percentile	50^{th} Percentile	90^{th} Percentile
Agreeableness	-0.022^{***}	-0.006	-0.017^{***}	-0.044^{***}	-0.017^{***}	-0.005	-0.016^{**}	-0.024^{*}
	(0.003)	(0.004)	(0.005)	(0.008)	(0.003)	(0.007)	(0.006)	(0.011)
Conscientiousness	0.006^{*}	0.010^{*}	0.011^{*}	0.000	0.019^{***}	0.017^{*}	0.010	0.026^{*}
	(0.003)	(0.005)	(0.005)	(0.008)	(0.003)	(0.007)	(0.007)	(0.012)
Extraversion	0.014^{***}	0.002	0.012^{*}	0.016^{*}	-0.003	0.001	0.002	-0.016
	(0.003)	(0.004)	(0.005)	(0.008)	(0.003)	(0.007)	(0.007)	(0.012)
Neuroticism	-0.025^{***}	-0.016^{***}	-0.024^{***}	-0.028^{***}	-0.036^{***}	-0.005	-0.028^{***}	-0.052^{***}
	(0.003)	(0.004)	(0.005)	(0.007)	(0.003)	(0.007)	(0.007)	(0.011)
Openness	-0.002	-0.006	-0.001	0.004	-0.008^{*}	-0.010	-0.009	0.016
	(0.003)	(0.004)	(0.005)	(0.008)	(0.004)	(0.008)	(0.007)	(0.012)
R^2	0.375	0.161	0.382	0.176	0.384	0.192	0.373	0.170
$R^2_{restricted}$	0.372	0.159	0.380	0.173	0.380	0.191	0.371	0.166
ΔR^2	0.003	0.001	0.002	0.003	0.004	0.001	0.002	0.003
δR^2	0.940^{***}	0.722^{***}	0.560^{***}	1.840^{***}	1.091^{***}	0.366^{***}	0.577^{***}	1.968^{***}
	(0.011)	(0.014)	(0.008)	(0.024)	(0.014)	(0.010)	(0.010)	(0.032)

Notes: Standard errors (in parentheses) and R^2-values are derived from bootstrapping with 400 replications. The dependent variable is the natural logarithm of the hourly wage. Significance levels: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Source: UKHLS 2009-2015.

Table 9: Results of UQR & least square regressions by gender (HILDA)

	Females (N=23,844)				Males (N=25,670)			
	OLS	10^{th} Percentile	50^{th} Percentile	90^{th} Percentile	OLS	10^{th} Percentile	50^{th} Percentile	90^{th} Percentile
Extraversion	0.001	0.000	0.001	0.001	−0.002	−0.007	−0.004	0.012
	(0.002)	(0.005)	(0.004)	(0.007)	(0.002)	(0.006)	(0.005)	(0.010)
Agreeableness	−0.022***	−0.014+	−0.018***	−0.028***	−0.025***	−0.010	−0.026***	−0.039***
	(0.003)	(0.007)	(0.005)	(0.008)	(0.003)	(0.007)	(0.006)	(0.010)
Conscientiousness	0.015***	0.009	0.011**	0.019*	0.013***	0.002	0.014**	0.012
	(0.002)	(0.006)	(0.004)	(0.008)	(0.002)	(0.007)	(0.005)	(0.009)
Neuroticism	0.004*	0.001	−0.001	0.012+	0.002	−0.005	0.001	0.010
	(0.002)	(0.005)	(0.004)	(0.007)	(0.002)	(0.006)	(0.005)	(0.010)
Openness	−0.001	−0.012+	−0.001	0.006	0.004	−0.003	0.003	0.004
	(0.002)	(0.006)	(0.004)	(0.007)	(0.003)	(0.007)	(0.006)	(0.010)
Locus of control	−0.025***	−0.019***	−0.027***	−0.031***	−0.041***	−0.033***	−0.039***	−0.043***
	(0.002)	(0.006)	(0.004)	(0.007)	(0.003)	(0.007)	(0.005)	(0.009)
R^2	0.483	0.169	0.288	0.219	0.512	0.203	0.401	0.206
$R^2_{restricted}$	0.478	0.167	0.385	0.215	0.512	0.201	0.395	0.202
ΔR^2	0.005	0.002	0.004	0.004	0.008	0.002	0.005	0.004
δR^2	1.143***	0.988***	0.915***	1.637***	1.481***	1.011***	1.321***	2.174***
	(0.013)	(0.022)	(0.013)	(0.033)	(0.014)	(0.018)	(0.013)	(0.032)

Notes: Standard errors (in parentheses) and R^2-values are derived from bootstrapping with 400 replications. The dependent variable is the natural logarithm of the hourly wage. Significance levels: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Source: HILDA 2001-2015.

Table 10: Results of UQR- & least square regressions, non-linearities (SOEP)

	OLS	10^{th} Percentile	50^{th} Percentile	90^{th} Percentile
Extraversion				
Bottom 25%	-0.012^{*}	-0.033^{**}	-0.013^{*}	0.008
	(0.005)	(0.012)	(0.006)	(0.011)
Top 25%	-0.009	-0.050^{***}	-0.006	0.013
	(0.006)	(0.013)	(0.006)	(0.012)
Agreeableness				
Bottom 25%	0.011^{+}	-0.018	0.012^{+}	0.040^{**}
	(0.005)	(0.012)	(0.006)	(0.013)
Top 25%	-0.027^{***}	0.003	-0.035^{***}	-0.038^{***}
	(0.006)	(0.014)	(0.006)	(0.011)
Conscientiousness				
Bottom 25%	0.000	-0.010	0.001	-0.006
	(0.006)	(0.012)	(0.006)	(0.013)
Top 25%	0.011^{+}	0.018	0.001	0.010
	(0.006)	(0.014)	(0.006)	(0.011)
Neuroticism				
Bottom 25%	0.014^{*}	-0.017^{+}	0.004	0.060^{***}
	(0.006)	(0.010)	(0.007)	(0.013)
Top 25%	-0.001	-0.012	0.001	0.010
	(0.006)	(0.013)	(0.007)	(0.011)
Openness				
Bottom 25%	0.000	0.017	0.000	-0.001
	(0.005)	(0.013)	(0.006)	(0.011)
Top 25%	-0.005	-0.015	-0.001	0.002
	(0.006)	(0.013)	(0.006)	(0.013)
Locus of control				
Bottom 25%	0.033^{***}	0.008	0.019^{**}	0.071^{***}
	(0.006)	(0.012)	(0.006)	(0.013)
Top 25%	-0.045^{***}	-0.065^{***}	-0.035^{***}	-0.028^{**}
	(0.006)	(0.014)	(0.006)	(0.010)
Positive reciprocity				
Bottom 25%	-0.018^{**}	-0.039^{**}	-0.012^{+}	-0.013
	(0.006)	(0.013)	(0.006)	(0.013)
Top 25%	-0.001	-0.020	-0.003	0.020
	(0.006)	(0.013)	(0.007)	(0.012)
Negative reciprocity				
Bottom 25%	-0.012^{*}	-0.008	-0.003	-0.034^{**}
	(0.006)	(0.013)	(0.007)	(0.013)
Top 25%	-0.010^{+}	-0.005	-0.009	-0.023^{*}
	(0.005)	(0.013)	(0.007)	(0.012)
Risk taking				
Bottom 25%	0.003	0.039^{***}	-0.011^{*}	0.000
	(0.004)	(0.011)	(0.005)	(0.009)
Top 25%	0.030^{***}	0.018	0.016^{**}	0.068^{***}
	(0.005)	(0.012)	(0.006)	(0.012)
R^2	0.578	0.273	0.448	0.266
$R^2_{restricted}$	0.573	0.272	0.443	0.261
ΔR^2	0.005	0.002	0.003	0.006
δR^2	0.812^{***}	0.557^{***}	0.755^{***}	2.147^{***}
	(0.005)	(0.005)	(0.005)	(0.016)

Notes: Standard errors (in parentheses) and R^2-values are derived from bootstrapping with 400 replications. The dependent variable is the natural logarithm of the hourly wage. The sample consists of 135,135 observations. Significance levels: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Source: SOEP v30 1991-2013.

Table 11: Results of UQR- & least square regressions, non-linearities (UKHLS)

	OLS	10^{th} Percentile	50^{th} Percentile	90^{th} Percentile
Extraversion				
Bottom 25%	−0.008	−0.002	-0.017^{+}	0.012
	(0.007)	(0.009)	(0.009)	(0.017)
Top 25%	0.010	0.011	0.020^{*}	0.005
	(0.007)	(0.008)	(0.010)	(0.017)
Agreeableness				
Bottom 25%	0.019^{*}	0.004	0.016	0.031^{+}
	(0.007)	(0.007)	(0.010)	(0.016)
Top 25%	-0.032^{***}	−0.005	-0.032^{***}	-0.066^{***}
	(0.007)	(0.008)	(0.009)	(0.014)
Conscientiousness				
Bottom 25%	-0.043^{***}	-0.026^{***}	-0.038^{***}	-0.059^{***}
	(0.007)	(0.008)	(0.010)	(0.014)
Top 25%	-0.019^{*}	0.005	-0.023^{*}	-0.038^{*}
	(0.008)	(0.008)	(0.009)	(0.015)
Neuroticism				
Bottom 25%	0.046^{***}	0.024^{**}	0.027^{**}	0.061^{***}
	(0.007)	(0.007)	(0.009)	(0.018)
Top 25%	-0.030^{***}	-0.015^{+}	-0.033^{***}	-0.026^{+}
	(0.007)	(0.008)	(0.009)	(0.014)
Openness				
Bottom 25%	−0.001	0.003	−0.011	0.001
	(0.007)	(0.008)	(0.010)	(0.015)
Top 25%	-0.014^{+}	-0.024^{***}	-0.017^{+}	0.030
	(0.008)	(0.007)	(0.010)	(0.019)
R^2	0.377	0.162	0.372	0.171
$R^2_{restricted}$	0.371	0.161	0.369	0.166
ΔR^2	0.004	0.001	0.004	0.004
δR^2	1.560^{***}	0.856^{***}	1.012^{***}	2.650^{***}
	(0.009)	(0.011)	(0.008)	(0.025)

Notes: Standard errors (in parentheses) and R^2-values are derived from bootstrapping with 400 replications. The dependent variable is the natural logarithm of the hourly wage. The sample consists of 68,614 observations. Significance levels: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Source: UKHLS 2009-2015.

Table 12: Results of UQR- & least square regressions, non-linearities (HILDA)

	OLS	10^{th} Percentile	50^{th} Percentile	90^{th} Percentile
Extraversion				
Bottom 25%	0.004	0.000	−0.001	0.016
	(0.007)	(0.009)	(0.007)	(0.015)
Top 25%	0.005	−0.007	−0.002	0.013
	(0.007)	(0.009)	(0.007)	(0.015)
Agreeableness				
Bottom 25%	0.030^{***}	0.016^{+}	0.024^{**}	0.055^{***}
	(0.007)	(0.009)	(0.008)	(0.015)
Top 25%	-0.028^{***}	−0.016	-0.024^{**}	-0.033^{*}
	(0.006)	(0.011)	(0.007)	(0.014)
Conscientiousness				
Bottom 25%	-0.019^{**}	0.001	−0.002	-0.032^{*}
	(0.007)	(0.010)	(0.007)	(0.013)
Top 25%	0.019^{**}	0.016^{+}	0.025^{***}	0.018
	(0.006)	(0.009)	(0.007)	(0.015)
Neuroticism				
Bottom 25%	-0.010^{+}	−0.009	0.001	−0.018
	(0.006)	(0.010)	(0.007)	(0.013)
Top 25%	0.005	−0.007	0.005	0.014
	(0.007)	(0.010)	(0.007)	(0.015)
Openness				
Bottom 25%	−0.006	0.015^{+}	−0.008	−0.003
	(0.007)	(0.009)	(0.008)	(0.014)
Top 25%	−0.009	−0.011	−0.010	−0.009
	(0.007)	(0.009)	(0.008)	(0.015)
Locus of control				
Bottom 25%	0.027^{***}	0.013	0.028^{***}	0.042^{**}
	(0.006)	(0.008)	(0.007)	(0.014)
Top 25%	-0.045^{***}	-0.033^{***}	-0.049^{***}	-0.050^{***}
	(0.006)	(0.009)	(0.007)	(0.011)
R^2	0.500	0.178	0.394	0.213
$R^2_{restricted}$	0.493	0.177	0.390	0.209
ΔR^2	0.006	0.002	0.004	0.004
δR^2	1.299^{***}	0.883^{***}	1.131^{***}	2.085^{***}
	(0.008)	(0.013)	(0.008)	(0.020)

Notes: Standard errors (in parentheses) and R^2-values are derived from bootstrapping with 400 replications. The dependent variable is the natural logarithm of the hourly wage. The sample consists of 49,514 observations. Significance levels: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Source: HILDA 2001-2015.

Table 13: Results of EIV-UQR & least square regressions

	Germany (SOEP, N=135,135)				United Kingdom (UKHLS, N=68,614)				Australia (HILDA, N=49,514)			
	OLS	10^{th} Percentile	50^{th} Percentile	90^{th} Percentile	OLS	10^{th} Percentile	50^{th} Percentile	90^{th} Percentile	OLS	10^{th} Percentile	50^{th} Percentile	90^{th} Percentile
Extraversion	-0.016^{*}	-0.015	-0.010	-0.026^{+}	0.005	0.005	0.016^{*}	-0.016	-0.002	-0.006	-0.003	0.000
	(0.007)	(0.015)	(0.008)	(0.015)	(0.006)	(0.007)	(0.007)	(0.015)	(0.004)	(0.005)	(0.004)	(0.008)
Agreeableness	-0.063^{***}	-0.033	-0.059^{***}	-0.106^{***}	-0.054^{***}	-0.021^{*}	-0.049^{***}	-0.089^{***}	-0.037^{***}	-0.016^{*}	-0.030^{***}	-0.058^{***}
	(0.011)	(0.027)	(0.013)	(0.028)	(0.008)	(0.009)	(0.011)	(0.019)	(0.005)	(0.007)	(0.005)	(0.011)
Conscientiousness	0.016^{+}	0.029	0.005	0.033	0.041^{***}	0.035^{**}	0.034^{*}	0.060^{**}	0.019^{***}	0.009^{+}	0.015^{***}	0.025^{**}
	(0.009)	(0.018)	(0.010)	(0.021)	(0.010)	(0.011)	(0.013)	(0.022)	(0.004)	(0.005)	(0.004)	(0.008)
Neuroticism	-0.010	-0.001	-0.008	-0.028^{*}	-0.039^{***}	-0.018^{**}	-0.030^{***}	-0.046^{***}	0.004	0.000	0.000	0.010
	(0.006)	(0.013)	(0.007)	(0.013)	(0.005)	(0.006)	(0.007)	(0.012)	(0.004)	(0.005)	(0.004)	(0.008)
Openness	0.013^{+}	-0.012	0.011	0.018	-0.004	-0.019^{*}	-0.004	0.033^{*}	0.006	-0.010	0.004	0.009
	(0.008)	(0.017)	(0.008)	(0.015)	(0.007)	(0.008)	(0.009)	(0.015)	(0.005)	(0.007)	(0.005)	(0.010)
Locus of control	-0.065^{***}	-0.065^{***}	-0.042^{***}	-0.071^{***}					-0.041^{***}	-0.025^{***}	-0.042^{***}	-0.054^{***}
	(0.007)	(0.015)	(0.008)	(0.014)					(0.004)	(0.006)	(0.004)	(0.007)
Positive reciprocity	0.017^{***}	0.010	0.017^{**}	0.037^{***}								
	(0.005)	(0.011)	(0.005)	(0.011)								
Negative reciprocity	-0.008	-0.002	-0.012^{+}	-0.018^{+}								
	(0.005)	(0.013)	(0.006)	(0.011)								
Risk taking	0.003	-0.014^{*}	0.007^{*}	0.015^{**}								
	(0.003)	(0.006)	(0.003)	(0.006)								
R^2	0.585	0.273	0.455	0.271	0.388	0.164	0.381	0.178	0.509	0.179	0.401	0.220
$R^2_{restricted}$	0.577	0.272	0.451	0.265	0.382	0.192	0.377	0.174	0.501	0.177	0.395	0.214
ΔR^2	0.008	0.002	0.005	0.006	0.006	0.002	0.003	0.004	0.008	0.002	0.005	0.005
δR^2	1.406^{***}	0.706^{***}	1.030^{***}	2.403^{***}	1.558^{***}	1.115^{***}	0.882^{***}	2.389^{***}	1.633^{***}	0.939^{***}	1.356^{***}	2.434^{***}
	(0.010)	(0.009)	(0.009)	(0.026)	(0.013)	(0.018)	(0.010)	(0.035)	(0.012)	(0.015)	(0.011)	(0.025)

Notes: Standard errors (in parentheses) and R^2-values are derived from bootstrapping with 400 replications. The dependent variable is the natural logarithm of the hourly wage. Significance levels: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Sources: SOEP v30 1991-2013, UKHLS 2009-2015, HILDA 2001-2015.

Figures

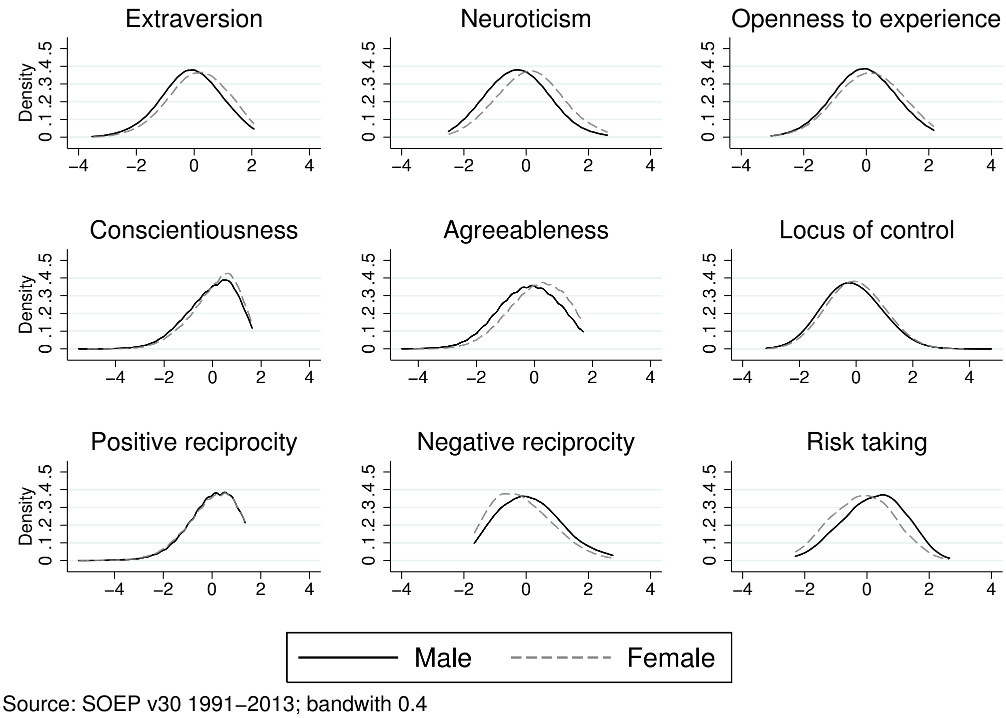


Figure 1: Character Traits in the German data (SOEP)

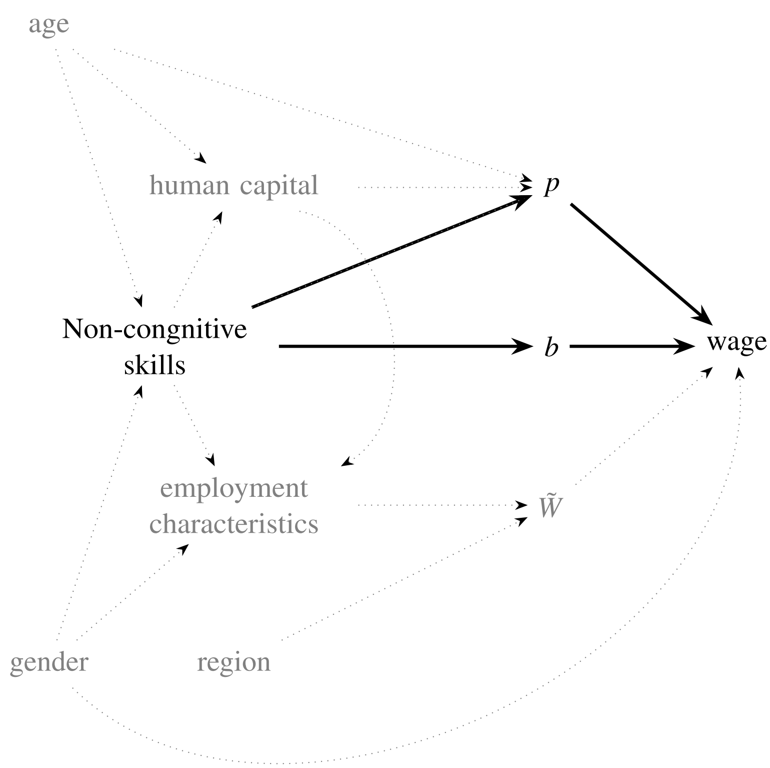


Figure 2: The channels through which personality traits could affect wages in the empirical model. The dotted lines are mechanisms that I want to rule out with controls, the solid lines are the mechanisms suggested by the hypotheses as described in Section 2.3.

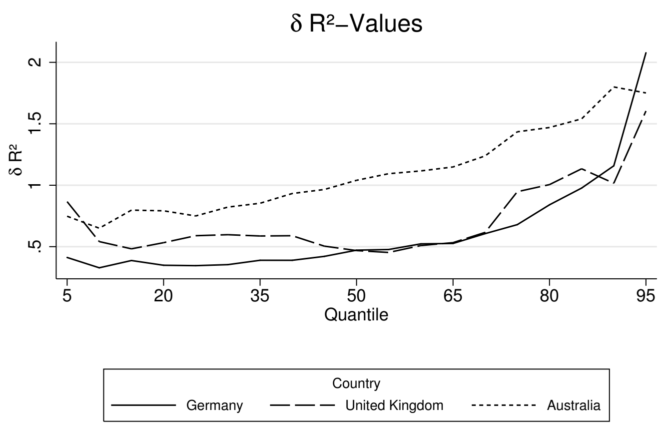
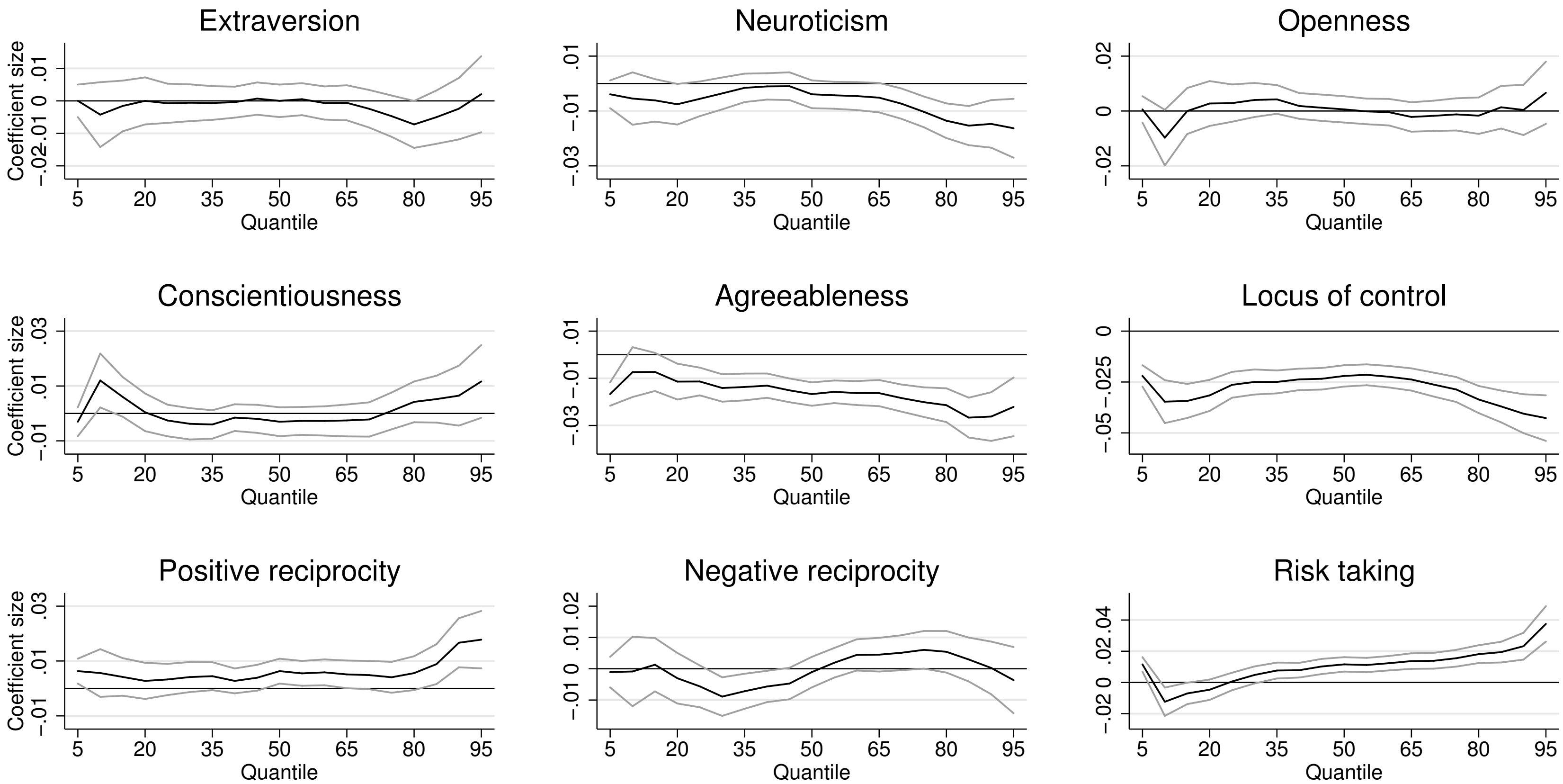
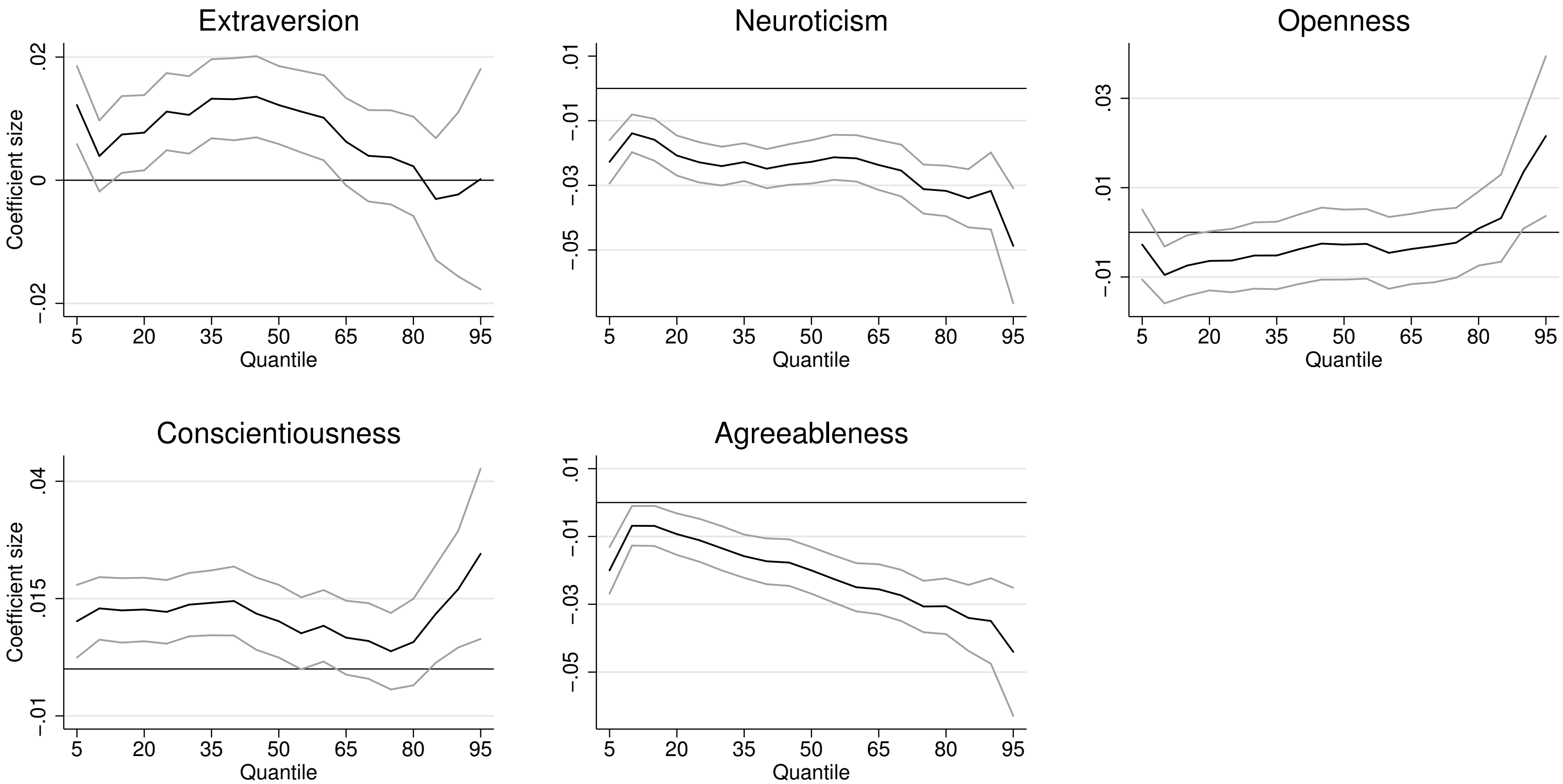


Figure 3: δR^2 values across the distribution of wages for all countries. The graphs include the models displayed in Table 3.



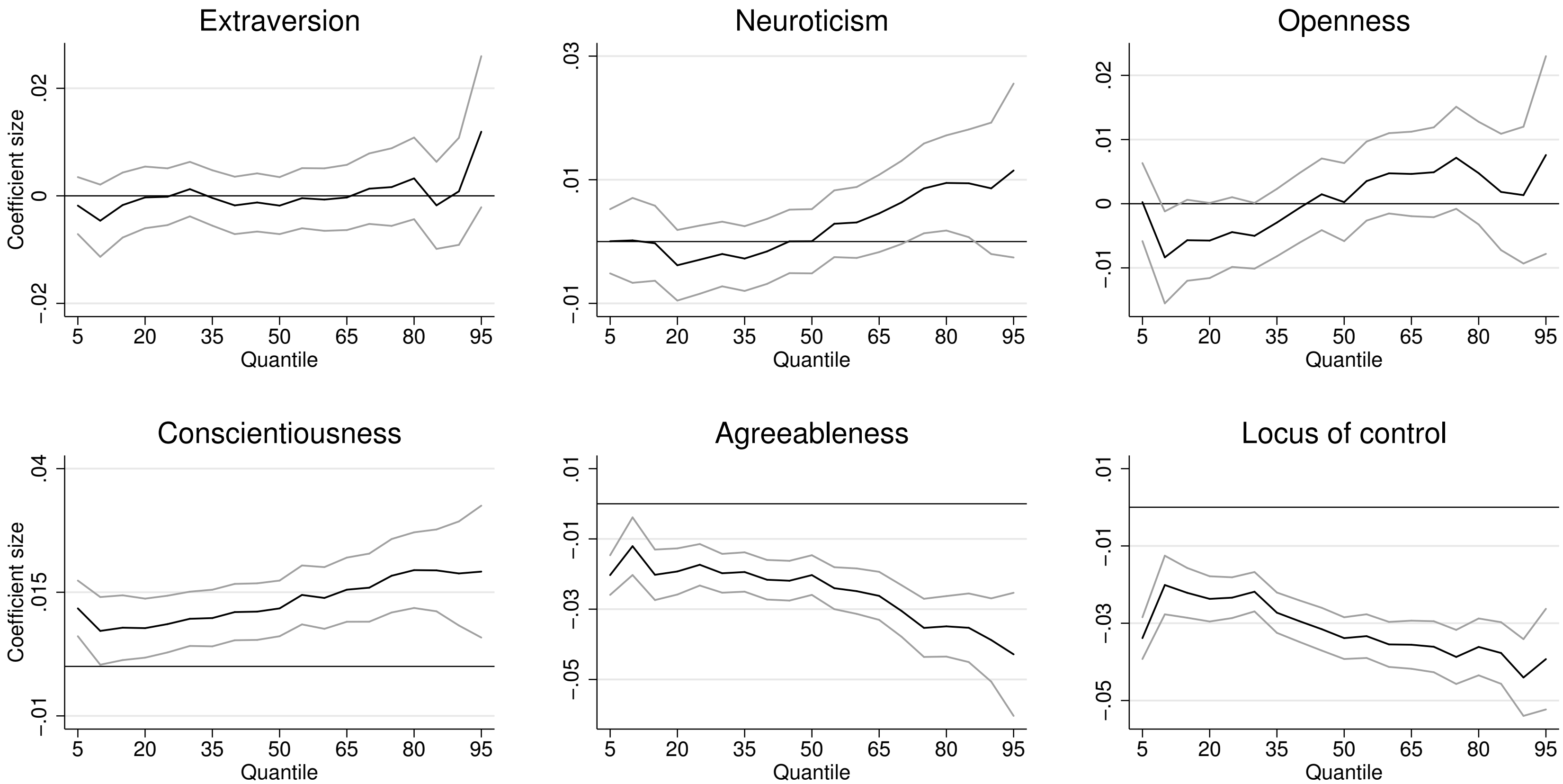
Source: SOEP v30 1991–2013; Coefficients with 90%–CIs.

Figure 4: The effect of personality traits on wages with 90%-confidence intervals for the German sample (corresponding to Table 3).



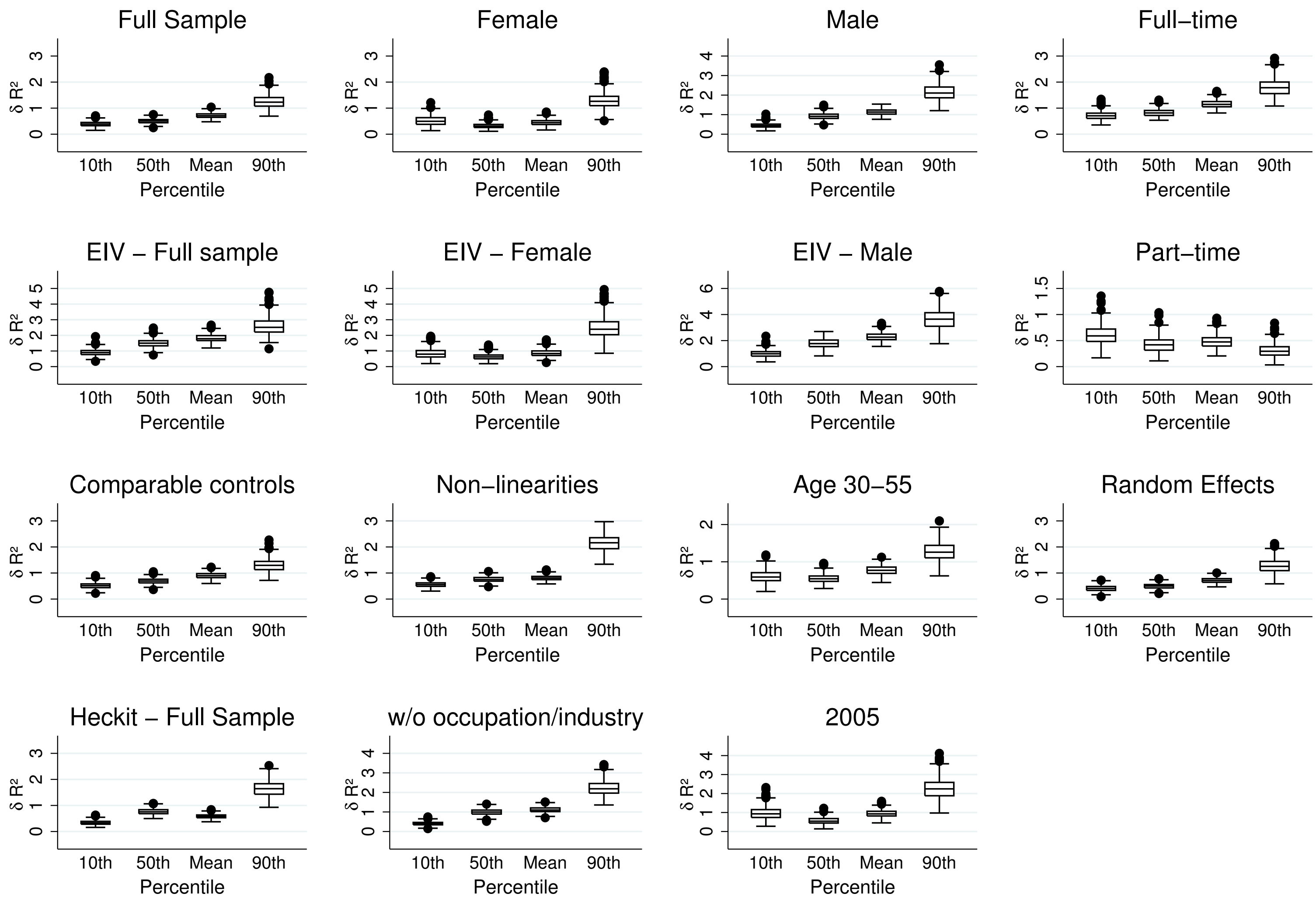
Source: UKHLS 2009–2015; Coefficients with 90%–CIs.

Figure 5: The effect of personality traits on wages with 90%-confidence intervals for the British sample (corresponding to Table 3).



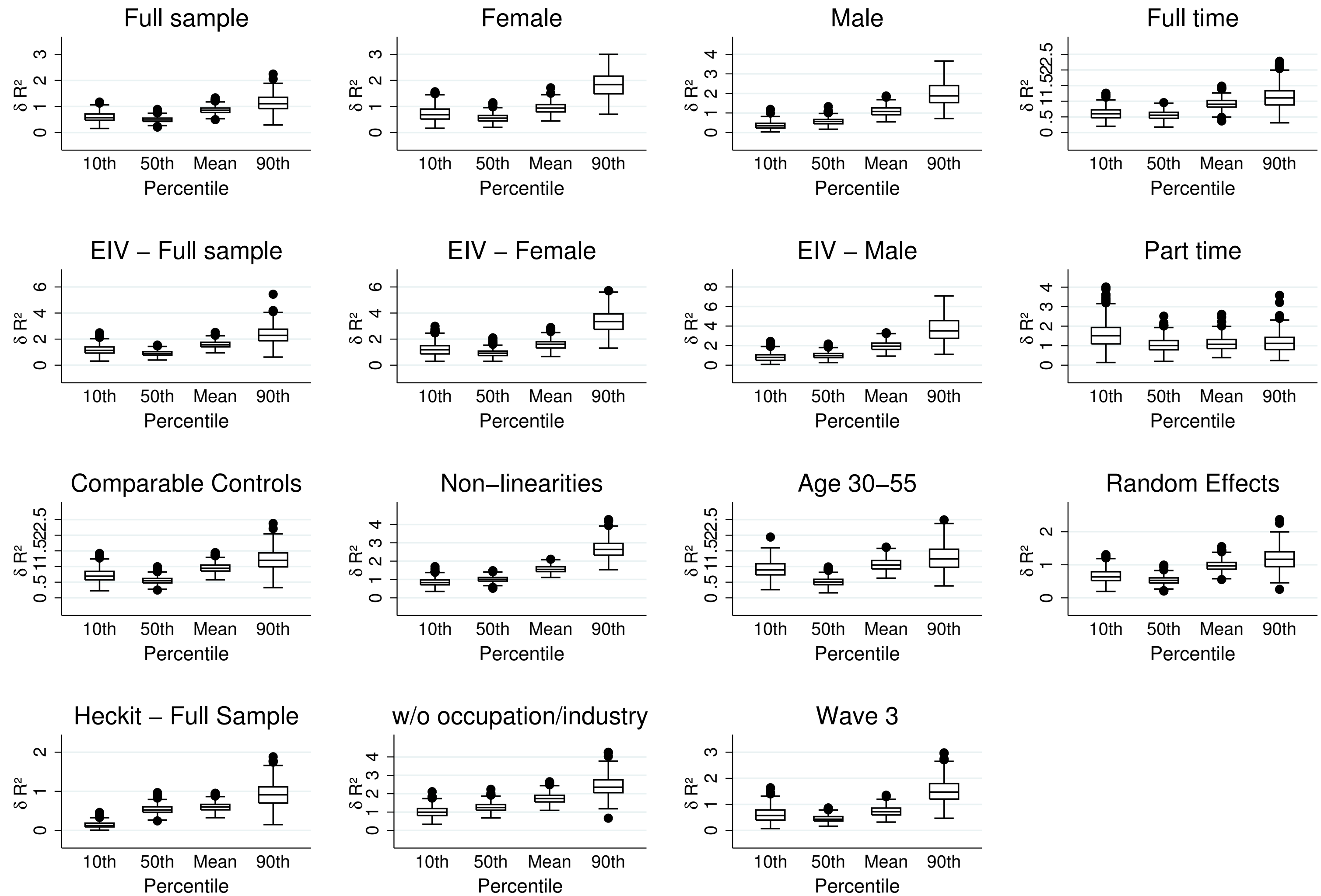
Source: HILDA 2001−2015; Coefficients with 90%−CIs.

Figure 6: The effect of personality traits on wages with 90%-confidence intervals for the Australian sample (corresponding to Table 3).



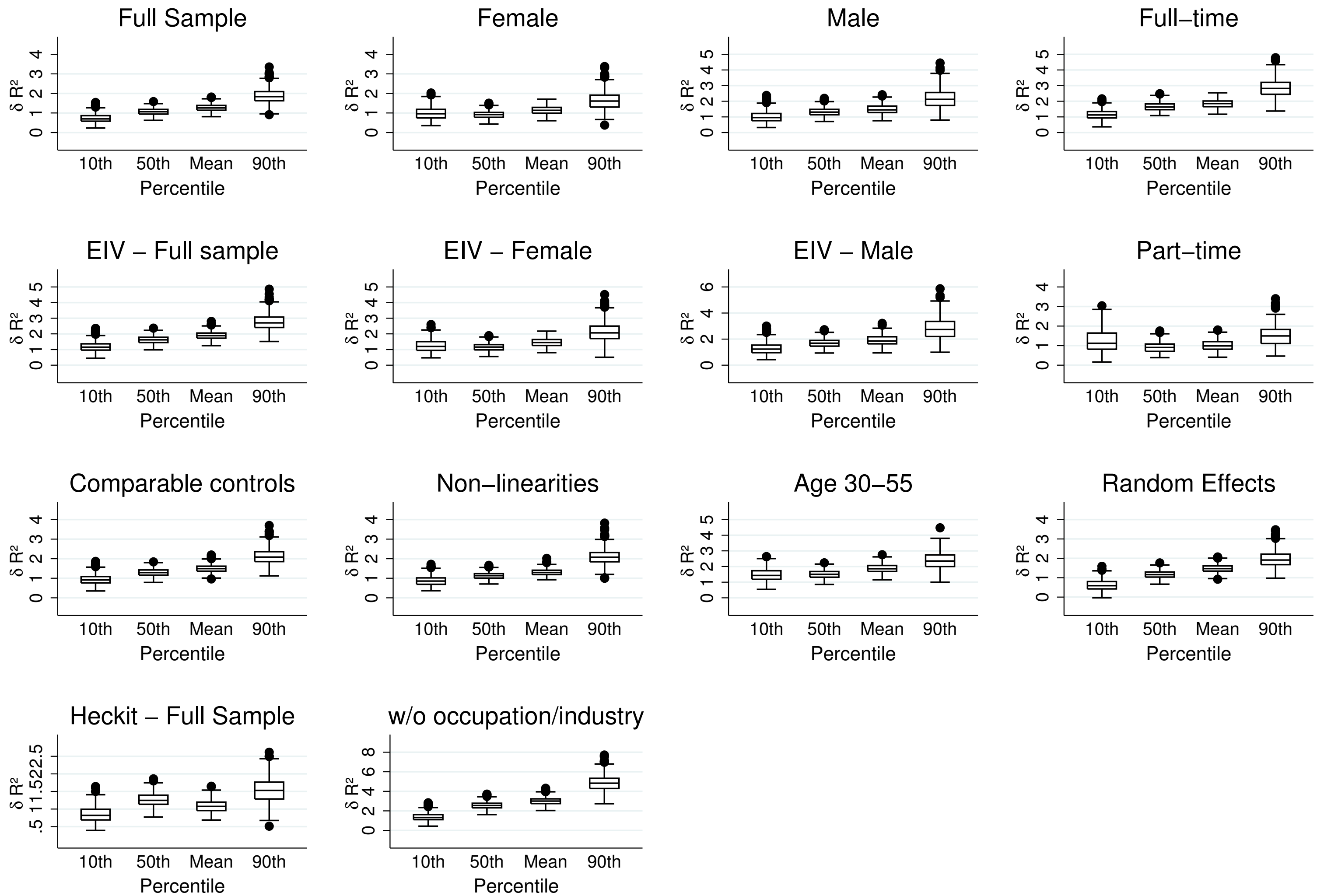
Source: SOEP v30 1991–2013.

Figure 7: The bootstrapped (400 replications) δR^2 values (computed as described in equation 10) for the combined importance of personality traits in the SOEP for all specifications estimated. The horizontal line inside the boxes is the median, the upper and lower hinge indicate the 25th and 75th percentile. The vertical line displays the range. Dots outside the box are $> 1.5*$ interquartile range. Robustness refers to models without the EIV-correction, Comparable controls refers to a model that only includes controls that are only included in all three data sets (displayed in Table C4), Heckit refers to to the estimation with sample selection correction based on parental education.



Source: UKHLS 2009–2015.

Figure 8: The bootstrapped (400 replications) δR^2 values (computed as described in equation 10) for the combined importance of personality traits in the UKHLS for all specifications estimated. The horizontal line inside the boxes is the median, the upper and lower hinges indicate the 25th and 75th percentile. The vertical line displays the range. Dots outside the box are $> 1.5*$ interquartile range. Robustness refers to models without the EIV-correction, Comparable controls refers to a model that only includes controls that are only included in all three data sets (displayed in Table C4), Heckit refers to to the estimation with sample selection correction based on parental education.



Source: HILDA 2001–2015.

Figure 9: The bootstrapped (400 replications) δR^2 values (computed as described in equation 10) for the combined importance of personality traits in the HILDA for all specifications estimated. The horizontal line inside the boxes is the median, the upper and lower hinges indicate the 25th and 75th percentile. The vertical line displays the range. Dots outside the box are $> 1.5*$ interquartile range. Robustness refers to models without the EIV-correction, Comparable controls refers to a model that only includes controls that are only included in all three data sets (displayed in Table C4), Heckit refers to the estimation with sample selection correction based on parental education.

Appendices

A. Jobs & Wages

In my theoretical considerations I assume that higher wages are associated with more complex tasks and thus more uncertainty concerning productivity. To further discuss this assumption, I will look at the ten best and worst paid occupations[17] (ISCO-88, 3-digit) in the pooled data from Understanding Society for the UK, presented in Table A1.

Table A1: Worst- and best-paid occupations in the UK

Occupation	Mean hourly wage
Worst-paid occupations	
Domestic and related helpers, cleaners and launderers	7.526
Agricultural, fishery and related labourers	7.567
Food processing and related trades workers	8.055
Housekeeping and restaurant services workers	8.060
Shop salespersons and demonstrators	8.108
Felt, leather and shoemaking trades workers	8.231
Textile, fur and leather products machine operators	8.359
Fishery workers, hunters and trappers	8.518
Street vendors and related workers	8.620
Manufacturing labourers	8.657
Best-paid occupations	
Legislators	21.853
Other departmental managers	21.885
College, university and higher education teaching profession	21.996
Locomotive engine-drivers and related workers	23.064
Senior officials of special interest organizations	23.588
Legal professionals	25.704
Police inspectors and detectives	25.715
Health professionals (except nursing)	27.413
Ship and aircraft controllers and technicians	27.699
Directors and chief executives	49.885

Notes: Occupation is the 3-digit-ISCO-88, hourly wage is the computed gross hourly wage. Source: UKHLS 2009-2015.

One can imagine relatively simple measures for productivity in most of the low-paying occupations. For example, the hourly production of processes parts could be a measure for manufacturing laborers. In contrast, there is no simple measure of productivity for executives or managers. Thus, I expect that uncertainty on productivity is larger in these occupations compared to low-paying occupations.

[17] I exclude “other personal service workers“ because the actual activity is unclear.

B. Explaining δR^2

This section further expands upon the properties of δR^2. I pose the same research question as in the main paper, namely:

Does the explanatory power of personality traits on wages increase across the distribution of wages?

To examine this question, I generate a data set which contains two human capital variables and four personality items. The simulation allows me to generate data for which I know the answer to the research question. Thus, I can test if the R^2 is suitable to investigate this topic. I generate data with 150,000 observations. Next, I predict a dependent variable y (e.g. wages) for these observations, based on the equation:

$$y_i = 0.75x_{1i} - 0.5x_{2i} + x_{3i} - x_{4i} + 0.5x_{5i} + 0.005\tau t_{1i} + 1[0.5 + 0.01(\tau^2/100)]t_{2i} + \epsilon_i$$

Where $x_1 - x_5, t_1$ and t_2 are covariates and ϵ is the error term with the following distributions:

x_1	$N \sim (40, 8)$
x_2	$N \sim (10, 1)$
x_3	$N \sim (45, 10)$
x_4	$N \sim (50, 10)$
x_5	$N \sim (8, 2)$
t_1	$N \sim (10, 2)$
t_2	$N \sim (10, 2)$
ϵ	$N \sim (0, 10)$

The returns to the x-covariates are identical at any given point of y. t_1 and t_2 are covariates whose effect on y depend on the distribution of y, with τ being the respective percentile of y from 0 to 100. Thus, the effects of t_1 and t_2 on y increase across the distribution of y.

With the data set up like this, one can regress y on all covariates at different quantiles of interest via RIF-OLS and the mean via classical OLS and then compute R^2-statistics to compare them (in this case based on bootstrapping). t_1 and t_2 represent the personality traits in this example.

Table B1 shows the results. δR^2 is suitable to test the hypothesis. It increases across the distribution of y and is maximal at the 90th percentile, because it is not, as for example the F-test and ΔR^2, based on the absolute amount of explained variance.

One can easily perform statistical inference using T-tests, because the distribution of δR^2 obtained by bootstrapping at a given quantile is approximately normal. In the case of this paper, 400 bootstrapping

Table B1: Statistical properties of the estimation on the simulation sample

	OLS	10^{th} Percentile	50^{th} Percentile	90^{th} Percentile
$R^2_{unrestricted}$	0.703	0.238	0.450	0.242
$R^2_{restricted}$	0.697	0.237	0.447	0.237
ΔR^2	0.006	0.001	0.003	0.005
δR^2	0.841***	0.356***	0.627***	1.980***
	(0.002)	(0.003)	(0.002)	(0.007)
F-statistic joint effects of t_1 & t_2	1481.06 ***	82.81 ***	380.06 ***	458.74 ***

Notes: Standard errors (in parentheses) and R^2-values are derived from bootstrapping with 400 replications. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Source: own simulation.

repetitions are deemed sufficient to calculate T-tests. These T-tests that compare δR^2 at the 90th percentile to δR^2 at other statistics of interest also show that it is significantly larger than all other δR^2 values.

Additionally, as can be seen, R^2 and also ΔR^2 are maximal in the mean case, because this is what classical OLS maximizes by minimizing the residual sum of squares. As a consequence, the F-statistic is larger in the mean estimation compared to the other statistics of interest. This example shows that both the F-statistic and the simple rise in absolute explanatory power, ΔR^2, are not suitable to describe the additional explanatory contribution of a set of control variables across multiple quantiles of interest, because I know that the explanatory power for the combined personality items peaks at the 90th percentile compared to the other quantiles of interest.

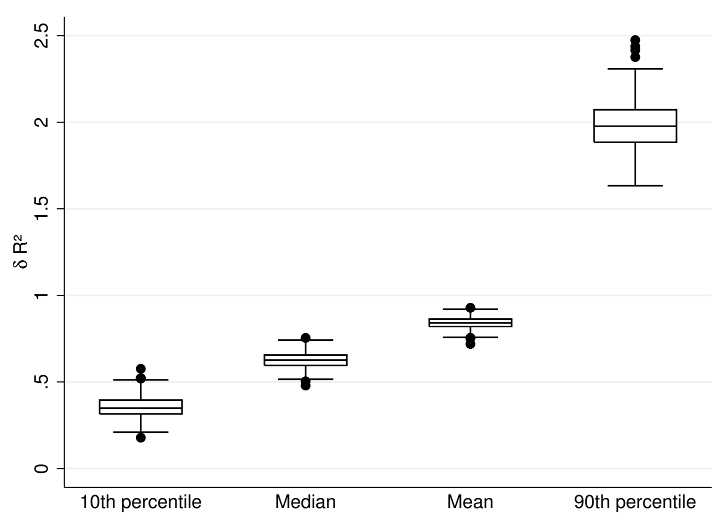


Figure B1: The bootstrapped (400 replications) δR^2 values (computed as described in equation 10) for the joint effect of t_1 and t_2. The horizontal line inside the boxes is the median, the upper and lower hinges indicate the 25th and 75th percentile. The vertical line displays the range. Dots outside the box are $> 1.5*$ interquartile range.

However, the simulation also shows that the significance tests for δR^2 can be misleading when it comes to magnitude. The standard errors and thus the confidence intervals of this analysis are rather small and thus the statistical significance of these differences does not necessarily capture the actual magnitude of the differences.

Figure B1 displays graphical evidence for δR^2. As can be seen, δR^2 at the 90th percentile exceeds its values compared to the other percentiles at all points of its range. Thus, it rightfully indicates the the effect of t_1 and t_2 on y increase significantly across the quantiles investigated of y.

One might argue that δR^2 is larger at the 90th percentile compared to the mean, because there is simply more variance that cannot be explained by the other covariates. The mean, in contrast, has already a high share of explained variance and thus, the relative increase has to be smaller. However, with the simulated data, I can test this objection. Thus, I estimate the same model as previously described in the equation but in contrast to the previous example, I will now compute δR^2 for x_2 and x_5 and simply control for the other covariates (including t_1 and t_2). The results are presented in Figure B2. As can be seen, δR^2 does not vary substantially across the distribution of y. Thus, the optimization procedure of OLS does not minimize δR^2 by nature. However, this also shows the shortcoming of δR^2 if I would rely solely on standard errors as a test for significant differences: all differences between the 10th, 50th, 90th percentile and the mean are statistically significant, even if the magnitude of these differences is marginal, as displayed in the plot.

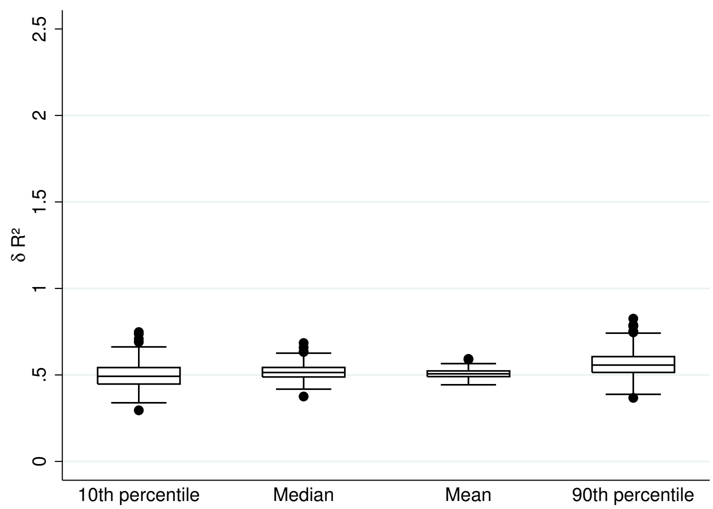


Figure B2: The bootstrapped (400 replications) δR^2 values (computed as described in equation 10) for the joint effect of x_2 and x_5. The horizontal line inside the boxes is the median, the upper and lower hinges indicate the 25th and 75th percentile. The vertical line displays the range. Dots outside the box are $> 1.5*$ interquartile range.

C. Additional Figures & Tables

Table C1: Summary statistics for the SOEP

Variable	Mean	Std. Dev.
Hourly wages	15.688	11.479
Female (dummy)	0.467	0.499
Age	42.023	11.084
Years of schooling	12.548	2.721
Experience full-time employment	16.2	11.476
Experience part-time employment	2.635	5.266
Experience unemployment	0.487	1.329
Tenure	11.031	10.028
Public sector employment	0.279	0.449
Full time employed (dummy)	0.742	0.438
Married (dummy)	0.637	0.481
Child aged younger or 16 in household (dummy)	0.343	0.475
Migrant (dummy)	0.074	0.263
East Germany (dummy)	0.23	0.421
Establishment size: $\leq$ 10 employees	0.14	0.347
Establishment size: 11-100 employees	0.3	0.458
Establishment size: 101-200 employees	0.074	0.262
Establishment size: 201-2000 employees	0.236	0.425
Establishment size: $\geq$ 2001 employees	0.25	0.433

Notes: Based on 135,135 observations. ISCO (2-digit) and NACE (top groups) are not shown but included in the data. Source: SOEP v30 1991-2013.

Table C2: Summary statistics for the UKHLS

Variable	**Mean**	**Std. Dev.**
Hourly wages	15.003	37.198
Female (dummy)	0.576	0.494
Age	40.67	11.491
Public sector employment	0.401	0.49
Full-time employed (dummy)	0.755	0.43
Overtime work (dummy)	0.448	0.497
Married (dummy)	0.101	0.301
Child aged younger 16 in household (dummy)	0.402	0.49
Establishment size: $\leq$ 24 employees	0.299	0.458
Establishment size: 25-100 employees	0.263	0.44
Establishment size: more than 100 employees	0.437	0.496
Education: Higher degree	0.154	0.361
Education: 1st degree or equivalent	0.223	0.416
Education: Diploma in higher education	0.097	0.296
Education: Teaching qual not pgce	0.016	0.126
Education: Nursing/other med qual	0.029	0.168
Education: Other higher degree	0.002	0.043
Education: A level	0.107	0.309
Education: Welsh baccalaureate	0	0.012
Education: I'nationl baccalaureate	0.001	0.029
Education: AS level	0.013	0.114
Education: Highers (scot)	0.015	0.12
Education: Cert 6th year studies	0.004	0.061
Education: GCSE/O level	0.257	0.437
Education: CSE	0.056	0.231
Education: Standard/o/lower	0.015	0.12
Education: Other school cert	0.012	0.107

Notes: Based on 68,614 observations. ISCO (2-digit) and SIC (top groups) are not shown but included in the data. Source: UKHLS 2009-2015.

Table C3: Summary statistics for the HILDA

Variable	**Mean**	**Std. Dev.**
Hourly wages	28.859	15.587
Female (dummy)	0.482	0.5
Age	40.007	11.625
Experience unemployment	0.477	1.268
Tenure	7.612	8.276
Child aged younger or 14 in household (dummy)	0.337	0.473
Hiring employee (dummy)	0.025	0.157
Married (dummy)	0.711	0.453
Establishment size: Less than 20	0.035	0.185
Establishment size: 20 to 99	0.102	0.302
Establishment size: 100 to 499	0.195	0.397
Establishment size: 500 to 999	0.087	0.282
Establishment size: 1000 to 4999	0.181	0.385
Establishment size: 5000 to 19,999	0.173	0.378
Establishment size: 20,000 or more	0.227	0.419
Education: Postgrad - masters or doctorate	0.065	0.247
Education: Grad diploma, grad certificate	0.082	0.275
Education: Bachelor or honours	0.197	0.398
Education: Adv diploma, diploma	0.109	0.312
Education: Cert III or IV	0.223	0.416
Education: Year 12	0.154	0.361
Education: Year 11 and below	0.169	0.374
Full-time employed (dummy)	0.756	0.429
Migrant: English speaking (dummy)	0.095	0.293
Migrant: Other (dummy)	0.104	0.305
Casual employment (dummy)	0.114	0.318

Notes: Based on 49,514 observations. ISCO (2-digit) and ANZSIC06 (top groups) are not shown but included in the data. Source: HILDA 2001-2015.

Table C4: Results of UQR & least square regressions with comparable controls

	Germany (SOEP, N=135,135)				United Kingdom (UKHLS, N=68,614)				Australia (HILDA, N=49,514)			
	OLS	10^{th} Percentile	50^{th} Percentile	90^{th} Percentile	OLS	10^{th} Percentile	50^{th} Percentile	90^{th} Percentile	OLS	10^{th} Percentile	50^{th} Percentile	90^{th} Percentile
Extraversion	-0.001	-0.003	-0.001	-0.003	0.007^{*}	0.005	0.013^{**}	-0.001	-0.002	-0.006	-0.003	0.001
	(0.003)	(0.006)	(0.003)	(0.006)	(0.003)	(0.003)	(0.004)	(0.008)	(0.003)	(0.004)	(0.003)	(0.006)
Agreeableness	-0.020^{***}	-0.009	-0.021^{***}	-0.028^{***}	-0.023^{***}	-0.008^{*}	-0.022^{***}	-0.036^{***}	-0.025^{***}	-0.012^{*}	-0.020^{***}	-0.040^{***}
	(0.003)	(0.006)	(0.003)	(0.006)	(0.003)	(0.004)	(0.005)	(0.007)	(0.003)	(0.005)	(0.004)	(0.007)
Conscientiousness	0.004	0.012^{*}	-0.002	0.007	0.015^{***}	0.015^{***}	0.013^{**}	0.019^{**}	0.015^{***}	0.008^{+}	0.013^{***}	0.019^{**}
	(0.003)	(0.006)	(0.003)	(0.007)	(0.003)	(0.004)	(0.005)	(0.007)	(0.003)	(0.004)	(0.003)	(0.006)
Neuroticism	-0.009^{***}	-0.009	-0.005^{+}	-0.016^{**}	-0.027^{***}	-0.013^{***}	-0.022^{***}	-0.031^{***}	0.004	0.000	0.000	0.009
	(0.003)	(0.006)	(0.003)	(0.006)	(0.003)	(0.003)	(0.005)	(0.007)	(0.003)	(0.004)	(0.003)	(0.007)
Openness	-0.001	-0.011^{+}	-0.001	0.000	-0.002	-0.010^{*}	-0.001	0.016^{*}	-0.002	-0.011^{*}	-0.004	0.001
	(0.003)	(0.006)	(0.003)	(0.006)	(0.003)	(0.004)	(0.005)	(0.008)	(0.003)	(0.005)	(0.003)	(0.007)
Locus of Control	-0.038^{***}	-0.038^{***}	-0.027^{***}	-0.042^{***}					-0.036^{***}	-0.022^{***}	-0.037^{***}	-0.047^{***}
	(0.003)	(0.006)	(0.003)	(0.005)					(0.003)	(0.004)	(0.003)	(0.006)
Positive reciprocity	0.009^{***}	0.010^{+}	0.007^{*}	0.017^{**}								
	(0.003)	(0.005)	(0.003)	(0.006)								
Negative reciprocity	0.000	-0.003	0.000	0.000								
	(0.003)	(0.007)	(0.003)	(0.005)								
Risk taking	0.006^{*}	-0.016^{**}	0.009^{***}	0.021^{***}								
	(0.002)	(0.006)	(0.003)	(0.005)								
R^2	0.565	0.261	0.432	0.265	0.371	0.160	0.371	0.170	0.497	0.174	0.388	0.214
$R^2_{restricted}$	0.460	0.260	0.429	0.265	0.368	0.159	0.369	0.168	0.490	0.172	0.383	0.209
ΔR^2	0.005	0.001	0.003	0.003	0.003	0.001	0.002	0.002	0.007	0.002	0.005	0.004
δR^2	0.901^{***}	0.516^{***}	0.694^{***}	1.302^{***}	0.951^{***}	0.713^{***}	0.554^{***}	1.214^{***}	1.495^{***}	0.943^{***}	1.294^{***}	2.115^{***}
	(0.006)	(0.005)	(0.005)	(0.012)	(0.007)	(0.010)	(0.006)	(0.016)	(0.010)	(0.013)	(0.010)	(0.020)

Notes: Standard errors (in parentheses) and R^2-values are derived from bootstrapping with 400 replications. The dependent variable is the natural logarithm of the hourly wage. All models additionally account for: age, age squared, education, child in the household, married, establishment size, full-time employment, public sector employment, occupation (2-digit), industry (major groups), East Germany (SOEP only). Significance levels: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Sources: SOEP v30 1991-2013, UKHLS 2009-2015, HILDA 2001-2015.

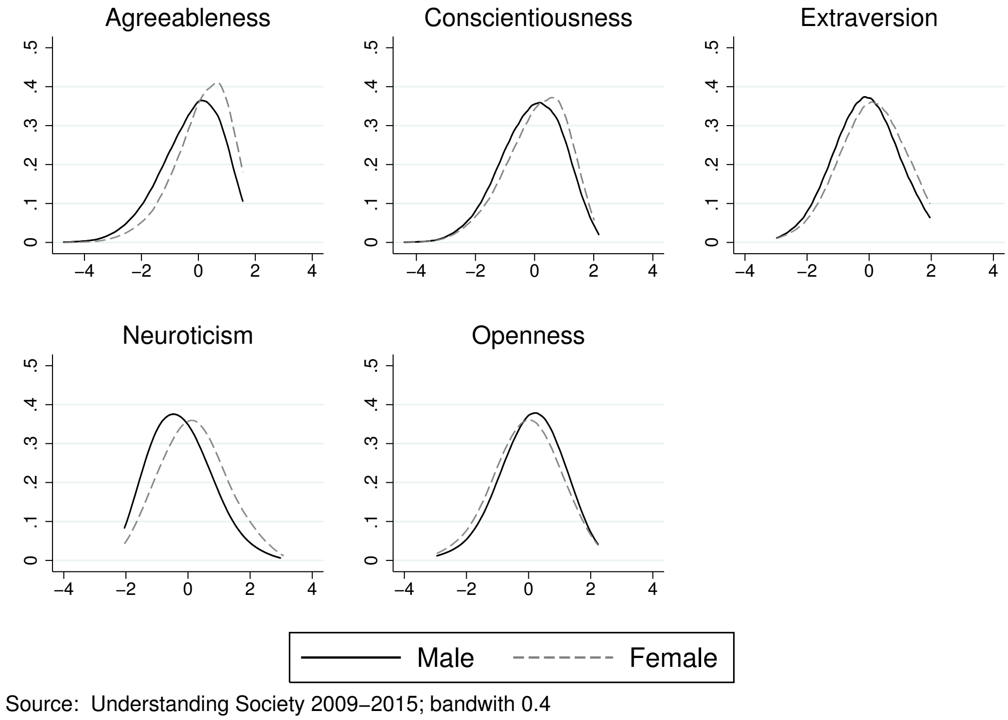


Figure C1: Character traits in the British data (UKHLS)

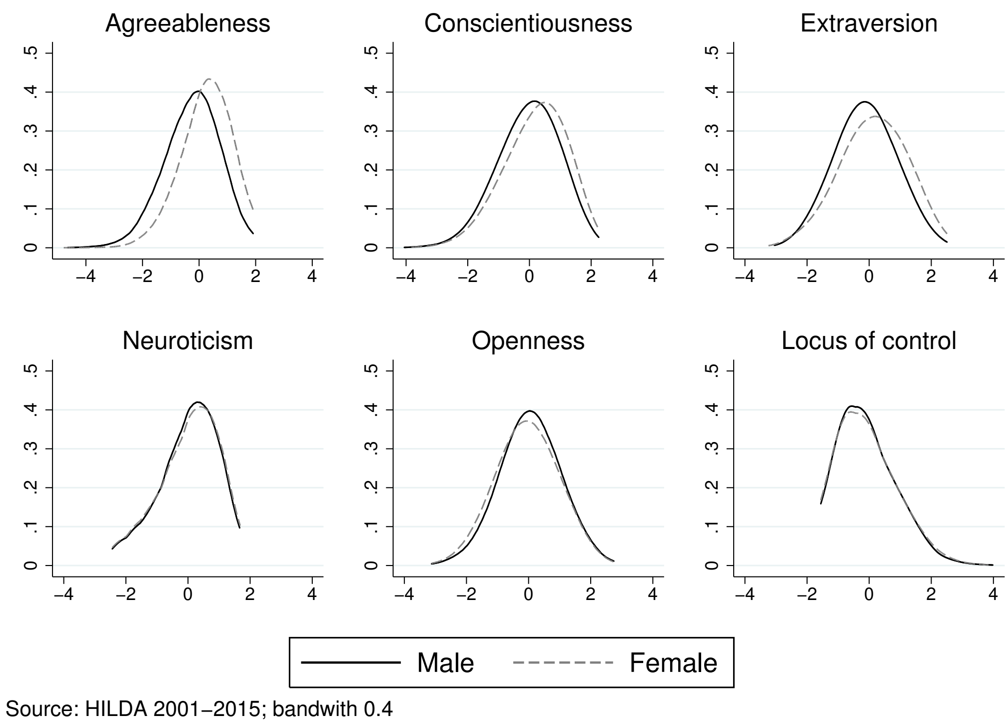
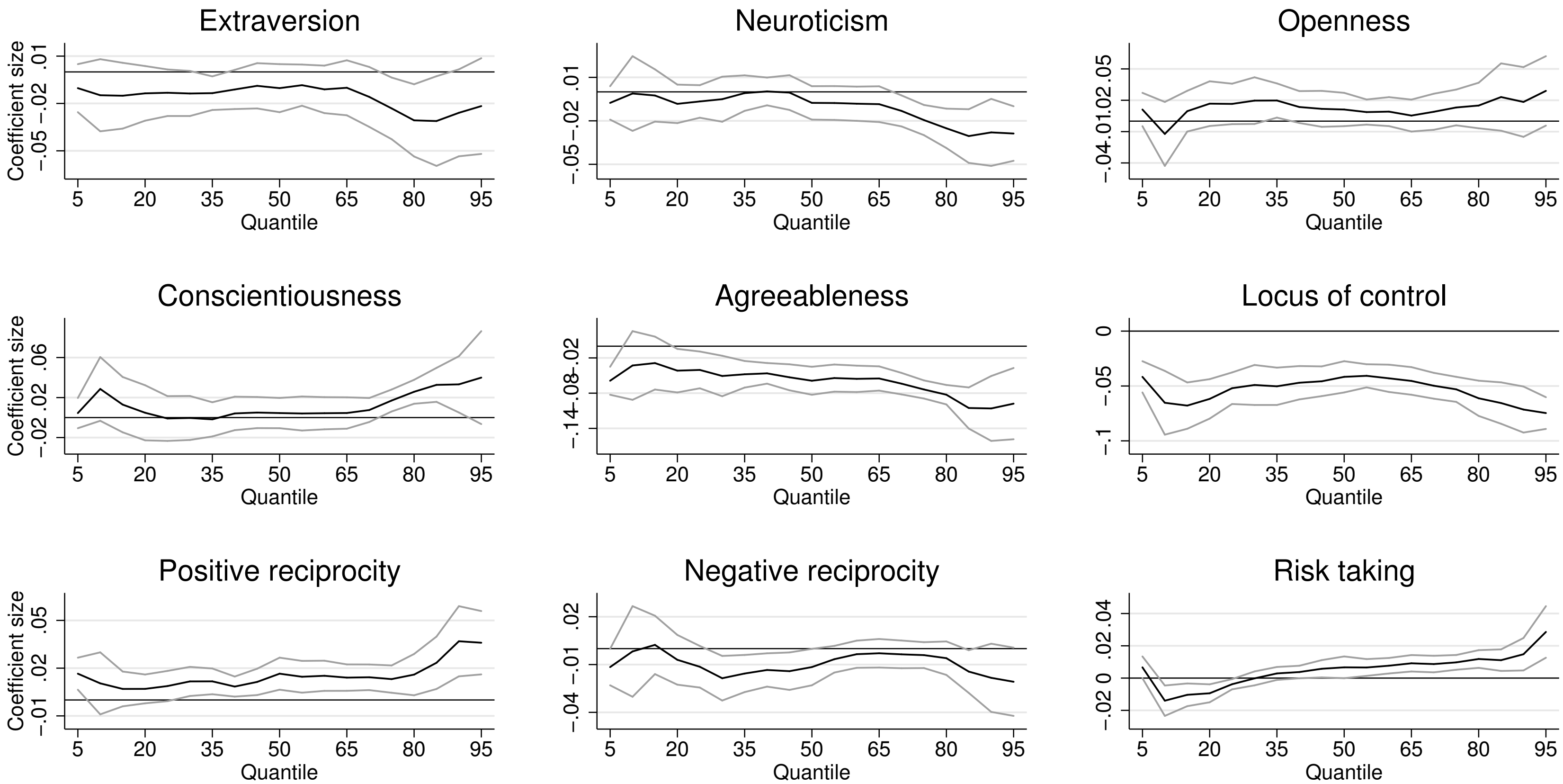
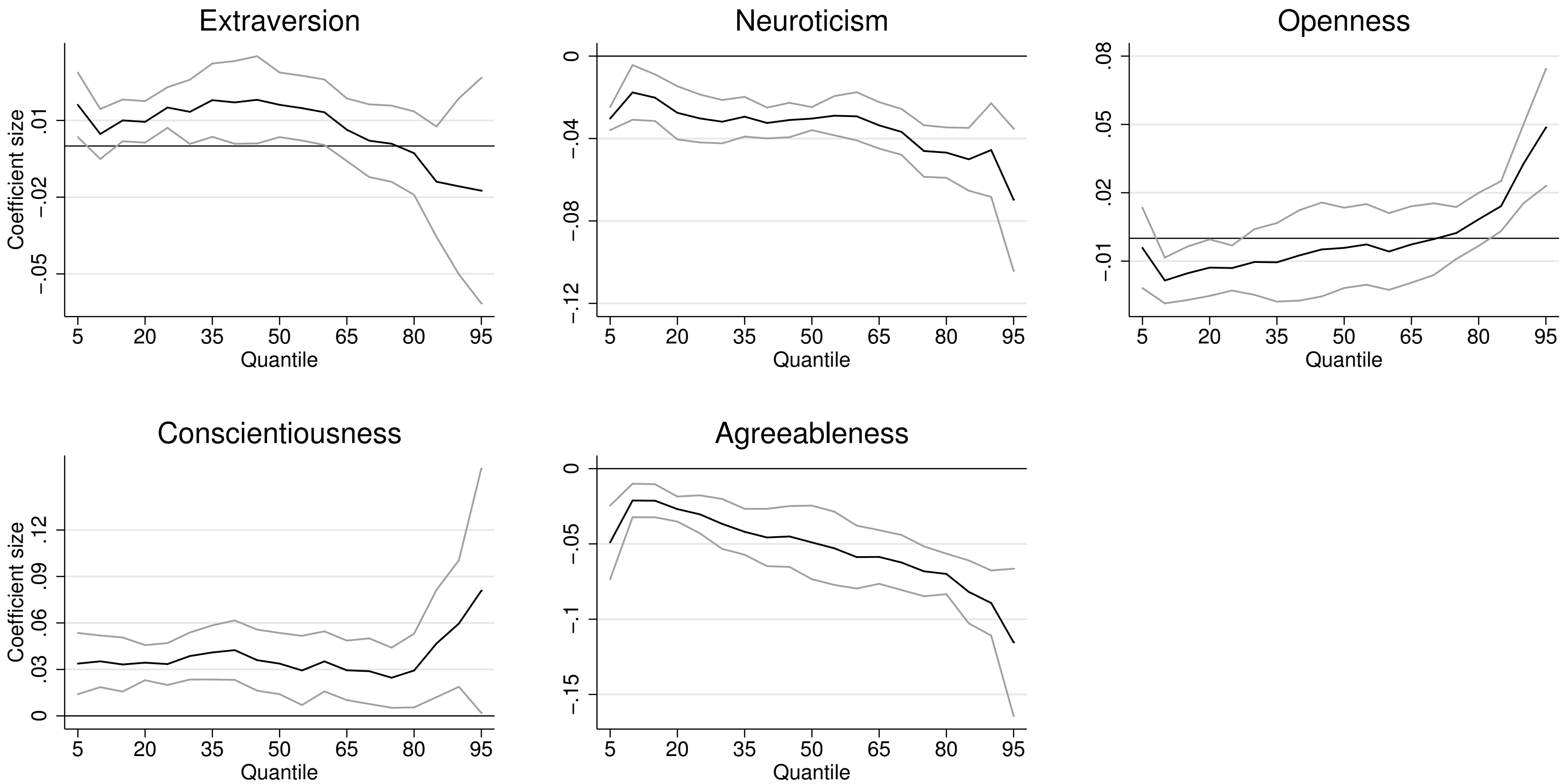


Figure C2: Character traits in the Australian data (HILDA)



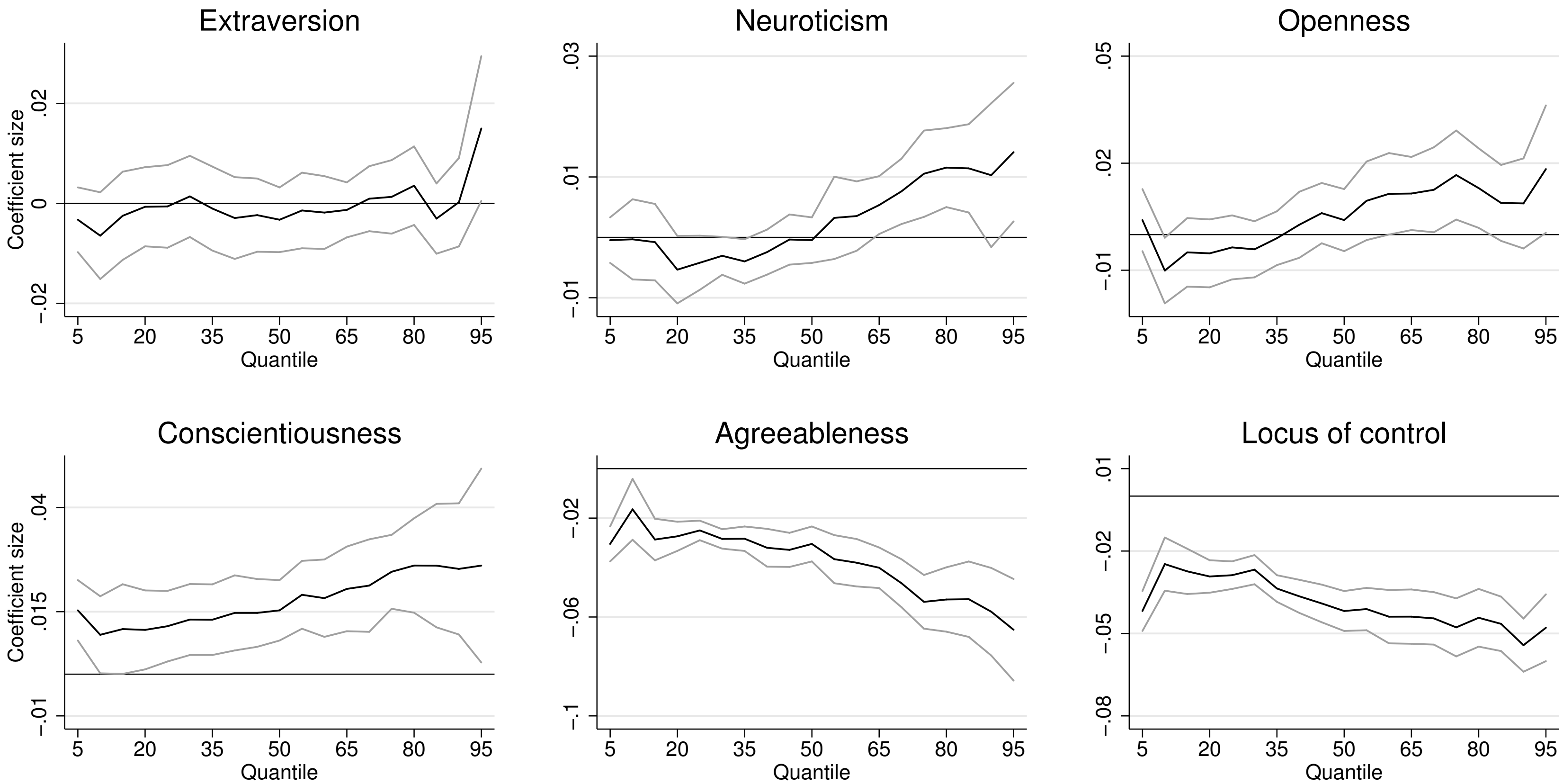
Source: SOEP v30 1991–2013; Coefficients with 90%–CIs; EIV–regressions.

Figure C3: The effect of personality traits on wages with 90%-confidence intervals for the German sample with the EIV-correcion (corresponding to Table 13).



Source: UKHLS 2009−2015; Coefficients with 90%−CIs; EIV−regressions.

Figure C4: The effect of personality traits on wages with 90%-confidence intervals for the British sample with the EIV-correcion (corresponding to Table 13).



Source: HILDA 2001–2015; Coefficients with 90%–CIs; EIV–regressions.

Figure C5: The effect of personality traits on wages with 90%-confidence intervals for the Australian sample with the EIV-correcion (corresponding to Table 13).