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The Relationship Between the Big Five Personality Traits and Earnings: Evidence from a Meta Analysis

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THE RELATIONSHIP BETWEEN THE BIG FIVE PERSONALITY TRAITS AND EARNINGS: EVIDENCE FROM A META ANALYSIS

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Abstract

The role and importance of personality traits in determining labour market outcomes remain largely contested. This meta-analytic review addresses the question of whether the Big Five traits are related to earnings. A comprehensive literature search identified 52 studies that met the inclusion criteria (1,307 regression coefficients). The findings indicate that Openness to Experience, Conscientiousness and Extraversion are positively correlated with earnings, while Agreeableness and Neuroticism are inversely correlated with earnings. The study finds that the magnitudes of the earnings effects are modest to small, show a high degree of heterogeneity and are largely scaled down after accounting for publication bias. The main contributors to the observed heterogeneity are identified as being socioeconomic background, occupation, cognitive ability, and educational attainment. The study suggests that environmental factors play an important role in the relationship between personality traits and earnings, so omitting relevant factors from the empirical model could lead to omitted variable bias in the estimates.

JEL Classification

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1. INTRODUCTION

Over the past three decades, non-cognitive skills have become an important curriculum in labour economics. It is argued that cognition, while important, does not alone affect labour market outcomes (Almlund et al., 2011). The developing economics literature also recognises that, in addition to economic preferences and social skills, personality traits may also interact with labour market outcomes.

Various mechanisms are at play in how personality traits affect labour market outcomes. Personality traits are often seen similarly to skills, which, like cognition, enter the production function separately and employers reward workers whose traits match those ideal for the job (Bowles et al., 2001; Heckman, Stixrud, and Urzua, 2006; Borghans et al., 2008; Almlund et al., 2011) and reduce the coordination costs with other workers (Deming, 2017). Personality types can also be linked to economic preferences, such as risk, time and social preferences, which then explains health, educational and labour market outcomes (Becker et al., 2012). It is therefore not surprising that one would expect predictive power for personality.

This paper focuses on the relationship between personality and earnings. Although the body of work on this topic has increased recently, albeit still limited, the results do not provide a clear picture. The relationship between personality traits and earnings is complex and multifaceted, and likely influenced by a variety of other factors, such as a person's education, skills, and advancement opportunities. In addition, the relationship can vary depending on the industry or profession in which a person works. For example, we expect that individuals who are conscientious, eager to learn, calm and composed are likely to do better in their careers and generate higher earnings.

In the context of confounding factors, the relationship between personality traits and earnings is even more complex and difficult to disentangle. One confounding factor that influences the relationship between personality traits and earnings is education. Individuals with higher levels of education are expected to be more likely to exhibit certain traits, such as openness and conscientiousness, that are associated with higher earnings, and may also have more access to more opportunities that affect their earnings. As a result, the relationship between personality traits and earnings appears to be stronger than it actually is, and omitting education from the earnings specification would result in omitted variable bias of the personality effect. Other confounding variables are skills and work experience.

In this paper, I conduct a meta-analysis to combine empirical findings from multiple studies to identify patterns and trends across studies and better understand the relationship between personality traits and earnings. By using a multivariate meta-regression analysis, I investigate which study characteristics account for variances in the findings that have been published in the literature. This study also tests for the presence of publication bias, which occurs when journals and authors are more likely to report statistically significant results. The presence of publication bias would be undesirable as it can lead to an overestimation of the true earnings effects of personality traits.

Although there is already a study that offers a meta-analytical review of the empirical literature on this relationship (Alderotti, Rapallini and Traverso, 2021), I offer a different perspective. I contribute to the literature by including only estimates from a semi-log wage equation (in this case the regressand appears in the logarithmic form) to aid comparability when quantifying the overall associations of the Big Five traits.[1] To identify the sources of the observed heterogeneity in the reported effects, I additionally

[1] The five-factor model (McCrae and John, 1992) was the natural candidate for the basis of the current meta-analysis because these dimensions are believed to be broad and capture the fundamental and general aspects of thought, feeling, and behaviour that people typically do differently (John, Naumann, and Soto, 2010). The five-factor model has also taken a prominent place in economic research and is considered a standard module in most longitudinal data sets. Although the five-factor model is not without criticism (Block, 2010; Eysenck, 1992), it has been extensively linked to life outcomes, such as wages, health, and

include all estimates of the selected studies into the meta-analysis. Instead of using a different regression model for each group of detected components, I integrate all identified control variables (including standard errors of reported effects to detect publication bias) collectively in the meta-regressions, while making sure that multicollinearity is not unduly high. This strategy has clear advantages over bivariate analysis as it allows one to explore the relationship between multiple variables and understand how they are all related. Furthermore, the robustness of the meta-regression model to changes in the assumptions is assessed using a variety of sensitivity tests, in part due to the fact that many estimates from a single paper can be dependent, as well as the fact that the most significant sources of heterogeneity of the studies being analysed are unknown. The presented meta-analysis also addresses these needs.

The overall summary results suggest that Openness to Experience and Conscientiousness are positively related to earnings, Extraversion is also positively but weakly related, while Agreeableness and Neuroticism are negatively related to earnings. By using a multi-regression approach, I find that educational attainment, family background, as well as the individual's cognitive ability and career choice are important factors explaining differences in personality assessments. I also find publication bias in the relationship between personality traits and earnings, and both magnitude and significance decrease substantially after accounting for it.

The paper is structured as follows. Section 2 considers the theoretical reasons why personality traits may affect earnings. Section 3 outlines the process of selecting studies and presents an overview of the dataset. Section 4 reports and discusses the empirical results. Section 5 summarises and concludes.

2. CONCEPTUAL FRAMEWORK

Personality traits are defined as "relatively enduring patterns of thoughts, feelings, and behaviours that differentiate individuals from one another" (Roberts, 2009, p. 2). Personality traits are believed to consist of behavioural and emotional patterns in all situations rather than isolated occurrences. There are five dimensions of personality, often referred to as the Big Five taxonomy. These five dimensions are: Openness to Experience (ability to be creative, curious, intellectually engaged, honest/humble and inquisitive), Conscientiousness (self-discipline, punctuality, and organised and general competence), Extraversion (how talkative, friendly, energetic, and outgoing the person is), Agreeableness (the tendency to be kind, charitable, warm, and generous), and Neuroticism (fear, worry, paranoia, and stress). The Big Five traits are based on a broad and comprehensive taxonomy, which means that each trait contributes to behaviour in a *ceteris paribus* context rather than acting as the sole determinant of behaviour. In this way, the Big Five traits can be utilised to comprehend a person's motives, objectives, and preferences as well as to predict and understand a person's behaviour.

The personality traits of each individual are not directly observable and are typically measured through self-report questionnaires that ask people to rate their positive to negative level of agreement with the statement that describes their personality on a Likert scale. For example, a 7-item Likert scale range from 1 = 'does not apply to me at all' to 7 = 'applies to me perfectly'. As an alternative to self-report measures, peer-report measures involve evaluating other people on their personality traits, and objective measures, on the other hand, are based on observed behaviour.

In order to measure personality, it is frequently necessary to determine if the correlations between a group of observed self-report items are caused by their relationship to a specific latent variable, each of which takes the form of a linear model, in the data. The Five Factor Model identifies five distinct latent factors. The factor score that estimates the dimension of the underlying factor, is a linear combination of items, with each item weight generated from its factor loading. Each factor's scale has a standard deviation of one and a mean of zero.

It is worth mentioning here that many studies in economics make use of factor-based scores. A simpler approach involves averaging a pre-selected set of items. This is considered undesirable because they

longevity (Heckman, Jagelka, and Kautz, 2019) and has long been recognised as internally consistent, stable, and enjoy cross-cultural support (John, 2021).

ignore weights and cannot handle measurement errors as factor scores. Nonetheless, factor scores are not context-free constructs, and they are still likely to correlate with unobserved factors, such as skills (for example, Borghans, Meijers, and ter Weel, 2008). In fact, personality traits cannot be conceptualised without a context. To say that a person is an extrovert because they have an Extraversion disposition is meaningless. We would need to know where this disposition comes from and how it affects his behaviour.

The relationship between personality traits and earnings can be expressed as an extension of the functional form of Mincer's equation. It can be expressed as follows:

$$\ln Y_i = \alpha + \beta P_i + \gamma X_i + \varepsilon_i \qquad (1)$$

where Y_i denotes earnings; P_i is a vector of personality traits (Openness to Experience, Conscientiousness, Extraversion, Agreeableness, Neuroticism); X_i is a vector of characteristics that are thought to affect earnings (e.g., educational attainment, occupation, cognitive ability); and ε_i is the error term. The interest lies in β, which is a vector of parameters, and captures the relationship between earnings and each of the respective personality traits, *ceteris paribus*. The percentage effect of one standard deviation increase in P_i on Y_i is equal to $\{\exp(\beta) - 1\} \cdot 100$.

Certain personality traits are expected to be associated with higher earnings. For example, individuals who are more conscientious, extraverted, and open are likely to earn higher earnings. In part because traits like a willingness to work hard, the ability to work well with others, and the ability to think critically are all positive traits that are valued positively in the labour market. Conversely, people who score higher on measures of agreeableness and neuroticism are likely to earn less. However, the relationship between personality traits and wages is not straightforward. Estimated values of β can vary from one study to another, and these variations can be so large such that they can swing from negative to positive. The relationship can be influenced by a variety of factors that are not necessarily directly related to their personality traits. Here I list the six most prominent factors that can affect the relationship between personality traits and wages.

2.1 Educational Attainment

The relationship between personality traits and earnings can be influenced by the person's level of education. The link is not surprising. For starters, there is a wealth of evidence linking the Big Five traits with educational attainment. A meta-analysis by Vedel and Poropat (2017) and other studies (e.g., Spengler et al., 2013, 2016; Lechner, Anger and Rammstedt., 2019; Bergold and Steinmayr, 2018; Brandt et al., 2020) identify Conscientiousness and Openness to Experience as the personality traits most relevant to educational attainment. In contrast, no strong associations are reported with education and academic performance for Agreeableness, Emotional Stability, and Extraversion (e.g., Caspi et al., 2005; Poropat, 2009; Lechner, Anger and Rammstedt., 2019; Vedel and Poropat, 2017; Gensowski, 2018).

There is also good reason to believe that education can, in part, confound the effect of personality traits on earnings. To name a few, programs that invest in children's cognitive and noncognitive skills at an early stage, such as the General Educational Development (GED) Program (Heckman and Rubinstein, 2001), the Perry Preschool Project (Heckman, Stixrud, and Urzua, 2006), the Jamaican Study (Gertler et al., 2014) and the Columbia study (Attanasio et al., 2020), were found to have a number of positive effects on the life outcomes of children who participated in these programs.

Many studies on the relationship between personality traits and earnings condition on education in the wage equation. A typical interpretation of the coefficients would then be that personality traits would directly influence income. Despite the fact that the size of the direct impact is technically incorrect due to omitted variable bias, I will use the same approach to examine variations in effect estimates between studies.

Reverse causality is another issue with the current conceptual framework. While it is widely acknowledged that some personality traits affect education, it is also possible to argue that education itself has an influence on a person's traits. Higher educated people might, for instance, be exposed to particular surroundings and experiences that could influence personality development, and in turn earnings. Evidence is still scarce, and Extraversion is the only personality attribute that appears to get better with training (Dahmann and Anger, 2014).

2.2 Occupation and Selection Effects

The relationship between personality traits and earnings is also expected to be correlated with people's career choices. The selection effect would be that individuals with certain characteristics or attitudes may be more likely to choose certain occupations. In this case, the relationship between personality traits and earnings may be stronger for individuals who have chosen occupations that require or prefer certain personality traits than for individuals whose individual skills do not match the job requirements.

Studies have looked at whether personality can predict job success in order to better understand how personality traits influence people's career decisions. This is important since firms are interested in hiring people who will match their organisation. For instance, evidence from several meta-analyses suggest that Conscientiousness significantly predicts job performance (Salgado et al., 2003; Ones et al., 2007), while Openness to Experience is a strong predictor of job performance in situations that require training (LePine et al., 2000), Extraversion is important in a context involving social interaction and leadership position, while Agreeableness is positively associated with performance in team environments (Bell, 2007; Peeters et al., 2006). By contrast, Neuroticism is associated with underperformance in many organisational settings (Ones et al., 2007).

2.3 Cognitive Skills

It is well known that if the earnings specification does not include a measure of cognitive ability, the coefficients of interest are likely to suffer from omitted variable bias when personality traits also happen to be correlated with IQ.

While intelligence and personality have traditionally been viewed as distinct constructs, recent research suggests that cognitive skills and personality traits are both conceptually and empirically related. DeYoung (2020) provides a detailed account of why such correlations exist. One potential explanation for the relationship between personality traits and cognitive ability is that certain personality traits associated with certain attitudes might affect cognitive abilities. For example, individuals who score high on measures of Openness to Experience are more likely to be engaged in training, which in turn fosters the development of intelligence. In contrast, individuals who score low on measures of Emotional Stability are more likely to experience anxiety and negative emotions, that impair cognitive development (Moutafi, Furnham and Tsaousis, 2006).

Additionally, an association between the measured levels of personality traits and cognitive ability is probably present due to a common error. Because performance on personality and cognitive ability tests depends in part on achievement motivation, anxiety, and commitment to completing the questionnaire as accurately as possible, the results collected are related. In fact, although conceptually cognitive ability and personality traits are two separate constructs, they are usually viewed as "impure" measures (Borghans et al., 2011) since the fact that the measures were measured impurely implies that they are connected in some way.

2.4 Family Background

Families with higher socioeconomic status (SES) are more likely to have better life outcomes, including higher earnings, access to better education, more social capital, and recognition in well-paying jobs and social networks. It then follows that the SES is an important factor in predicting individuals' labour market outcomes. SES refers to an individual's social and economic status, which is typically measured by parents' education, occupation, and income.

The relationship between personality traits and earnings is likely to interact with family SES, meaning that the influence of personality traits on earnings may be different for individuals from different socioeconomic backgrounds. Collischon (2020), for example, suggests the relationship between Agreeableness, Conscientiousness, Neuroticism and wages is stronger for high-wage employees.

One reason for the interaction between personality traits and earnings and family socioeconomic background is that people from high SES have more resources and opportunity to advance their career-related abilities, which may make personality traits more significant in determining their pay. In fact, a child's personality is strongly predicted by the SES of their parents (Deckers et al., 2015). According to a meta-analytical review by Ayoub et al. (2018), parental SES is positively correlated with all traits, albeit with small effect sizes. Ignoring SES would incorrectly ascribe the entire influence to personality traits because these variables directly affect earnings.

2.5 Gender

Gender may moderate the impact of personality traits on earnings, although results are mixed (Nyhus and Pons, 2012). According to Mueller and Plug (2006), Agreeableness is one of the most important factors contributing to disparities across men, where antagonistic men earn more than agreeable men. In contrast, others such as Heineck and Anger (2010), Cobb-Clark and Tan (2011) and Heineck (2011) find a negative association between Agreeableness and earnings for men and women.

Some mixed results are found for Neuroticism. Mueller and Plug (2006) found that individuals who scored higher on Neuroticism measures earned significantly lower wages than those who scored lower on Neuroticism measures. However, Heineck (2011) found that this relationship is partly moderated by gender, suggesting that the relationship between Neuroticism and wages may be unique to female workers.

According to Heineck and Anger (2010), the correlation between openness, extraversion, and wages can also be moderated by gender. Women with higher Openness to Experience scores earn significantly higher wages than women with lower scores, whereas men with higher Openness to Experience scores earn significantly less than men with lower scores. Contrarily, Extraversion was found to be linked to lower pay for women and higher wages for men.

2.6 Age

Another factor that merits discussion is age. While the overall personality profile is known to remain more or less stable after puberty, adolescents are likely to become more outgoing, conscientious and emotionally stable (Bleidorn et al., 2022; Roberts et al., 2006), and so personality development is inextricably linked to age, known as the “maturity principle”. The effects of maturity appear to be particularly pronounced, with important behavioural consequences on life outcomes such as a lower likelihood of committing crimes and lower levels of Dark Triad personality traits. One could posit that the positive and negative effects of personality traits on earnings seem to work with age, with the association being found to be stronger for younger workers than for older workers, or vice versa (Maczulskij and Viinikainen, 2018). However, the relationship may not be found to significantly vary by age (Cobb-Clark, D. & Schurer, 2012).

3. EMPIRICAL STRATEGY

A meta-analysis of regression coefficients combines the results of several studies that used regression analysis to examine the relationship between a dependent variable and one or more independent variables. Assuming that all studies had used the proper identification approach, the meta-analysis provides a more precise assessment of the overall association between the variables by combining the findings of many research.

The overall size of the relationship would be the mean or median of the regression coefficients, if all studies were equally accurate. However, when the studies come to different point estimates, we want to give more weight to studies with more information. A simple way around this is to consider the standard error of the regression coefficient when determining the weight of each study. This is because the accuracy of the regression coefficient is measured by its standard error, which also represents the degree of uncertainty surrounding the estimate.

3.1 Estimation Strategy

Suppose there is an identified set of n studies that have used regression analysis to examine the relationship between personality traits and earnings. Then I can extract the regression coefficients and other relevant statistical information from each study i, and combine the results to estimate the overall true effect size. Here, the regression coefficient (i.e., semi-elasticity as in Equation 1) is an effect size that gives the relationship between the variables of interest, and the known standard error is reported in each study.

For the purpose of this study, I estimate a random effects model which assumes that the studies that were included in the meta-analysis were chosen from a distribution of many studies and that the overall effect represents the mean effect in that distribution.[2] As a result, the overall effect size is calculated by taking into account both the within-study variability observed in the fixed-effect model as well as the variability between studies. In the random effects model:

$$\hat{\beta}_i = \alpha_0 + u_i + \epsilon_i, \tag{2}$$

where $\hat{\beta}_i$ is the estimated coefficient in study i, $\theta_i \sim N(\alpha_0, \tau^2)$, $u_i \sim N(0, \tau^2)$ and $\epsilon_i \sim N(0, \sigma_i^2)$. Here, θ_i follows a normal distribution around the intercept α_0 (i.e., the overall semi-elasticity). τ^2 is the between-study variance and is estimated from the data.

Equation (2) can be estimated using ordinary least squares (OLS). However, there are two problems in estimating this specification.

First, the estimates are likely to violate the assumption of homoskedasticity. Heteroskedasticity is present when the error variances are systematically different for each observation, so that some studies provide more reliable estimates of θ_i than others. Equation (2) is then weighted by the inverse-variance of the reported $\hat{\beta}_i$. This is analogous to saying that I give more weight to the studies with more information, in the calculation of θ_i. Here, under the random effects model, the weight to be assigned to Equation (2) is therefore composed of the variance of the estimated effect, σ_i^2, plus the between-study variance, τ^2. Equation (2) becomes:

$$\hat{t}_i = \alpha_0 \frac{1}{\sigma_i^2 + \tau^2} + \frac{\varepsilon_i}{\sigma_i^2 + \tau^2} \tag{2`}$$

[2] The fixed-effect model assumes that all studies share a common true effect size, θ, and all differences in the observed effects are due to within-study sampling error. In the context of meta-analysis, the term "fixed-effect" has a different definition than "fixed effects" in econometrics. The random-effects method is generally recommended for use in meta-analysis.

where t_i is the conventional t-value of the estimated beta. Estimating Equation (2`) by OLS is equivalent to estimating Equation (2) by weighted least squares (WLS) using the inverse of the variance as discussed above (Stanley and Doucouliagos, 2016).

The second issue is brought about by the possibility of correlation between effect sizes, particularly if they come from the same study. To address this issue, I report cluster-robust standard errors at study level to take into account correlation within studies. As an additional robustness test, I compare the findings of two sets of specifications: one that equally weights each estimate, giving the results of studies with more reported estimates greater weight; and the other that equally weights each study. The supplemental document discusses the results.

It is expected that the results of the relationship between personality traits and earnings will vary, with some studies finding strong associations and others reporting weaker associations. In order to analyse the sources of heterogeneity in the reported effects, Equation (2) can be expanded to include variables pertaining to the observed heterogeneity. These variables include, *inter alia*, person's education, skills, and the socioeconomic background, as well as other study characteristics.

If θ is linear function of X_i, then Equation (2) can be expressed as:

$$\hat{\beta}_i = \alpha_0 + \sum_{k=1}^{K} \alpha_{1,n} X_{i,k} + u_i + \epsilon_i, \tag{3}$$

where $\theta_i \sim N(\alpha_0 + \sum_{k=1}^{K} \alpha_{1,n} X_{i,k}, \tau^2)$, $u_i \sim N(0, \tau^2)$ and $\epsilon_i \sim N(0, \sigma_i^2)$. $X_{i,k}$ is the kth variable that captures a relevant characteristic of the ith study which explains heterogeneity in the estimated effects; $\alpha_{1,k}$ denotes the coefficient to be estimated and K is the number of variables identified to explain heterogeneity. α_0 is the overall effect size after accounting for the other relevant characteristics $X_{i,k}$.

The presented empirical strategy suffers from the same limitation found in other meta-analyses. For the meta-analysis to be meaningful, the studies to be combined must be comparable in terms of study design, variables used, and other characteristics. One way to get around this, as suggested by Aloe and Becker (2012), is to encode a dummy variable that indicates the presence or absence of a specific covariate or set of covariates in the regression model. By coding the absence of a particular covariate or set of covariates as 0 and the presence as 1, and then performing a meta-regression using these indicator variables as predictors, the regression coefficient for the dummy variable indicates the sources of heterogeneity.

3.2 Publication Bias

It is likely that equation (3) suffers from publication bias which arises when journals and authors are more likely to publish studies that support a particular conclusion, i.e., estimates with the expected sign and significance. If only studies that show significant effects are included in the meta-analysis, personality traits may appear to be highly significant when in fact they may not be. As a result of publication bias, meta-analysis may overestimate the true impact of personality.

Publication bias is detected when the observed regression coefficient gets larger as the standard error increases, *ceteris paribus*. The fact that when samples are small and standard errors are larger, researchers are compelled to conduct a more thorough search of model specifications and econometric methodologies to find statistical significance, which explains for the positive correlation between the reported effects and their standard errors. They report larger estimates as a result; otherwise, their findings would not be statistically significant. In contrast, researchers with larger sample sizes and smaller standard errors are less likely to try different model specifications, and consequently settle for smaller estimated empirical effects. Another way to look at publication bias is as incidental truncation (Stanley and Doucouliagos, 2014), since only statistically significant estimates are reported or published.

To examine the publication bias, I follow Stanley and Doucouliagos (2012) and regress the collected regression coefficients on their corresponding standard errors. Then, Equation (3) becomes

$$\hat{\beta}_i = \alpha_0 + \sum_{k=1}^{K} \alpha_{1,k} X_{i,k} + \alpha_2 \sigma_i + u_i + \epsilon_i, \tag{4}$$

The regression test of Equation (4) is usually referred to as the Funnel Asymmetry Test Precision Effect Test (FAT-PET) method, first proposed by Egger et al. (1997).

If the intercept term α_2 is not statistically different from zero, the distribution of the regression coefficients is asymmetric, suggesting the presence of publication bias. In the presence of publication bias, $\alpha_2 > 0$ when the true value of beta is positive (e.g., as with Conscientiousness), and $\alpha_2 < 0$ when the true beta value is negative (e.g., as with Neuroticism) for θ_i to be overestimated.

Similar to Equation (2`), to account for heteroskedasticity, Equation (4) is weighted by the inverse-variance of the reported $\hat{\beta}_i$.

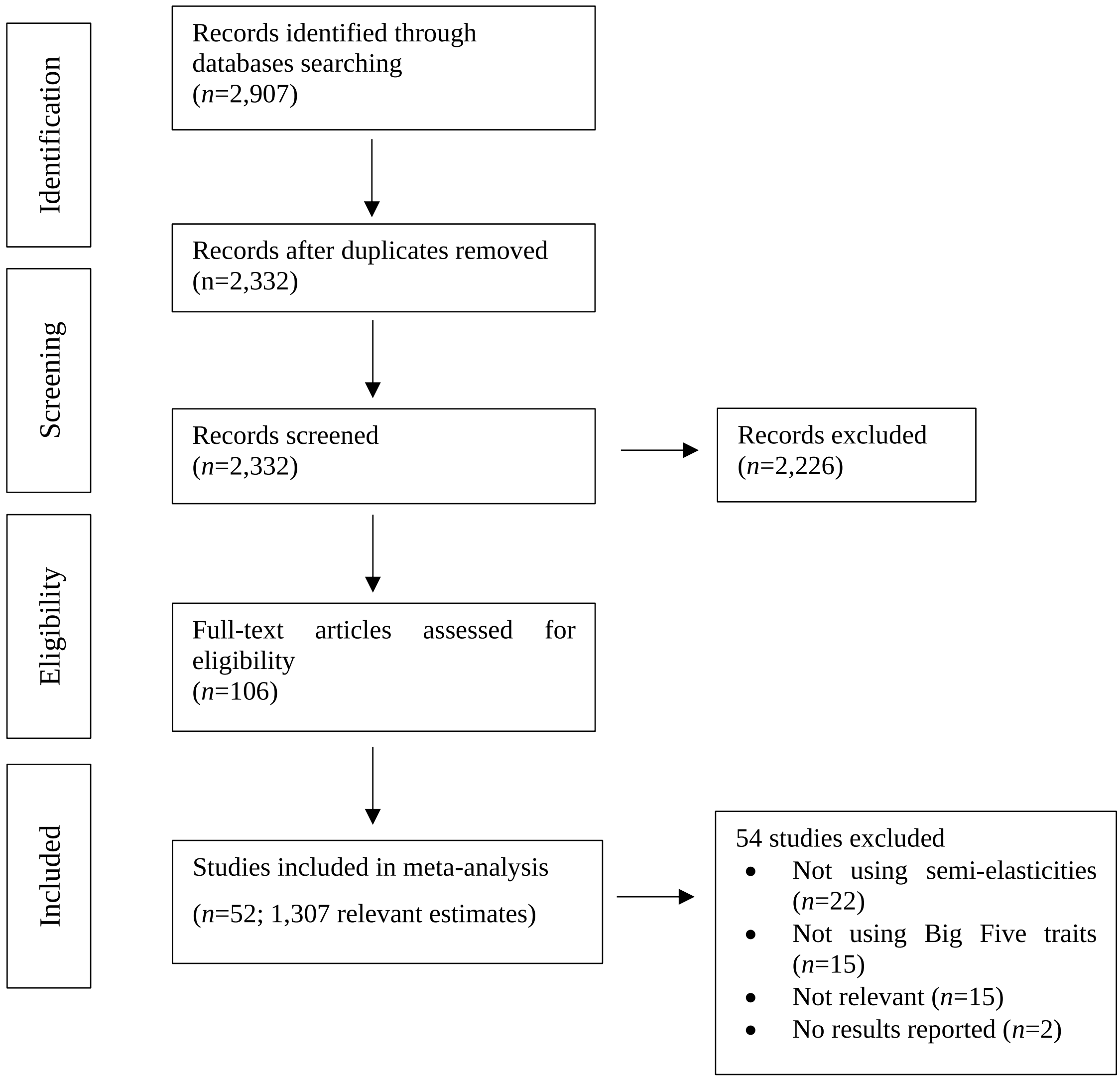
3.3 The Dataset

To construct the dataset used for meta-analysis I follow the reporting guidelines for meta-analysis in economics (Havránek et al., 2020; Moher et al., 2009). The meta-analysis includes studies that meet the following seven criteria: a) the study must examine the relationship between one's personality and earnings as the dependent variable; b) the study must include at least one empirical estimate that quantifies the effect of personality on the dependent variable using econometric analysis, eliminating theoretical studies or systematic reviews; c) the study should report the value of the standardised personality trait coefficient and its corresponding standard error (or t-statistic or p-value)[3]; d) only studies using the log-transformed estimation strategy as in Equation (1) were included; e) only studies using the Big Five traits were included, as they are widely used by economists as well as personality researchers; and f) the study was written in English.

Given the moderate number of available studies on earnings and the inclusion criteria identified above, I surveyed the literature in three steps. The chosen approach closely follows that of Havránek et al. (2020). I searched in eleven electronic databases (i.e., Business Source Complete, EconLit, Emerald, Google Scholar, JSTOR, RePEc, ScienceDirect, Scopus, ProQuest, PsychInfo, and Web of Science). The search was limited to publications in peer-reviewed journals to ensure quality control. Reference pyramid schemes were also employed to identify papers through the search engine process and extensive reading. The last literature search was carried out in April 2022. The following combinations of search terms were used in the electronic databases: "Big Five", "income", "earnings", "labour market outcomes", "non-cognitive skills", "non-cognitive abilities", "return to personality", "personality", "personality development", "personality traits", "salary", and "wages". The list of included studies refers to the Appendix. Figure 1 summarises the literature search and the screening procedure.

[3] Seven studies included in the meta-analysis do not report the relevant standard errors. The standard error is therefore obtained by dividing the value of the coefficient by the t-statistic. Seven studies report the p-value along with the sample size and number of explanatory factors included in the regression so that the corresponding standard error could be calculated.

Figure 1: Flow chart of the search and screening process



A total of 106 studies were identified. Then the list was narrowed down to 52 studies based on the defined inclusion criteria. As a result, the final dataset consists of 1,307 estimates. Each study included in the dataset contains a number of estimates for each personality trait that vary from 1 to 120. The reason why most of the included studies report more than one estimate relate to a sensitivity analysis. By way of example, different techniques allow authors to assess whether the magnitude of the regression coefficient remains valid using different empirical techniques. Some studies also test whether there are systematic coefficient differences between different groups or whether including some variables (e.g., family background) in the same study would affect the baseline results.

While it is standard practice to include all identified studies that meet the inclusion criteria, a major drawback is that multiple estimates from a single paper may be interdependent, violating the assumption of independence. For this reason, in the empirical strategy, I account for within-study dependency, by reporting clustered standard errors at the study level.

The table in the Appendix shows the studies included in the dataset that meet the inclusion criteria. For each study, I report information on the author(s), year of publication, year(s) of data collection, country(ies) coverage, and number of the effect sizes collected. It becomes clear that, despite the selection criteria, the regression coefficients are only comparable if exactly the same independent and dependent variables and estimation strategies were used.[4]

To start with, some studies use cross-sectional data and other panel data in different methods. Most studies use the (pooled) OLS method, while others use random effects and fixed effects. It is also clear that several studies in the dataset do not control for omitted variable bias. Other studies looking at endogeneity associated with personality use either instrumental variables (IV), correlated random effects, Hausman-Taylor IV, or within-group estimators.[5]

As already mentioned, several studies in the dataset test whether the overall association of personality with earnings holds after controlling for other explanatory variables. Education, cognitive ability, and family background stand out as the most evident control variables. I also collect information on the country coverage and gender in the selected studies. When there are confounding variables, like education, the regression coefficients need to be interpreted cautiously. Even though the majority of publications interpret the regression coefficient on personality trait as a direct effect, such an approach only offers a descriptive analysis unless the bias caused by the omitted variable is taken into account.

Finally, while some studies collect information about individuals' personality in the same wave as earnings, others use personality scores collected in childhood or just shortly before entering the labour market. This is because if personality traits are endogenous, it is appealing to lag personality traits by one or more periods. In the dataset, the time lag value from the outcome variable ranges from 0 to 65 years. The disadvantage of using lagged values is that in some cases it can lead to a loss of precision.

To construct the dataset, I collected from each study and for each personality trait the standardised regression coefficient and its respective standard error, sample size and degrees of freedom. I also coded variables for data type (cross-sectional or panel data), econometric method used (OLS or otherwise), empirical setting (age cohort, country coverage, sex), year of data used for income and personality traits, and dummy variables for the inclusion of theoretically relevant variables (cognitive abilities, education, occupation, family background), publication characteristics, and methodological dummies, one for endogeneity control and the use of factor score personality measures.

Table 1 shows all explanatory variables included in the multi-regression approach along with the mean of each personality trait. As expected, the averages are marked with the significant heterogeneity. For example, the earnings elasticity of Openness to Experience is positive for those of 35 or over and negative for those under 35.

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[4] For the purpose of constructing the dataset, Kindness and Cooperation have been coded as Agreeableness, Constructiveness as Conscientiousness, Sociability as Extraversion, Withdrawal, Aggression, the negative value of Emotional Stability as Neuroticism.

[5] Another issue affecting the effect of personality on wages is sample selection bias, as wage rates are observed only for individuals who have chosen to work. When the choice to employment is determined by unmeasured individual attributes that may also have influenced personality, the estimated coefficients are biased. Gelissen and de Graaf (2005) and Lenton (2014) use a two-stage Heckman estimator to account for bias in sample selection.

Table 1: Variable definitions and descriptive statistics

	Definition	O	C	E	A	N
Age Category						
Working Age	Study data is from population age more than 35	.028	.029	.011	-.029	-.033
Young	Study data is from population age less than 35	-.047	.117	.006	.003	-.061
Gender						
Not Controlled (Base Category)	Sample is mix	.024	.059	.014	-.024	-.052
Males	Sample is only males	.010	.021	.004	-.024	-.017
Females	Sample is only females	.010	.018	.008	-.022	-.030
Education Control						
No (Base Category)	No control for education	.033	.065	-.006	-.024	-.041
Yes	Controls for education	.014	.035	.016	-.024	-.037
Family Background Control						
No (Base Category)	No control for family background	.034	.050	.011	-.030	-.043
Yes	Controls for family background	.003	.035	.011	-.018	-.032
Occupation Control						
No (Base Category)	No control for occupation	.025	.054	.020	-.020	-.026
Yes	Controls for occupation	.011	.029	-.001	-.028	-.051
Cognition Control						
No (Base Category)	No control for cognitive ability	.027	.040	.015	-.021	-.047
Yes	Controls for cognitive ability	.007	.045	.006	-.027	-.026
Time Interval						
0 (Base Category)	No time lag	.021	.040	.010	-.026	-.039
1-65	With time lags	-.001	.055	.016	-.015	-.034
Unobserved Heterogeneity Controlled						
No (Base Category)	No control for unobserved heterogeneity	.020	.048	.016	-.026	-.040
Yes	Controls for unobserved heterogeneity	.007	.000	-.027	-.009	-.019
Use of Personality Factor Scores						
No (Base Category)	Uses average or sum of personality items	-.003	.038	-.003	-.026	-.037
Yes	Uses factor personality scores	.046	.049	.030	-.021	-.038
Data Type						
Cross-sectional Data (Base Category)	Uses cross-sectional data	.018	.043	.003	-.028	-.036
Panel Data	Uses panel data	.018	.041	.035	-.010	-.044
Country Coverage						
Europe, US (Base Category)	Country in Europe and US	.209	.407	.255	-.200	-.275
Australia	Australia	-.004	.021	.005	-.022	.000
Asia Pacific	Country in Asia Pacific region	.119	.018	-.025	-.051	-.187
World	Country, other than the above	-.041	.080	-.052	-.033	-.042
Publication Type						
Working Paper (Base Category)	Study published as a working paper	-.025	.053	-.024	-.026	-.031
Journal	Study published in a peer-reviewed journal	.033	.039	.022	-.023	-.040

Notes: O – Openness to Experience, C – Conscientiousness, E – Extraversion, A – Agreeableness, N – Neuroticism. Standard errors are reported in parentheses. Statistics give equal weight to each study.

4. RESULTS

4.1 Overall Effects

From the data collected, the estimation results of Equation (2`) are presented in Table 2.[6] I do not report results derived from the fixed-effect method because, unlike the random effects method, it assumes that all the heterogeneity can be explained by the covariates. The fixed-effect method results in excessive Type I errors when residual or unexplained heterogeneity is present.

The first column shows the main results using the restricted maximum likelihood (REML) method. It is clear from these results that the point estimate of the overall regression coefficients for all personality traits are highly statistically significant from zero (p-value < .0001). For Openness to Experience, a beta value of 0.019 indicates that a one standard deviation increase in Openness to Experience correlates with a 1.92% increase in earnings. Similarly, Conscientiousness (β=0.016, 1.61%) and Extraversion (β=0.003, 0.30%) are positively correlated with earnings, while Agreeableness (β=-0.017, -1.69%) and Neuroticism (β=-0.018, -1.78%) are negatively correlated.

Table 2: Overall effect sizes, random effects

	O	C	E	A	N
Effect Size	0.019***	0.016***	0.003*	-0.017***	-0.018***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
I^2 (%)	99.2%	99.3%	97.5%	98.3%	99.2%
Q-statistic	1926.60***	1216.05***	640.81***	1577.67***	7542.53***
N	216	231	245	246	246

Notes: O – Openness to Experience, C – Conscientiousness, E – Extraversion, A – Agreeableness, N – Neuroticism. The approach gives equal weight to each estimate. Standard errors are reported in parentheses, and clustered at the study level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

To account for the possibility that various effect estimates from the same study may be dependent, the robust estimate of variance (RVE) approach was also used. Dependent effects arise, for example, when effect sizes are nested or when multiple measures are collected for the same individuals. The overall earnings effects are similar to the main results across the Big Five traits and did not change remarkedly when assuming different values of the within-study effect size correlation.[7] In addition to this, four sensitivity analyses were performed to check the robustness of the REML results. The results are presented in the supplemental material.

The summary statistics also indicate significant heteroskedasticity in the results. Indeed, from the I^2 score more than 99% of total variation across studies is due to between-study variability rather than sampling error. The Q-statistic test, that is commonly used to test whether effect sizes are distributed around the mean, strongly reject the null hypothesis of no heterogeneity (p-value < .0001), and thus confirm the appropriateness of the random-effects model. Overall, the two tests decisively indicate that there is a lot of between-study variability in the regression coefficients and that the overall results of the meta-analysis may not be very reliable.

4.2 Publication Bias

In this study, I use Doi plots to visually assess publication bias. The Doi plot is constructed by serially ranking the reported coefficients of each study. However, instead of plotting the coefficients against the

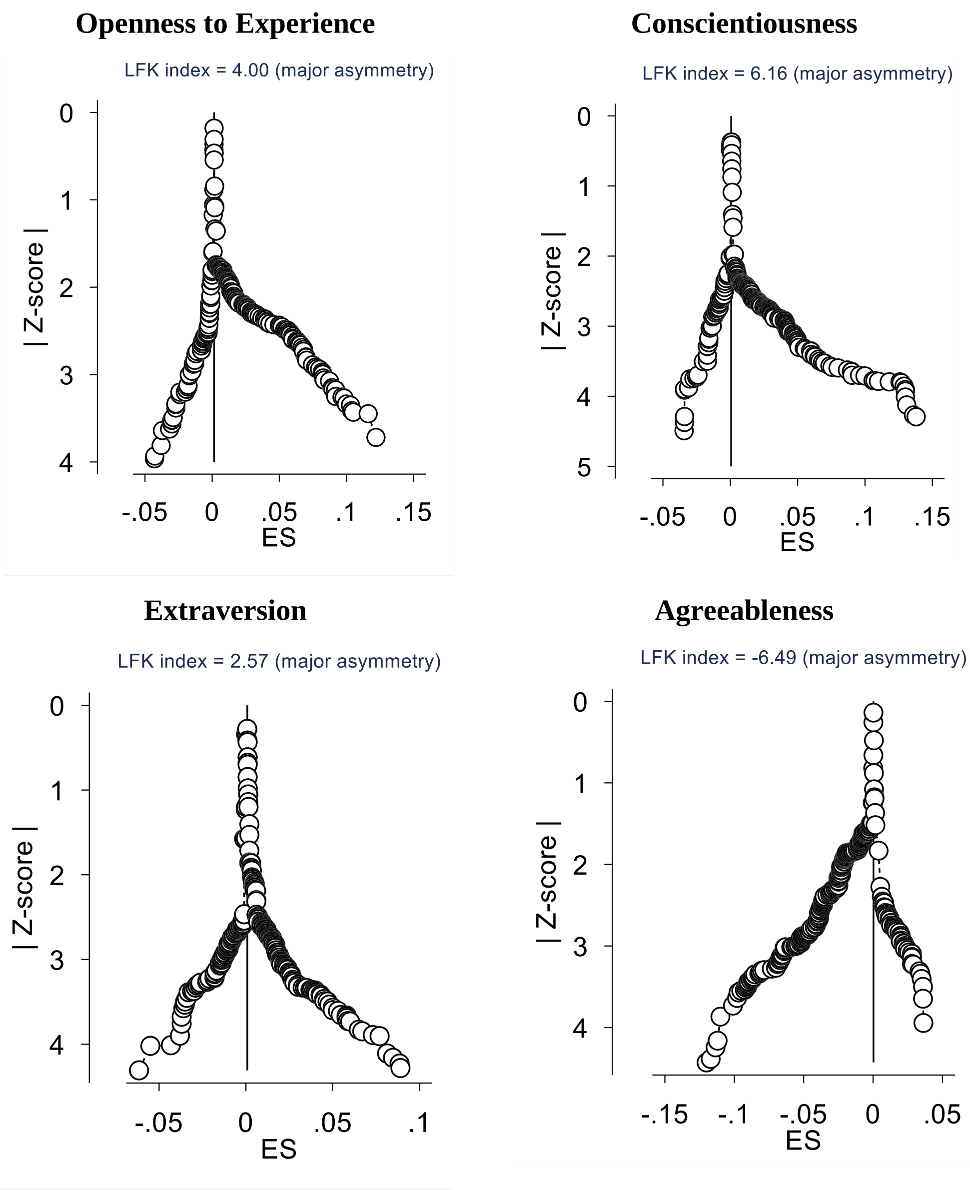
[6] Regression coefficients below the 5th percentile and above the 95th percentile are dropped in order to lessen the impact of outliers.

[7] For the RVE method, τ^2 was estimated using the method-of-moments.

sample size as in the funnel plot, the coefficients are plotted against a folded normal quantile (Z-score).[8] In the absence of publication bias, studies should be evenly distributed across the plot, with similar number of studies at each level of precision. When there is publication bias, we expect a disproportionate number of studies concentrated in the bottom-right or bottom-left quadrants of the plot, suggesting that studies with larger effect sizes and high precision are more likely to be published.

The Doi plots produced in Figure 2 show that the regression coefficients in the dataset are not evenly distributed across the plot. The LFK index exceeds the value of 2 for all Big Five traits, indicating the presence of strong publication bias.

Figure 2: Doi plots



[8] A detailed description of the Doi Plot is given in Furuya-Kanamori et al. (2018).

Neuroticism

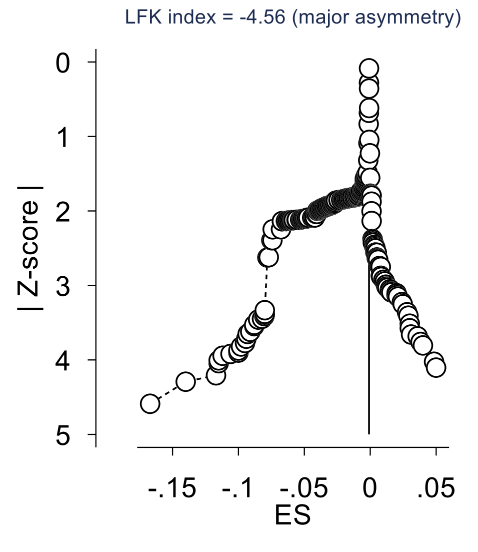


Table 3 shows the results of the FAT-PET regression based on Equation (4), initially without the covariates $X_{i,k}$. After accounting for the publication bias effect, the overall earnings effects are only statistically significant from zero for Openness to Experience and Agreeableness.

The test in Table 3 confirms the existence of publication bias for Conscientiousness, Agreeableness, and Neuroticism, and as a result, the overall regression coefficients presented in Table 2 are likely to have been overestimated due to publication bias.

Table 3: Publication Bias, FAT-PET

	O	C	E	A	N
Effect beyond bias (precision effect)	.015**	.006	.000	-.008**	-.006
	(.006)	(.004)	(.002)	(.004)	(.005)
Standard Error (publication bias)	.302	.906***	.386	-.786***	-1.007***
	(.201)	(.255)	(.231)	(.229)	(.275)
Adjusted R-sq	.275	.358	.063	.363	.366
N	216	31	245	246	245

Notes: O – Openness to Experience, C – Conscientiousness, E – Extraversion, A – Agreeableness, N – Neuroticism. The approach gives equal weight to each estimate. Standard errors are reported in parentheses, and clustered at the study level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Because studies with significant results are more likely to be published, the evidence of publication bias raises concerns that the results of the meta-analysis may not be representative of all the research that have been undertaken on the topic. In fact, if publication bias is not taken into account, it might result in misleading findings and inaccurate estimations of the effects of personality traits on earnings. To illustrate the impact of publication bias on the overall effect calculated from the meta-analysis, consider the meta-analysis on Conscientiousness. If publication bias is left unaddressed, a one standard deviation increase in Conscientiousness is correlated with a 1.16% increase in earnings. After accounting for publication bias, the effect drops to 0.60%.

One can conclude that most personality traits have little to no impact on earnings because of the modest and insignificant computed overall effects, however this conclusion must be approached with caution. The insignificance of the coefficients does not necessarily mean that personality traits are not valued in the labour market; on the contrary, heterogeneous effects can have compensating effects that hide the overall effect. Indeed, PET is known to perform poorly when there is large heterogeneity (I^2>80%)

(Stanley, 2017). For this reason, four additional tests were carried out in an effort to detect publication bias, in line with the methodology of recent studies. The results of these estimates are presented in the supplemental material. All methods confirm that the overall magnitude of the semi-elasticities is nearly zero, supporting the idea that the overall relationship for all personality traits is virtually zero after correcting for publication bias.

4.3 Heterogeneity

The next step is to identify the sources of the observed heterogeneity since I^2 was found to be very high. The main variables discussed in the literature are included in the earnings specification as per Equation (4). The results are shown in Table 4.

First, the results of the main model confirm the presence of publication bias as found in previous tests, since the standard error coefficients for all Big Five features are statistically significant at the 1% level.

Table 4: Explaining Heterogeneity in the Estimated Effects of Personality on Wages

	O	C	E	A	N
Constant	55.803***	-15.594**	-.994	-27.385***	-3.629
	(.176)	(.150)	(.128)	(.148)	(.161)
Standard Error	.361**	.838***	.535***	-.838***	-1.020***
	(.176)	(.150)	(.128)	(.148)	(.161)
Age Category	-.004	.015**	.017***	-.001	.014**
	(.176)	(.150)	(.128)	(.148)	(.161)
Males	-.000	-.000	-.005**	-.004	.009***
	(.176)	(.150)	(.128)	(.148)	(.161)
Females	.003	-.001	-.003	.000	.001
	(.176)	(.150)	(.128)	(.148)	(.161)
Education	-.020***	-.002	.007***	-.002	.009***
	(.176)	(.150)	(.128)	(.148)	(.161)
Family Background	-.011**	-.007**	.000	.002	.017***
	(.176)	(.150)	(.128)	(.148)	(.161)
Occupation controlled	.002	-.013***	-.005**	.001	-.002
	(.176)	(.150)	(.128)	(.148)	(.161)
Cognitive ability controlled	-.004	.011***	.001	-.004	.002
	(.176)	(.150)	(.128)	(.148)	(.161)
Time Lag	-.016*	-.005	-.019***	.024***	-.004
	(.176)	(.150)	(.128)	(.148)	(.161)
UH controlled	-.020***	-.007	-.001	.007	.002
	(.176)	(.150)	(.128)	(.148)	(.161)
OLS method	-.024***	-.009*	-.001	-.001	-.007
	(.176)	(.150)	(.128)	(.148)	(.161)
Measurement error controlled	.001	.008**	.001	-.001	.011***
	(.176)	(.150)	(.128)	(.148)	(.161)
Panel Data	.004	.007*	-.003	-.005	-.023***
	(.176)	(.150)	(.128)	(.148)	(.161)
Australia	.004	.004	-.004	-.013**	.001
	(.176)	(.150)	(.128)	(.148)	(.161)
Asia Pacific	-.001	.025***	.008	.023***	.022***
	(.176)	(.150)	(.128)	(.148)	(.161)
World (Other)	.036***	-.003	-.001	-.002	-.005
	(.176)	(.150)	(.128)	(.148)	(.161)
Journal	-.001	-.004	-.004*	.005	.006
	(.176)	(.150)	(.128)	(.148)	(.161)

	O	C	E	A	N
Pub Year (logs)	-7.328***	2.051**	.132	3.599***	.477
	(.176)	(.150)	(.128)	(.148)	(.161)
N	216	231	245	248	245
R-sq	0.494	0.560	0.510	0.527	0.599

Notes: O – Openness to Experience, C – Conscientiousness, E – Extraversion, A – Agreeableness, N – Neuroticism. The approach gives equal weight to each estimate. Standard errors are reported in parentheses, and clustered at the study level. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Second, the set of demographic variables supports the finding that studies using populations under 35 years of age indicate higher wage effects for Extraversion and Conscientiousness and that the wage penalty is higher for Neuroticism among populations over 35. The results do not confirm that personality returns are stable over an individual's career, just that there is no apparent difference between studies that restrict their sample to young people and studies that use a broader age definition of the working-age population, with exception a few traits. In addition, gender does not appear to predict variability in effect size for most personality traits, suggesting that relationships are robust and apply to both males and females. However, compared to studies utilising both male and female samples, studies using solely male samples find a lower Neuroticism penalty on earnings. Compared to studies that do not differentiate between men and women, studies tend to indicate lower wage elasticities for Extraversion.

The third set of variables relates to the individual's socioeconomic status and family background. The meta-regression results show that studies that do not control for educational attainment are overestimating the effect of Openness to Experience on earnings, everything else remaining constant. I also find that studies that control for education, report higher wage elasticities for Extraversion and lower penalty for Neuroticism. It should be emphasised that the purpose of this meta-analysis is not to examine the confounding effect of education on the personality-income relationship, but merely to explain the heterogeneity in the estimated semi-elasticities. The results of the model are in line with my expectations, since Openness to Experience is the personality trait most relevant to educational success, whereas Neuroticism is generally associated with poorer performance in achievement tests.

The results of the mega-regression demonstrate that family background affects the link between the Big Five traits and earnings. The findings in particular demonstrate that studies that exclude family background factors from the earnings equation (such as parental education, household income, and parents' occupation) are likely to overestimate the earnings effect of Openness to Experience, Conscientiousness, and Neuroticism. This could imply that individuals with high socioeconomic status have higher aspirations for their education and careers, and better access to other opportunities that enable them to progress. The development of a person's personality is also likely to be influenced by their familial history, especially when they are young, and in turn affect the association between personality traits and earnings.

Another important source of variation in empirical results is cognitive ability. I find that studies that control for cognitive ability produce a higher wage effect for Conscientiousness than studies that do not control for it, everything else remaining constant. The result is consistent with other studies and implies that people who score high in Conscientiousness tend to also score lower on measures of cognitive ability. This suggests that while people with high ability levels have greater intelligence, memory, and attention skills, they are also less likely to be well-organised and hard-working. Having said that, Conscientiousness can also influence a person's motivation or engagement with the tasks on an IQ test, which can have an indirect impact on IQ scores. This demonstrates that studies that do not account for ability suffer from an omitted variable bias.

The results of the meta-regression further support the idea that occupation significantly contributes to the account of some of the heterogeneity in empirical findings, particularly for Extraversion and Conscientiousness. The confirmation of the significance of occupation lends weight to the idea that a person's personality traits can influence the job choices they make.

Along with the above, I also assess whether the use of different econometric techniques, type of data collected, and publication characteristics can be significant sources of variation in empirical results. I compare research that simultaneously measure personality traits and the outcome (no time lag is the bas category) with studies that have a positive time lag between the personality traits and the outcome variable. The findings indicate that only Extraversion and Agreeableness show systematic variations for time lags. The econometric techniques adopted by researchers in an effort to quantify the relationship between personality traits and incomes are less conclusive. But in this case, a word of caution is necessary. Since almost 80% of the studies in the dataset employ an OLS approach that does not account for unobserved heterogeneity, the dataset's limited sample size prevents a thorough evaluation of the effects of various study design methods.

I also find that studies that report factor scores rather than sum or average of the items reveal different wage elasticities for Conscientiousness and Neuroticism, everything else remaining constant. Furthermore, in studies of Asian populations compared to studies of American and European populations, Conscientiousness has higher wage effects whereas Agreeableness and Neuroticism have less negative wage effects. Comparatively to the base category, research of the Australian population indicates a larger penalty for Agreeableness. In addition, the year of publication has a systematic effect on the reported effects. Recently published literature report higher wage elasticities with respect to Conscientiousness and Agreeableness and lower elasticity with respect to Openness to Experience and Agreeableness.

Equation (4) was re-estimated using seven distinct strategies to assess the robustness of the regression coefficients obtained from the main model. The findings broadly corroborate the findings of Table 4, with the discrepancies being negligibly small. The multicollinearity is not overly high, according to the sensitivity analysis. In the supplemental material, the findings are covered in greater detail.

5. CONCLUSION

The paper evaluates the sparse but expanding body of research on how personality affects earnings. The recent surge in research on personality traits is motivated by the growing association of non-cognitive skills with life outcomes. In economics, it is still unclear which personality traits influence wages, to what extent, and in what ways. This is due in part to the complexity of personality traits, which can be influenced by many factors and also affect life outcomes. Therefore, it is important to understand if personality traits are related to earnings and what explains the disparate empirical findings within- and between-studies. The goal of this work was to employ meta-analysis methods to find a solution to this lack of clarity and to test if omitting important explanatory variables results in biased estimates.

The overall wage effects of personality traits suggest that Openness to Experience and Conscientiousness are positively related to wages, Extraversion is also positively but weakly related, while Agreeableness and Neuroticism are negative related to wages. However, once publication bias is taken into account, both the magnitude and significance of the earnings effects decrease, particularly for Openness to Experience, Agreeableness, and Neuroticism. This finding is supported by a number of robustness tests, and none of them contradict the main conclusions.

Given the intense interest in the subject and the intuitively appealing notion that personality traits are related to academic success, it is critical to explore why the estimated effects of personality traits are small. One explanation is that the reported semi-elasticities for each of the Big Five traits show significant heterogeneity. Another possibility is that studies that found modest personality effects were tainted by measurement problems.

Overall, the results of the meta-regression analysis reveal the main sources of between-study variation in the estimated effect of each personality trait. The most important factors appear to be socioeconomic characteristics. In particular, the effect of Extraversion is increased while the effects of Openness to Experience and Neuroticism are decreased when education is excluded from the specification. The return to Openness to Experience and Conscientiousness is likewise increased and the penalty of Neuroticism is increased when family-related variables are excluded. In addition, controlling for occupation decreases returns from Conscientiousness, while keeping cognitive ability out of the model increases Conscientiousness's impact. The results suggest that personality traits may be susceptible to omitted variable bias, and caution should be exercised in interpreting the regression coefficients. In particular, the meta-regressions confirm that the Big Five traits are contextual constructs and special care needs to be taken into account when developing an identification strategy.

The results of the meta-analysis point in several ways where future research should go to better understand personality and labour market outcomes. First, since too many studies simply rely on self-reported scores, future research in economics needs to supplement self-reports of personality traits with alternative measures. For example, replicating the analysis with informant data or data that was not gathered very late in the career would tremendously help the literature. The presented meta-analysis also relies far too heavily on research from the United States or Europe. Studies from other continents may be helpful in evaluating how generalisable and really universal the results are.

Future studies can substantially benefit from knowing the underlying mechanism of personality formation, given that socioeconomic factors are significant contributors of heterogeneity in the empirical effects. It is still not clear if individuals create environments that suit their personalities or if personality can change depending on the environmental factors. Therefore, more research on personality development is required because, if personality traits are the result of previous interactions, they might serve as important confounders of life outcomes, along with genes, experiences, and other factors like cognitive ability.

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Appendix

Table: Number of estimates for each study

Study (Author(s) and year of publication)	Study Title	Country	O	C	E	A	N
Acosta et al. (2015)	Beyond Qualifications: Returns to Cognitive and Socio-Emotional Skills in Colombia	Colombia	7	7	7	7	7
Averett et al. (2018)	Behind Every High Earning Man Is a Conscientious Woman: A Study of the Impact of Spousal Personality on Wages	Australia	20	20	20	20	20
Averett et al. (2020)	Behind Every High Earning Man is a Conscientious Woman: The Impact of Spousal Personality on Earnings and Marriage	Australia	4	4	4	4	4
Brenzel and Laible (2016)	Does Personality Matter? The Impact of the Big Five on the Migrant and Gender Wage Gaps	Germany	4	4	4	4	4
Bühler et al. (2020)	Occupational Attainment and Earnings in Southeast Asia: The Role of Non-cognitive Skills	Thailand Vietnam	3	3	3	3	3
Collischon (2020)	The Returns to Personality Traits Across the Wage Distribution	Germany	3	3	3	3	3
Cubel et al. (2016)	Do personality traits affect productivity? evidence from the laboratory	UK	4	4	4	4	4
Cunningham et al. (2016)	Cognitive and Non-Cognitive Skills for the Peruvian Labor Market	Peru	1	1	1	2	1
Damian et al. (2015)	Can Personality Traits and Intelligence Compensate for Background Disadvantage? Predicting Status Attainment in Adulthood	United States of America	2	2	2	2	2
Denissen et al. (2017)	Uncovering the Power of Personality to Shape Income	Germany	1	1	1	1	1
Díaz et al. (2013)	Does Perseverance Pay as Much as Being Smart?: The Returns to Cognitive and Non-cognitive Skills in urban Peru	Peru	4	4	4	8	4
Drydakis (2013)	The Effect of Sexual Activity on Wages	Greece	3	3	3	3	3
Duckworth and Weir (2010)	Personality, lifetime earnings, and retirement wealth	United States of America	1	1	1	1	1
Duckworth et al. (2012)	Who does well in life? Conscientious adults excel in both objective and subjective success	United States of America	1	1	1	1	1
Fletcher (2013)	The effects of personality traits on adult labor market outcomes: Evidence from siblings	United States of America	7	7	7	7	7
Flinn et al. (2018)	Personality traits, intra-household allocation and the gender wage gap	Australia	2	2	2	2	2
Flinn et al. (2020)	Personality Traits, Job Search and the Gender Wage Gap	Germany	4	4	4	4	4
Gelissen and Graaf (2006)	Personality, social background, and occupational career success	Netherlands	3	3	3	3	3
Hagmann-von Arx et al. (2016)	Testing relations of crystallized and fluid intelligence and the incremental predictive validity of conscientiousness and its facets on career success in a small sample of German and Swiss workers	Germany/Switzerland	0	1	0	0	0
Hamilton et al. (2019)	The right stuff? Personality and entrepreneurship	United States of America	2	2	2	2	2
Heineck (2011)	Does it pay to be nice? personality and earnings in the united kingdom	United Kingdom	24	24	24	24	24
Heineck and Anger (2010)	The returns to cognitive abilities and personality traits in Germany	Germany	8	8	8	8	8
John and Thomsen (2013)	Heterogeneous returns to personality: the role of occupational choice	Germany	16	16	16	16	16
Judge et al. (2012)	Do Nice Guys—and Gals—Really Finish Last? The Joint Effects of Sex and Agreeableness on Income	United States of America	6	6	6	6	6
Kajonius and Carlander (2017)	Who gets ahead in life? Personality traits and childhood background in economic success	Sweden	1	1	1	1	1
Lee and Ohtake (2018)	The Effect of Personality Traits and Behavioral Characteristics on Schooling, Earnings and Career Promotion	Japan	16	16	16	16	16
Lenton (2014)	Personality Characteristics, Educational Attainment and Wages: An Economic Analysis Using the British Cohort Study	United Kingdom	4	4	4	4	4

Maczulskij and Viinikainen (2018)	Is personality related to permanent earnings? evidence using a twin design	Finland	0	0	15	15	15
Maksimova (2019)	The return to non-cognitive skills on the Russian labor marke	Russia	12	12	12	12	12
Mohammed et al. (2021)	Gender Differences in Earnings Rewards to Personality Traits in Wage-employment and Selfemployment Labour Markets	Ghana	9	9	9	9	9
Mueller and Plug (2006)	Estimating the effect of personality on male and female earnings	USA	12	12	12	12	12
Nordman et al (2018)	Skills, personality traits, and gender wage gaps: evidence from Bangladesh	Bangladesh	4	4	4	4	4
Nyhus and Pons (2005)	The effects of personality on earnings	Netherlands	0	6	6	6	6
Nyhus and Pons (2012)	Personality and the gender wage gap	Netherlands	4	4	4	4	4
O'Connell and Sheikh (2011)	'Big Five' personality dimensions and social attainment: Evidence from beyond the campus	United Kingdom	2	2	2	2	2
Osborne Groves (2005)	How important is your personality? labor market returns to personality for women in the US and UK	USA	0	0	0	0	2
Otten (2020)	Gender-Specific Personality Traits and Their Effects on the Gender Wage Gap: A Correlated Random Effects Approach using SOEP Data	Germany	4	4	4	4	4
Palczynska (2021)	Wage premia for skills: the complementarity of cognitive and non-cognitive skills	Poland	6	6	6	6	6
Prevoo and ter Weel (2015)	The importance of early conscientiousness for socio-economic outcomes: Evidence from the British Cohort Study	United Kingdom	0	8	8	8	8
Risse et al. (2018)	Personality and pay: Do gender gaps in confidence explain gender gaps in wages?	Australia	3	3	3	3	3
Sahn and Villa (2016)	Labor Outcomes during the Transition from Adolescence to Adulthood: The Role of Personality, Cognition, and Shocks in Madagascar	Madagascar	8	8	8	8	8
Schafer and Schwiebert (2018)	The impact of personality traits on wage growth and the gender wage gap	Germany	4	4	4	4	4
Scholz and Sicinski (2013)	Facial attractiveness and lifetime earnings: Evidence from a cohort study	United States of America	4	4	4	4	4
Seibert and Kraimer (2001)	The Five-Factor Model of Personality and Career Success	United States of America	1	1	1	1	1
Semeijn et al. (2020)	Personality Traits and Types in Relation to Career Success: An Empirical Comparison Using the Big Five	Netherlands	1	1	1	1	1
Shanahan et al. (2014)	Personality and the reproduction of social class	United States of America	1	1	1	1	1
Shi and Moody (2017)	Most likely to succeed: Long-run returns to adolescent popularity	United States of America	1	1	1	1	1
Viinikainen et al. (2010)	Personality and labour market income: Evidence from longitudinal data	Finland	4	6	8	4	4
Viinikainen et al. (2014)	Labor market performance of dropouts: the role of personality	Finland	0	0	0	0	2
Wichert and Pohlmeier (2010)	Female labor force participation and the big five	Germany	3	3	3	3	3
Williams and Gardiner (2018)	The power of personality at work: Core self-evaluations and earnings in the United Kingdom	UK	1	1	1	1	1
Yu et al. (2017)	Effect of cognitive abilities and non-cognitive abilities on labor wages: empirical evidence from the Chinese Employer-Employee Survey	China	3	3	3	3	3
Total			238	255	271	272	271

Notes: O – Openness to Experience, C – Conscientiousness, E – Extraversion, A – Agreeableness, N – Neuroticism

SUPPLEMENTAL MATERIAL

Appendix A

Robustness Tests for Overall Effects

Table A.1 lists two additional heterogeneity statistics that supplement the results using the restricted maximum likelihood (REML) method, as shown in Table 2 of the main text.

To determine whether effect sizes are distributed symmetrically or asymmetrically, the Q-statistic is often used. The test is performed under the null hypothesis that there is no heterogeneity. The existence of heterogeneity between the studies can also be deduced from the statistic I^2.[9] The derived indices demonstrate that more than 99% of the variability in the effect size estimates is due to differences between studies and not to sample variations, and that the semi-elasticities are marked by significant heterogeneity.

The prediction interval is the range within which a hypothetical new study's effect size would fall if it were chosen at random from the same population of studies included in the meta-analysis. When there is significant heterogeneity, the prediction intervals are anticipated to be wider than the summary effect size's 95% confidence interval.[10] According to the extracted results, the larger range in the prediction interval supports the existence of heterogeneous effects due to factors other than within-study variance.

Four additional sensitivity analyses were performed to check the robustness of the REML results. All methods use different algorithms to estimate between-study variance, τ^2.

First, three different random effects estimators – Sidik-Jonkman, DerSimonian-Laird, and Paule-Mandel – are used to calculate the overall effect sizes, or semi-elasticities. The iterative methods REML and Paule-Mandel make the assumption that the distribution of random effects is normally distributed. On the other hand, no distributional assumptions about random effects are made by the Sidik-Jonkman and DerSimonian-Laird estimators. For large between-study variance, the Sidik-Jonkman and Paule-Mandel estimators are the best estimators in terms of bias. When variability is high and the number of studies is low, the DerSimonian-Laird estimator may underestimate τ^2. However, DerSimonian-Laird estimator is more efficient than Sidik-Jonkman when the variability is not large and the studies are of comparable size. Overall, they all support the existence of significant variability between studies.

The Hartung-Knapp adjustment to the overall effect size's standard error was also used to confirm the results. When assessing the overall effect sizes and their confidence intervals, the Hartung-Knapp adjustment uses the *t*-distribution rather than the standard normal distribution. Regardless, I still conclude that the derived overall effect sizes are statistically significant.

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[9] Ranges for interpreting I^2 are as follows: (i) 0% to 40%: heterogeneity may not be important; (ii) 30% to 60%; may represent moderate heterogeneity; (iii) 50% to 90% may represent substantial heterogeneity; and (iv) 75% to 100% considerable heterogeneity.

[10] The prediction interval is typically interpreted as the uncertainty we expect in the summary effect when a new study is included in the meta-analysis.

Table A.1: Summary statistics of the overall estimation results

	Restricted Maximum Likelihood (1)	Sidik-Jonkman (2)	DerSimonian and Laird (3)	Paule-Mandel (4)
Openness to Experience				
Effect size (SE) [p-value]	0.019 (0.002) [0.000]	0.019 (0.002) [0.000]	0.015 (0.001) [0.000]	0.019 (0.002) [0.000]
95% Confidence Interval	[0.015, 0.023]	[0.015, 0.023]	[0.010, 0.028]	[0.015, 0.023]
Q-statistic [p-value]	1926.60 [0.000]	1926.60 [0.000]	1926.60 [0.000]	1926.60 [0.000]
I2 (%)	99.23	99.23	88.84	99.13
95% Prediction interval	[-0.032, 0.070]	[-0.035, 0.073]	[0.001, 0.028]	[-0.032, 0.070]
Conscientiousness				
Effect size (SE) [p-value]	0.016 (0.002) [0.000]	0.017 (0.002) [0.000]	0.007 (0.001) [0.000]	0.016 (0.002) [0.000]
95% Confidence Interval	[0.013, 0.020]	[0.013, 0.021]	[0.006, 0.008]	[0.013, 0.020]
Q-statistic [p-value]	1216.05 [0.000]	1216.05 [0.000]	1216.05 [0.000]	1216.05 [0.000]
I2 (%)	99.28	99.57	81.12	99.38
95% Prediction interval	[-0.024, 0.056]	[-0.034, 0.069]	[-0.000, 0.014]	[-0.027, 0.059]
Extraversion				
Effect size (SE) [p-value]	0.003 (0.001) [0.001]	0.004 (0.001) [0.004]	0.002 (0.000) [0.000]	0.004 (0.001) [0.001]
95% Confidence Interval	[0.001, 0.005]	[0.001, 0.007]	[0.001, 0.003]	[0.001, 0.006]
Q-statistic [p-value]	640.81 [0.000]	640.81 [0.000]	640.81 [0.000]	640.81 [0.000]
I2 (%)	97.5	99.17	62.05	98.41
95% Prediction interval	[-0.016, 0.022]	[-0.029, 0.037]	[-0.002, 0.006]	[-0.020, 0.028]
Agreeableness				
Effect size (SE) [p-value]	-0.017 (0.002) [0.000]	-0.018 (0.002) [0.000]	-0.013 (0.001) [0.000]	-0.018 (0.002) [0.000]
95% Confidence Interval	[-0.021, -0.014]	[-0.022, -0.014]	[-0.015, -0.012]	[-0.021, -0.014]
Q-statistic [p-value]	1577.67 [0.000]	1577.67 [0.000]	1577.67 [0.000]	1577.67 [0.000]
I2 (%)	98.26	98.94	84.31	98.53
95% Prediction interval	[-0.057, 0.022]	[-0.069, 0.032]	[-0.025,-0.001]	[-0.060, 0.025]
Neuroticism				
Effect size (SE) [p-value]	-0.018 (0.002) [0.000]	-0.026 (0.004) [0.000]	-0.016 (0.001) [0.000]	-0.018 (0.002) [0.000]
95% Confidence Interval	[-0.023, -0.017]	[-0.023, -0.015]	[-0.018, -0.014]	[-0.022, -0.015]
Q-statistic [p-value]	7542.53 [0.000]	7542.53 [0.000]	7542.53 [0.000]	7542.53 [0.000]
I2 (%)	99.16	99.45	96.78	99.3
95% Prediction interval	[-0.062, 0.026]	[-0.073, 0.035]	[-0.038, 0.007]	[-0.066, 0.030]

Notes: O – Openness to Experience, C – Conscientiousness, E – Extraversion, A – Agreeableness, N – Neuroticism. REML is the method of estimation of the between-study component of variance τ^2. The Q-statistic follows a χ^2 distribution with *N-1* degrees of freedom with *N* being the number of effect sizes. Hartung-Knapp standard errors are reported in round parentheses, and p-value in square brackets.

Appendix B

Robustness Tests for Publication Bias

Stanley (2017)'s Weighted Average of Adequately Powered (WAAP) estimator is used in the first sensitivity test. The WAAP calculates the unrestricted WLS-weighted average of the estimates that have reasonable statistical power. If the standard error of the estimates is smaller than the WLS estimate divided by 2.8, then the estimates have reasonable statistical power (80% or higher). This strategy's biggest drawback is that the majority of meta-analyses frequently do not contain studies with enough power. With the exception of Openness to Experience and Neuroticism, no studies with adequate validity were identified in this case.

The second approach only uses the fixed effect method for the 10% of reported estimates that are the most precise (have the smallest standard error). The most accurate estimates are less likely to be affected by selection bias or small sample size bias, which is one of the motivations for this method (Stanley, Jarrell, and Doucouliagos, 2010). According to the Top 10% method, the average effect is essentially negligible.

In the third approach, the Endogenous Kink (EK) method by Bom and Rachinger (2019) is used. The Precision-Effect Test and Precision-Effect Estimate with Standard Errors (PET-PEESE) technique is built upon and improved by the EK estimator, which aims to better account for the non-linearity of the relationship between the estimated effect and the standard error in the presence of publication bias. The rationale behind this methodology is that when the standard error is very small, there is no publishing bias, and selective publication increases with standard error. By estimating the endogenous cut-off value, the approach may determine when publication bias starts to take place when the standard error rises above that threshold. After accounting for publication bias, the results presented in Table B.1 confirm the claim that there is almost no correlation between personality traits and earnings in general. This relationship between personality traits and wages is almost zero.

In addition to the above, I also use the AK estimator by Andrews and Kasy (2019). To account for publication bias, this technique employs two strategies. With the symmetric estimator (AK1), the relative probability that an estimate will be published depends on whether it is statistically significant. In contrast, the asymmetric estimator (AK2) addresses the selective publication brought on by both the statistical significance and the sign of the estimates. The findings in Table B.1 demonstrate that the effect of personality traits on earnings is also very small.

I also compare the results of two sets of specifications, one of which weights each estimate equally – giving the findings of studies with more estimates reported greater weight – and the other of which weights each study equally. The outcomes are largely the same as when each estimate is given equal weight.

Table B.1: Bias-Adjusted Mean Effects with Modern Methods

	Mean Effect	Standard Error
Openness to Experience		
WAAP	0.001***	0.000
Top 10%	0.001***	0.000
EK	0.001***	0.000
AK (symmetric)	0.012	0.019
AK (asymmetric)	0.001***	0.000
Conscientiousness		
WAAP	N/A	N/A
Top 10%	0.000	0.001
EK	0.000	0.000
AK (symmetric)	0.008***	0.003
AK (asymmetric)	0.000	0.000
Extraversion		
WAAP	N/A	N/A
Top 10%	0.000	0.000
EK	0.000	0.000
AK (symmetric)	0.001	0.001
AK (asymmetric)	-0.002	0.003
Agreeableness		
WAAP	N/A	N/A
Top 10%	-0.000	0.001
EK	0.001**	0.000
AK (symmetric)	-0.012***	0.002
AK (asymmetric)	-0.003	0.003
Neuroticism		
WAAP	-0.001***	0.000
Top 10%	-0.001***	0.000
EK	-0.002	0.002
AK (symmetric)	-0.001***	0.000
AK (asymmetric)	-0.001***	0.000

Notes: *, **, and *** denote statistical significance at 10, 5, and 1%, respectively.

Appendix C

Robustness Tests for Meta-Regression

The random effects meta-regression is based on the assumption that the control variables explain only part of the heterogeneity, and a random-effects component is used to account for the remaining variance. It has been recognised that the WLS method with weights equal to the inverse of each estimate's standard error is preferred to the random effects method when there is publication bias and large heterogeneity (Stanley and Doucouliagos, 2016). The results of the WLS method are broadly consistent with those of the REML estimation method.

In a second check, I assess the sensitivity of the REML results by computing the standard errors using the Hartung-Knapp method. When determining a confidence interval for the true effect size, the Hartung-Knapp technique substitutes quantiles of the *t*-distribution for the normal distribution. As it provides a more accurate confidence interval for the average effect, the Hartung-Knapp approach is viewed as a significant improvement over the more conventional method. The results are essentially unchanged.

The validation of the model specification is tested in the following two tests. Because there are uncertainties about the true model for the estimates in Table 4 and because the large number of meta-regression variables, which can lead to multicollinearity, I use the Bayesian Model Averaging (BMA) and Weighted Average Least Squares (WALS) routines to remove any ambiguity regarding the specification of the meta-regression model. The BMA technique evaluates the degree of uncertainty related to the model specification and can be used to rank several model specifications in terms of relevance. It then gives weights to those models depending on how well they match the data, allowing it to identify which model specifications are not supported by the data. It estimates the model specification using all conceivable combinations of control variables. The posterior model probabilities (PIP), which assess each control variable's significance, are the weights used in BMA. In addition, the WALS estimator introduced by Magnus, Powell, and Patricia (2010) is a Bayesian combination of frequentist estimators and has advantages over other model averaging methods.[11] Overall, the main model's results largely support those of the BMA and WALS (Table C.1).

In the final robustness test, I replace the country selection variable with a dummy that takes the value one if the study uses an anglophone sample (e.g., Great Britain, United States of America, Australia). The results indicate that studies using English-speaking samples record higher returns on Conscientiousness and a stronger penalty on Agreeableness. I also ran a separate mega-regression which tests if the outcome measured, be it wages, salaries, earnings or income, has an effect on the overall effects. This control is important because depending on whether wages, earnings, or salaries are recorded, the amount of the regression coefficient can change. The results of both tests validate the results of the main model. This is in agreement with Alderotti, Rapallini and Traverso (2021).

[11] See Magnus and De Luca (2016) for more details.

Table C.1: Robustness Tests

	BMA					WALS				
	O	C	E	A	N	O	C	E	A	N
Standard Error	0.252	0.737***	0.363***	-0.389***	-0.920***	0.245**	0.619***	0.282***	-0.327***	-0.814***
	(0.166)	(0.108)	(0.081)	(0.084)	(0.151)	(0.103)	(0.105)	(0.078)	(0.081)	(0.146)
	[0.779]	**[1]**	**[0.999]**	**[0.999]**	**[1]**	**(2.390)**	**(5.910)**	**(3.633)**	**(-4.036)**	**(-5.571)**
Age Category	-0.001	0.005	0.017***	0.000	0.009	-0.000	0.008	0.013***	-0.000	0.017**
	(0.005)	(0.006)	(0.004)	(0.002)	(0.011)	(-0.038)	(1.094)	(3.245)	(-0.066)	(2.552)
	[0.085]	**[0.493]**	**[0.996]**	[0.054]	**[0.462]**	(0.050)	**(1.133)**	**(3.240)**	(-0.140)	**(2.536)**
Only male sample	-0.000	0.000	-0.001	-0.000	0.001	-0.001	0.001	-0.002	-0.001	0.004*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
	[0.055]	[0.056]	[0.225]	[0.09]	[0.286]	(-0.201)	(0.225)	**(-1.256)**	(-0.523)	**(1.733)**
Only female sample	0.000	-0.000	0.000	0.000	-0.001	0.000	-0.001	-0.000	0.001	-0.002
	(0.001)	(0.001)	(0.000)	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
	[0.058]	[0.062]	[0.057]	[0.06]	[0.164]	(0.162)	(-0.354)	(-0.166)	(0.542)	(-0.755)
Education	-0.022***	-0.000	0.000	0.000	0.014***	-0.019***	-0.003	0.004*	0.002	0.014***
	(0.004)	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)
	[1]	[0.083]	[0.125]	[0.069]	**[0.993]**	(-4.367)	**(-1.044)**	**(1.884)**	(0.688)	**(4.236)**
Family Background	-0.004	-0.000	-0.000	-0.000	0.018***	-0.008**	-0.002	0.000	0.001	0.013***
	(0.005)	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)
	[0.445]	[0.065]	[0.07]	[0.054]	**[1]**	**(-2.071)**	(-0.541)	(0.084)	(0.274)	**(4.220)**
Occupation	0.000	-0.012***	-0.000	0.000	-0.001	0.003	-0.011***	-0.004	0.001	-0.001
	(0.001)	(0.003)	(0.001)	(0.001)	(0.002)	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)
	[0.066]	**[0.993]**	[0.079]	[0.06]	[0.128]	(0.803)	**(-3.903)**	**(-1.610)**	(0.199)	(-0.496)
Cognitive ability	-0.000	0.010***	0.000	0.000	0.000	-0.002	0.009***	0.001	-0.000	0.002
	(0.001)	(0.003)	(0.000)	(0.001)	(0.001)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
	[0.078]	**[0.976]**	[0.062]	[0.054]	[0.08]	(-0.690)	**(3.584)**	(0.628)	(-0.157)	(0.888)
Time Interval	-0.015	0.000	-0.019***	0.019***	-0.006	-0.013	-0.002	-0.016***	0.016***	-0.011**
	(0.010)	(0.003)	(0.004)	(0.004)	(0.007)	(0.008)	(0.006)	(0.004)	(0.005)	(0.004)
	[0.786]	[0.135]	**[0.998]**	**[0.999]**	[0.452]	**(-1.548)**	(-0.350)	**(-3.720)**	**(3.382)**	**(-2.521)**
UH controlled	-0.018**	-0.000	-0.000	0.001	0.002	-0.018***	-0.003	0.001	0.006	0.004
	(0.009)	(0.002)	(0.001)	(0.003)	(0.004)	(0.006)	(0.005)	(0.004)	(0.005)	(0.005)
	[0.897]	[0.066]	[0.053]	[0.225]	[0.284]	**(-2.922)**	(-0.626)	(0.231)	**(1.248)**	(0.836)
OLS method	-0.024***	-0.001	0.000	-0.000	-0.004	-0.022***	-0.007	-0.000	-0.001	-0.005
	(0.007)	(0.003)	(0.001)	(0.001)	(0.005)	(0.006)	(0.005)	(0.003)	(0.004)	(0.004)
	[0.996]	[0.152]	[0.054]	[0.084]	**[0.414]**	**(-3.769)**	**(-1.454)**	(-0.026)	(-0.140)	**(-1.106)**
Measurement error	-0.000	0.001	0.000	0.000	0.004	-0.001	0.003	0.001	0.002	0.007**
	(0.001)	(0.003)	(0.001)	(0.002)	(0.005)	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)
	[0.056]	[0.238]	[0.067]	[0.116]	**[0.464]**	(-0.229)	(0.976)	(0.288)	(0.750)	**(2.389)**
Panel Data	-0.000	0.004	-0.000	-0.000	-0.025***	0.003	0.004	-0.002	-0.004	-0.018***
	(0.001)	(0.004)	(0.001)	(0.002)	(0.004)	(0.005)	(0.003)	(0.002)	(0.003)	(0.003)
	[0.061]	**[0.478]**	[0.072]	[0.114]	**[1]**	(0.732)	**(1.146)**	(-0.984)	**(-1.175)**	**(-5.227)**
Australia	0.001	0.003	-0.000	-0.018***	0.000	0.008	0.005	-0.005	-0.016***	0.004
	(0.002)	(0.005)	(0.001)	(0.005)	(0.002)	(0.006)	(0.005)	(0.003)	(0.005)	(0.005)
	[0.091]	[0.268]	[0.089]	**[0.991]**	[0.085]	**(1.452)**	(0.926)	**(-1.571)**	**(-3.213)**	(0.913)
Asia Pacific	0.000	0.028***	0.002	0.003	0.015	0.001	0.023***	0.007	0.011	0.015*
	(0.002)	(0.010)	(0.004)	(0.008)	(0.012)	(0.008)	(0.008)	(0.005)	(0.008)	(0.008)
	[0.059]	**[0.97]**	[0.199]	[0.223]	**[0.693]**	(0.142)	**(2.927)**	**(1.279)**	**(1.372)**	**(1.949)**
World (Other)	0.018***	-0.008	-0.000	-0.000	0.006	0.019***	-0.007	-0.005	0.000	0.006*
	(0.004)	(0.007)	(0.000)	(0.001)	(0.005)	(0.005)	(0.005)	(0.003)	(0.004)	(0.004)
	[0.998]	**[0.639]**	[0.057]	[0.063]	**[0.632]**	**(3.514)**	**(-1.536)**	**(-1.484)**	(0.098)	**(1.757)**
Journal	-0.000	-0.001	-0.000	0.001	0.000	-0.002	-0.002	-0.002	0.006*	0.004

	BMA					WALS				
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.004)	(0.004)	(0.002)	(0.003)	(0.003)
	[0.079]	[0.115]	[0.054]	[0.15]	[0.105]	(-0.614)	(-0.554)	(-0.670)	**(1.911)**	**(1.033)**
Pub Year (logs)	-6.452***	1.785	-0.002	4.222***	0.098	-6.361***	2.024**	0.409	3.480***	0.476
	(0.914)	(1.437)	(0.095)	(0.559)	(0.382)	(1.083)	(0.885)	(0.562)	(0.859)	(0.756)
	[1]	**[0.684]**	[0.054]	**[1]**	[0.112]	**(-5.875)**	**(2.286)**	(0.728)	**(4.050)**	(0.629)
Constant	49.141***	-13.578	0.018	-32.135***	-0.742	48.445***	-15.387**	-3.106	-26.489***	-3.625
	(6.954)	(10.930)	(0.724)	(4.255)	(2.908)	(8.238)	(6.738)	(4.273)	(6.537)	(5.754)
	[1]	**[1]**	**[1]**	**[1]**	**[1]**	**(5.881)**	**(-2.284)**	(-0.727)	**(-4.052)**	(-0.630)
N	216	231	245	246	245	216	231	245	246	245

Notes: O – Openness to Experience, C – Conscientiousness, E – Extraversion, A – Agreeableness, N – Neuroticism. Standard errors are reported in parentheses, and clustered at the study level. *, **, and *** denote statistical significance at 10, 5, and 1%, respectively. PIP scores are reported in squared brackets for BMA. *t*-values are recorded in the parentheses just below the standard errors for WALS. If a variable's PIP is greater than 0.5, it is regarded to have a strong effect in BMA; but, for WALS, the *t*-value must be bigger than one. PIPs greater than 0.5 and *t*-values greater than 1 are in bold.

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