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RESEARCH ARTICLE

The relationship between the Big Five personality traits and earnings: Evidence from a meta-analysis

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Abstract

This meta-analysis examines the relationship between the Big Five personality traits and earnings. The results reveal that openness to experience, conscientiousness, and extraversion exhibit positive correlations with earnings, whereas agreeableness and neuroticism are inversely correlated with earnings. Overall, personality has a modest-to-small effect on earnings, with variations in results depending on econometric models used. Accounting for publication bias, socioeconomic background, and cognitive ability in models affects effect sizes. The findings also underscore the potential for omitted variable bias in the reported personality effects on earnings when relevant factors are omitted from the earnings equation.

KEYWORDS
Big Five, earnings, meta-analysis, personality

JEL CLASSIFICATION
J24, J3

1 INTRODUCTION

Over the past three decades, it has become clear that although cognitive skills are important, they are not the sole determinants of labor market outcomes (Almlund et al., 2011). Noncognitive skills have gained importance in labor economics, with the evolving literature also recognizes that personality traits may interact with labor market outcomes, in addition to economic preferences and social skills.

Various mechanisms come into play when personality traits influence labor market outcomes. Similar to cognitive skills, personality traits can enter the production function separately, as employers often reward workers whose traits align with the ideal requirements of the job (Almlund et al., 2011; Borghans et al., 2008; Bowles et al., 2001; Heckman et al., 2006) or whose traits reduce coordination costs among workers (Deming, 2017). Personality traits can also be linked to economic preferences, such as risk, time, and social preferences, which, in turn, explain health, educational, and labor market outcomes (Becker et al., 2012). Therefore, it is not surprising that personality traits can predict earnings.

This paper explores the relationship between personality and earnings through a meta-analysis. Although there has been a recent increase in research on personality and earnings, no single study offers a comprehensive overview of the entire body of literature. The estimated personality effects vary among studies, with some reporting negative effects, others indicating positive ones, and with different statistical power, leaving it uncertain which personality traits affect earnings, to what degree, and in what specific ways.

The relationship between personality traits and earnings is complex and multifaceted and likely influenced by various factors, such as a person's education, skills, and advancement opportunities. Individuals with higher levels of education tend to have personality traits, such as openness to experience and conscientiousness, which are associated with higher earnings. Additionally, they may enjoy greater access to resources and opportunities that positively affect their earnings. However, the presence of omitted variables can introduce bias into the estimator of the personality trait under investigation. Even in the absence of unobserved heterogeneity, controlling for variables like education (which is both influenced by personality and has an impact on earnings) can still result in an overcontrol bias.

In this paper, I conduct a meta-analysis to combine empirical findings from multiple studies and determine the overall effect size of each personality trait on earnings. The meta-analysis also provides an opportunity to evaluate the consistency of results across studies and identify potential sources of variation in the reported findings in the literature. Identifying these sources can help uncover moderators or confounding factors contributing to observed heterogeneity. Additionally, this study examines the presence of publication bias, which occurs when journals and authors tend to favor reporting statistically significant results. This bias can lead to an overestimation of the true earnings effects of personality traits.

Although a previous study has already provided a meta-analytical review of the empirical literature on this relationship (Alderotti et al., 2021), this paper offers a distinct perspective. First, my analysis aims to enhance comparability by focusing on estimates derived from a semilog wage equation, where the dependent variable is in logarithmic form. Second, I include all estimates from the selected studies in the meta-analysis to identify the sources of observed heterogeneity in reported effects. Third, I integrate all identified control variables, including standard errors of reported effects used to detect publication bias, in the meta-regression, while ensuring that multicollinearity is not unduly high. This strategy offers clear advantages over bivariate analysis as it allows for an exploration of the relationships among multiple variables. Lastly, I assess the robustness of the meta-regression model through sensitivity tests, considering the potential interdependence among estimates within a single paper and the uncertainties surrounding the main sources of heterogeneity in the studies under analysis.

The results indicate that openness to experience and conscientiousness have a positive relationship with earnings, whereas extraversion also shows a positive but weaker correlation. On the other hand, agreeableness and neuroticism are negatively associated with earnings. These relationships vary across studies due to control factors, such as educational level, family background, cognitive ability, and career path, which play pivotal roles in explaining the varying effects of personality on earnings. Additionally, the analysis reveals the presence of publication bias in the reported personality effects on earnings. Accounting for this bias substantially reduces the strength and significance of the effect sizes.

The paper is structured as follows: Section 2 delves into the theoretical underpinnings of how personality traits can influence earnings. Section 3 outlines the methodology for study selection and provides an overview of the dataset. Section 4 presents and discusses the empirical results. Finally, Section 5 provides a summary of the results and conclusion.

2 | CONCEPTUAL FRAMEWORK

Personality traits are “relatively enduring patterns of thoughts, feelings, and behaviours that differentiate individuals from one another” (Roberts, 2009, p. 2). They are believed to consist of behavioral and emotional patterns prevalent in all situations rather than in isolated occurrences. The Big Five taxonomy proposes five dimensions of personality, namely, openness to experience (ability to be creative, curious, intellectually engaged, honest/humble, and inquisitive), conscientiousness (self-discipline, punctuality, and organized 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).[1] Each of these traits contributes to behavior ceteris paribus, meaning they are not the sole determinant of behavior. Together with other factors, these traits can be utilized to comprehend a person’s motives, objectives, and preferences as well as to predict and understand a person’s behavior.

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 (e.g., a 7-item Likert scale ranges from 1 = “does not apply to me at all” to 7 = “applies to me perfectly”). Instead of relying on self-reported information, peer-report measures involve evaluating someone’s personality traits based on the observations of others. Objective measures, on the other hand, are based on observed behavior.

After collecting responses, various methods can be employed for analysis. In economic studies, factor analysis is common approach to identify latent variables within the responses. This method

[1] The five-factor model (McCrae & 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 behavior that people typically do differently (John et al., 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 longevity (Heckman et al., 2021). The five-factor model has long been recognized as internally consistent, stable, and enjoys cross-cultural support (John, 2021).

uses the correlation structure among the observed self-report items to calculate factor scores, representing the dimensions of the underlying factors. These scores are linear combinations of the observed items, with each item's weight determined by its factor loading. Each factor's scale has a mean of zero and a standard deviation of one. The five-factor model identifies five distinct latent factors. Factor analysis has the appealing feature of not assuming that all items contribute equally to the construct being evaluated.

A simpler alternative involves summing or averaging a preselected set of items, assigning equal weight to each survey item. However, this method may not account for the possibility that different items measure different aspects of the construct being studied and may still correlate with unobserved factors, such as skills (e.g., Borghans et al., 2008).

The relationship between personality traits and earnings can be expressed as an extension of Mincer's earnings function. The standard model used to estimate the personality effects on earnings can be formulated as follows:

$$\ln Y_i = \alpha + \beta P_i + \gamma X_i + \varepsilon_i, \tag{1}$$

where Y_i represents earnings; P_i is a vector of personality traits; X_i is a vector of characteristics affecting earnings (e.g., educational attainment, occupation, and cognitive ability); and ε_i represents the error term. The parameter of interest is β, a vector capturing the strength of the relationship between earnings and each personality trait, holding other factors constant. The percentage effect of a one standard deviation increase in P_i on Y_i can be calculated as $\{\exp(\beta) - 1\} \times 100$.

Certain personality traits are expected to correlate with higher earnings. For example, traits like conscientiousness, extraversion, and openness to experience tend to be associated with higher income, as they encompass qualities, such as a strong work ethic, effective teamwork, and critical thinking, all highly valued in the labor market. Conversely, individuals with higher scores in agreeableness and neuroticism may earn less.

That being said, the relationship between personality traits and earnings is not always straightforward. The estimated personality effects vary among studies, with some reporting negative effects and others indicating positive ones. Various factors influence this relationship, including six key factors I will discuss in the following sections.

2.1 | Educational attainment

In the literature, there is consensus that the person's level of education, typically measured by years spent in education or degrees earned, can influence the relationship between personality traits and earnings. A wealth of evidence links the Big Five traits with educational attainment. For example, a meta-analysis by Vedel and Poropat (2017) and other studies (e.g., Bergold & Steinmayr, 2018; Brandt et al., 2020; Lechner et al.,2019 Spengler et al., 2013, 2016) highlight conscientiousness and openness to experience as the most relevant traits for educational achievement. In contrast, there is no strong association between higher education and traits like agreeableness, emotional stability, and extraversion (e.g., Caspi et al., 2005; Gensowski, 2018; Lechner et al., 2019; Poropat, 2014; Vedel & Poropat, 2017).

In many economic studies estimating the effects of personality traits on earnings, education is typically included as a control variable. Although interpreting these coefficients as direct effects of personality on earnings is technically incorrect, as education itself captures individual predispositions such as personality traits, this practice aligns with the methodological approaches employed by numerous studies in this field.

Furthermore, there is also good reason to believe that education can partly confound the effect of personality traits on earnings. Several programs that invest in enhancing both cognitive and noncognitive skills during early childhood, such as the General Educational Development (GED) Program (Heckman & Rubinstein, 2001), the Perry Preschool Project (Heckman et al., 2006), the Jamaican Study (Gertler et al., 2014), and the Columbia study (Attanasio et al., 2020), have demonstrated positive effects on the life outcomes of participants.

Reverse causality is another important consideration. Although some personality traits may directly influence educational choices, it is also plausible that education can shape personality traits. Higher education may expose individuals to experiences that impact both their personality development and earnings potential. However, limited evidence supports this notion, with only extraversion showing some potential for improvement through training (Dahmann & Anger, 2014). Further research is warranted to gain a deeper understanding of these complex relationships.

2.2 | Occupation and selection effects

The relationship between personality traits and earnings can also be influenced by an individual's career choices. The selection effect suggests that certain personality traits may lead individuals to choose specific occupations. Consequently, the link between personality traits and earnings may be more pronounced among those who have selected professions that require or value particular personality traits, compared to individuals whose aptitudes do not align with the demands of the occupation.

Evidence from various meta-analyses supports this idea. For instance, conscientiousness is a strong predictor of job performance (Salgado et al., 2003; Ones et al., 2007), whereas openness to experience is important in roles that require training (LePine et al., 2000). Extraversion is valuable in contexts involving social interaction and leadership roles, whereas agreeableness is positively correlated with performance in team-based environments (Bell, 2007; Peeters et al., 2006). On the other hand, neuroticism tends to be associated with underperformance across diverse organizational settings (Ones et al., 2007).

2.3 | Cognitive skills

It is well known in the existing literature that omitting cognitive skills measures from earnings specifications can introduce omitted variable bias, potentially compromising the accuracy of personality trait effect estimates.

Although intelligence and personality have traditionally been viewed as distinct constructs, recent research suggests that cognitive skills and personality traits are conceptually and empirically related. DeYoung (2020) provided a detailed account of why such correlations exist. An explanation for the relationship between personality traits and cognitive ability is that some aspects and facets of personality traits are also considerably related to cognitive ability. For example, individuals scoring high on openness to experience often engage in training, enhancing their cognitive development, whereas those with low emotional stability measures may experience anxiety that can hinder cognitive growth (Moutafi et al., 2006).

Another important consideration is the shared measurement error between personality traits and cognitive ability. This error stems from the fact that the tests employed to measure personality traits and cognitive ability are often administered to the respondent under the same conditions, consequently inducing a common response bias. Although conceptually, cognitive ability and personality traits are two separate constructs, the fact that the measures were impurely measured implies that they are linked systematically (Borghans et al., 2011). Indeed, personality traits like conscientiousness and neuroticism are closely associated with cognitive ability due to shared skills, such as attention to detail, organization, and anxiety management.

2.4 | Family background

Socioeconomic status (SES) plays a crucial role in predicting an individual's labor market outcomes, encompassing factors like education, occupation, and income of the individual or their parents. Higher SES families tend to lead to better life trajectories, including higher earnings, improved education, increased social capital, and access to well-paying jobs and social networks.

The relationship between personality traits and earnings is intertwined with SES, meaning that the impact of personality traits on earnings can differ among individuals from varying socioeconomic backgrounds. For example, Collischon (2020), using unconditional quantile regressions to estimate the effect of personality traits on wages at different points of the wage distribution, found that the effects of agreeableness, conscientiousness, and neuroticism on wages are stronger for workers at the top of the wage distribution, and these effects increase across the wage distribution.

This interplay among personality traits, earnings, and family socioeconomic background is influenced by the different resources and opportunities available to individuals from high SES backgrounds. Those with higher SES have better access to resources that enhance their career-related attributes, thereby amplifying the influence of personality traits on earnings. Deckers et al. (2015) demonstrated a robust link between a child's personality and their parents' SES, emphasizing the enduring impact of family background on personality development. A meta-analysis by Ayoub et al. (2018) also indicated correlations between parental SES and personality traits, although the effect sizes are relatively modest. Ignoring SES would erroneously attribute the entire influence to personality traits, as SES directly affects earnings.

2.5 | Gender

The effect of gender on the relationship between personality traits and earnings is a subject of mixed findings (Nyhus & Pons, 2012). For instance, regarding agreeableness, Mueller and Plug (2006) found that antagonistic men earned more than their agreeable counterparts, but other studies (Cobb-Clark & Tan, 2011; Heineck, 2011; Heineck & Anger, 2011) discovered a negative relationship between agreeableness and earnings for both men and women.

Similar mixed results were observed for neuroticism. Although higher neuroticism is generally associated with lower earnings, Heineck (2011) found this negative association only among female workers. Gender-specific patterns were also noted for other personality traits. Women with higher openness to experience tend to earn more, whereas among men, higher openness to experience was linked to lower earnings. Additionally, women with higher extraversion levels tended to earn less, whereas extroverted men commanded higher salaries compared to their counterparts with lower scores in this trait.

2.6 | Age

Age is an important factor in the context of personality development. Although the overall personality profile tends to remain stable after puberty, adolescents typically become more outgoing, conscientious, and emotionally stable as they mature, known as the "maturity principle" (Bleidorn et al., 2022; Roberts et al., 2006). This suggests that age is linked to personality development.

It is reasonable to assume that the effect of personality traits on earnings may vary with age. Some studies, such as Maczulskij and Viinikainen (2018), suggested that these effects might be more pronounced among younger workers than older ones, whereas others like Cobb-Clark and Schurer (2012) did not find significant variation in the relationship by age.

3 | EMPIRICAL STRATEGY

This study employs a meta-analysis approach to synthesize the estimated personality effects from the existing literature. This statistical approach allows us to generalize the findings across multiple studies, providing a more accurate and reliable estimation, especially because individual study results can vary significantly.

The overall effect size would be the mean or median of the regression coefficients, if all studies had the same research design and sample size. However, when these conditions do not hold, we want to assign more weight to studies that are more precise. One way to implement this is by considering 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. The inverse variance method, therefore, implies that larger studies with smaller standard errors are given more weight than smaller studies with larger standard errors.

3.1 | Estimation strategy

To determine the overall effect size of each personality trait, I extract the regression coefficient of interest (known as semi-elasticity, as shown in Equation 1) and its corresponding standard error (σ_i) from each identified study i.

The meta-analysis model used is the random-effects model. This model assumes that the observed differences in effects are due to within-study sampling error and actual heterogeneity in the true effects between studies. In this context, "random-effects" models are different from those in econometrics. The random-effects in meta-analysis work under the assumption that any variation in observed effects is a result of within-study sampling error, ϵ_i, and actual heterogeneity in the true effects between studies, u_i.[2] It assumes that the true effect size (θ_i) follows a normal

[2] In the context of meta-analysis, the term "fixed-effect" also has a different definition than "fixed-effects" in econometrics. The fixed-effect meta-analysis model assumes that there is only one true effect size, θ, and that any differences in the observed study-specific regression coefficients are due only to random error. The assumption of a single true effect size is not appropriate when the studies are heterogeneous, for example, in terms of design and survey population. The fixed-effect method results in excessive Type I errors when residual or unexplained heterogeneity is present.

distribution around the mean true effect, θ. Equivalently,

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

where $\hat{\beta}_i$ is the estimated coefficient in study i, $\theta_i \sim N(\theta, \tau^2)$, $\epsilon_i \sim N(0, \sigma_i^2)$, and $u_i \sim N(0, \tau^2)$. ϵ_i is the sampling error, and τ^2 represents the between-study variance and is estimated from the data.[3] Equation (2) can be estimated using ordinary least squares (OLS). However, there are two problems in estimating this specification.

First, the estimates may violate the assumption of homoskedasticity, where error variances differ systematically among observations. To address this, Equation (2) is adjusted by weighting it with the inverse of the square root of the within-study variance, σ_i^2, plus the between-study variance, τ^2 (represented by ω). When ω is large, the data is less informative, and observations are given less weight. This transformation of Equation (2) is as follows:

$$\hat{\beta}_i \frac{1}{\omega} = \theta \frac{1}{\omega} + v_i \frac{1}{\omega}, \tag{2'}$$

where $v_i = \epsilon_i + u_i$ and $\omega = \sqrt{\sigma_i^2 + \tau^2}$. Estimating Equation (2′) by OLS is equivalent to estimating Equation (2) by weighted least squares using the weights discussed before (Stanley & Doucouliagos, 2016).

Second, there is a concern that effect sizes may be correlated, especially if they are from the same study. To address this issue, I use cluster-robust standard errors at the study level to account for any correlation within studies. As an additional robustness test, I compare the findings of two sets of specifications: one that gives equal weight to each estimate, and one that gives equal weight to each study. The Supporting Information section discusses the results.

To better understand the differences in reported effects, Equation (2) can be adjusted by including k-dummy variables, where each variable represents a specific study characteristic (Aloe & Becker, 2012). The considered variables include factors like whether the model controls for the individual's education, skills, socioeconomic background, and the chosen econometric method. A value of 1 is assigned to each dummy variable if the study characteristic is prevalent in the study, and 0 if it is not. If the regression coefficient of a dummy variable is significantly different from zero, it indicates that the particular characteristic exerts a significant effect on the overall effect size. This method also addresses typical concerns in meta-analysis about combining studies in a meaningful way, ensuring comparability in terms of study design, variables, and other relevant characteristics.

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

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

where the true effect size of each study is $\theta_i \sim N(\theta + \sum_{k=1}^{K} \alpha_{1,k} X_{i,k}, \tau^2)$. $X_{i,k}$ represents characteristic k for study i, which explains variations in estimated effects. $\alpha_{1,k}$ is the coefficient to estimate, and K is the total number of identified variables explaining heterogeneity. θ represents the overall effect size after accounting for the other relevant characteristics $X_{i,k}$.

[3] The procedure used to estimate τ^2 is the residual maximum likelihood method.

3.2 | Publication bias

Equation (3) is susceptible to publication bias that arises when journals and authors are more likely to publish studies that support a particular conclusion, typically those with expected signs and significant results. For this reason, θ may be overestimated due to this bias. This overestimation can occur if only studies with anticipated signs and significance levels are published, making the effects of personality traits seem to be larger and more significant than they are.

Publication bias manifests as an increase in the observed regression coefficient as the standard error increases, holding all other factors constant. In cases where the sample size is small, and standard errors are large, researchers have to thoroughly examine model specifications and econometric methodologies to achieve statistical significance. This frequently results in a positive correlation between reported effect sizes and their standard errors, leading to the reporting of larger estimates. Conversely, researchers with larger sample sizes and smaller standard errors are less inclined to experiment with various model specifications and are more likely to report smaller empirical effects.

Another perspective on publication bias is viewing it as incidental truncation (Stanley & Doucouliagos, 2014), where only statistically significant estimates are reported or published.

To assess publication bias, I employ the method outlined by Stanley and Doucouliagos (2012), wherein I regress the collected regression coefficients against their corresponding standard errors. This results in the following formulation of Equation (3):

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

The regression test in Equation (4) is commonly known as the funnel asymmetry test–precision effect test (FAT–PET) method, proposed by Egger et al. (1997). When the intercept term α_2 is not statistically different from zero, it indicates an asymmetric distribution of the regression coefficients, suggesting the presence of publication bias. In the presence of publication bias, if the true effect size is positive (e.g., as with conscientiousness), $\alpha_2 > 0$, and if the true effect size is negative (e.g., as with neuroticism), $\alpha_2 < 0$. This can lead to an overestimation of θ_i.

Similar to Equation (2′), to account for heteroskedasticity, Equation (4) is weighted by the inverse of ω.

3.3 | The dataset

To create the dataset for the meta-analysis, I followed the established reporting guidelines (Havránek et al., 2020; Moher et al., 2009). The meta-analysis included studies that met seven specific criteria: (a) The study had to examine the relationship between personality and earnings; (b) it had to include at least one empirical estimate using econometric analysis to measure the effect of personality on the dependent variable, excluding theoretical studies or systematic reviews; (c) it needed to report the standardized personality trait coefficient along with its corresponding standard error, *t*-statistic, or *p*-value[4]; (d) only studies employing the log-

[4] Seven studies were included in the meta-analysis but did not report the relevant standard errors. The standard error is therefore obtained by dividing the value of the coefficient by the *t*-statistic. Another seven studies report the *p*-value along

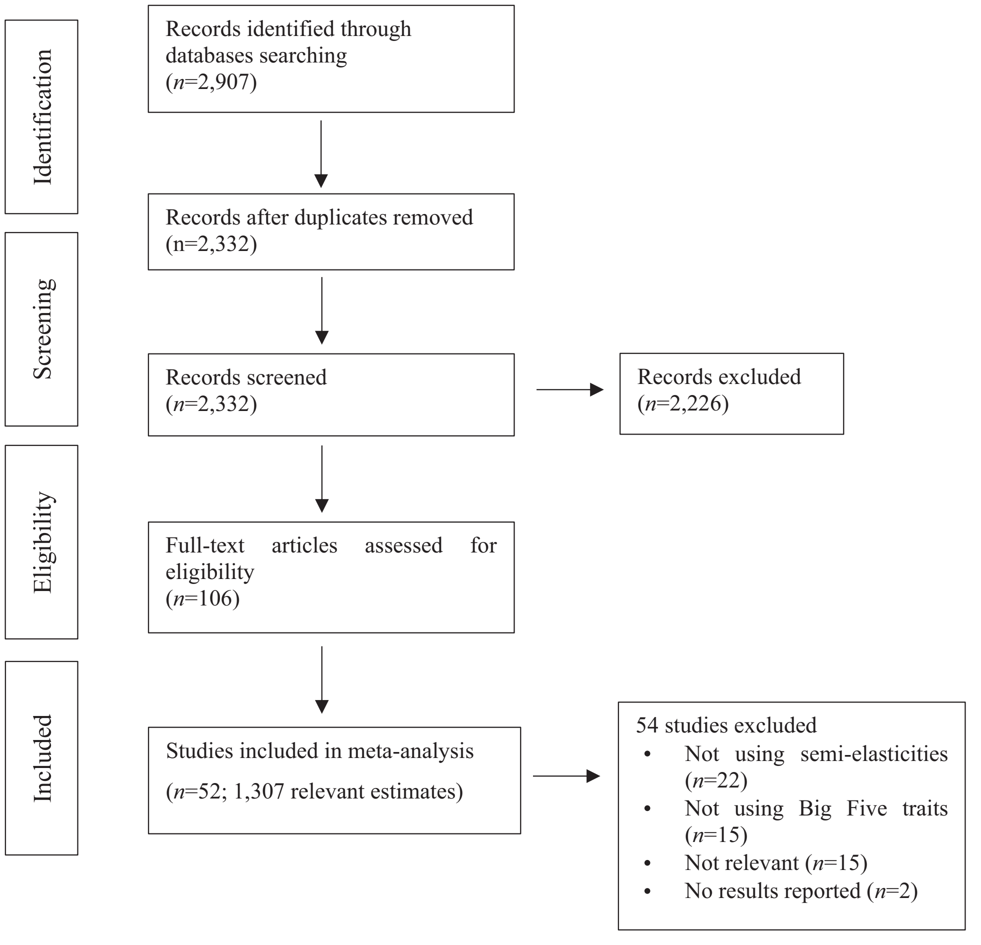

FIGURE 1 Flow chart of the search and screening process.

transformed estimation strategy as described in Equation (1) were considered; (e) only studies focusing on the Big Five personality traits were included, given their widespread use in both economics and personality research; and (f) the study had to be written in English.

Due to the relatively limited number of available studies on earnings and the predefined inclusion criteria, I conducted a comprehensive literature review following a methodology similar to Havránek et al. (2020). This process involved searching eleven electronic databases: Business Source Complete, EconLit, Emerald, Google Scholar, JSTOR, RePEc, ScienceDirect, Scopus, ProQuest, PsycInfo, and Web of Science. Only peer-reviewed publications were considered to ensure quality control. I also employed reference pyramid schemes to identify relevant papers. The literature search was completed in April 2022, and the following search terms were used: "Big Five," "income," "earnings," "labor market outcomes," "noncognitive skills," "noncognitive abilities," "return to personality," "personality," "personality development," "personality traits," "salary," and "wages." The included studies are listed in the Appendix section (Table 5), and Figure 1 provides an overview of the literature search and screening process.

with the sample size and number of explanatory factors included in the regression so that the corresponding standard error could be calculated.

A total of 106 studies were initially identified, and this list was then narrowed down to 52 studies based on the defined inclusion criteria. Consequently, the final dataset comprises 1307 estimates. Within this dataset, each study provides varying estimates for different personality traits, with estimates ranging from 1 to 120 per study. The inclusion of multiple estimates is due to the use of different techniques to ensure the validity of regression coefficients. Some studies also investigate systematic differences in coefficients among different groups or explore the impact of variables like family background on baseline results. For a detailed breakdown of the studies included in the dataset that meet the inclusion criteria, refer to Table A1. This table includes information about the author(s), publication year, data collection year(s), countries covered, and the number of effect sizes collected for each study.[5]

The compiled dataset includes studies utilizing both cross-sectional and panel data, analyzed with various econometric methods such as (pooled) OLS, random effects, and fixed-effects. However, it is evident that some studies in the dataset do not adequately address omitted variable bias, whereas others examining endogeneity associated with personality employ instrumental variables (IV), correlated random effects, Hausman–Taylor IV, or within-group estimators. Additionally, some studies employ personality scores measured concurrently with earnings, whereas others gather personality scores from childhood or just before individuals enter the workforce. This is done to account for the possibility that personality traits are influenced by prior experiences. The time lag between the outcome variable and the personality scores in the dataset ranges from 0 to 65 years, although using lagged values can sometimes result in less precise data.

In addition to the standardized regression coefficient and its corresponding standard error, the constructed dataset includes information on sample size, degrees of freedom, data type (cross-sectional or panel data), econometric method used (OLS or otherwise), empirical settings (age cohort, country coverage, sex), year of data used for income and personality traits, as well as dummy variables for the inclusion of theoretically relevant factors (cognitive abilities, education, occupation, family background), publication characteristics, and methodological dummies, including endogeneity control and factor score personality measures.

Table 1 shows all explanatory variables included in the multi-regression approach, along with the mean of each personality trait. Notably, significant heterogeneity is observed in the averages. For instance, the earnings elasticity of openness to experience is positive for individuals aged 35 or over but negative for those under 35.

4 | RESULTS

4.1 | Overall effects

The estimation results for Equation (2′) in Table 2 were obtained using the restricted maximum likelihood (REML) method.[6] These results clearly demonstrate that the overall regression coefficients for all personality traits are highly statistically significant (p-value <0.0001).

[5] To create the dataset, I categorized kindness and cooperation as agreeableness, constructiveness as conscientiousness, sociability as extraversion, withdrawal and aggression as negative values of emotional stability, and emotional instability as neuroticism.

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

TABLE 1 Variable definitions, descriptive statistics, and average size effect for every trait.

	Definition	*O*	*C*	*E*	*A*	*N*
Age category						
Above 35	Study data is from a population aged more than 35	0.028	0.029	0.011	−0.029	−0.033
Below 35	Study data is from a population aged less than 35	−0.047	0.117	0.006	0.003	−0.061
Gender						
Not controlled (base category)	Sample is mix	0.024	0.059	0.014	−0.024	−0.052
Males	Sample is only males	0.010	0.021	0.004	−0.024	−0.017
Females	Sample is only females	0.010	0.018	0.008	−0.022	−0.030
Education control						
No (base category)	No control for education	0.033	0.065	−0.006	−0.024	−0.041
Yes	Controls for education	0.014	0.035	0.016	−0.024	−0.037
Family background control						
No (base category)	No control for family background	0.034	0.050	0.011	−0.030	−0.043
Yes	Controls for family background	0.003	0.035	0.011	−0.018	−0.032
Occupation control						
No (base category)	No control for occupation	0.025	0.054	0.020	−0.020	−0.026
Yes	Controls for occupation	0.011	0.029	−0.001	−0.028	−0.051
Cognition control						
No (base category)	No control for cognitive ability	0.027	0.040	0.015	−0.021	−0.047
Yes	Controls for cognitive ability	0.007	0.045	0.006	−0.027	−0.026
Time interval						
0 (base category)	No time lag	0.021	0.040	0.010	−0.026	−0.039
1–65	With time lags	−0.001	0.055	0.016	−0.015	−0.034
Unobserved heterogeneity controlled						
No (base category)	No control for unobserved heterogeneity	0.020	0.048	0.016	−0.026	−0.040
Yes	Controls for unobserved heterogeneity	0.007	0.000	−0.027	−0.009	−0.019
Use of OLS						
No (base category)	No use of OLS	0.042	0.000	−0.022	−0.028	−0.055
Yes	Use of OLS	0.013	0.051	0.018	−0.023	−0.034
Use of personality factor scores						
No (base category)	Uses average or sum of personality items	−0.003	0.038	−0.003	−0.026	−0.037
Yes	Uses factor personality scores	0.046	0.049	0.030	−0.021	−0.038
Data type						
Cross-sectional data (base category)	Uses cross-sectional data	0.018	0.043	0.003	−0.028	−0.036
Panel data	Uses panel data	0.018	0.041	0.035	−0.010	−0.044

(Continues)

TABLE 1 (Continued)

	Definition	O	C	E	A	N
Country coverage						
Europe, the United States (base category)	Country in Europe and the United States	0.209	0.407	0.255	−0.200	−0.275
Australia	Australia	−0.004	0.021	0.005	−0.022	0.000
Asia Pacific	Country in Asia Pacific region	0.119	0.018	−0.025	−0.051	−0.187
World	Country, other than the above	−0.041	0.080	−0.052	−0.033	−0.042
Publication type						
Working paper (base category)	Study published as a working paper	−0.025	0.053	−0.024	−0.026	−0.031
Journal	Study published in a peer-reviewed journal	0.033	0.039	0.022	−0.023	−0.040

Note: *A*, agreeableness; *C*, conscientiousness; *E*, extraversion; *N*, neuroticism; *O*, openness to experience. Standard errors are reported in parentheses. Statistics give equal weight to each study.
Abbreviation: OLS, ordinary least squares.

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

Note: *A*, agreeableness; *C*, conscientiousness; *E*, extraversion; *N*, neuroticism; *O*, openness to experience. 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.

For openness to experience, the true effect size is 0.019, indicating that a one standard deviation increase in openness to experience corresponds to a 1.92% increase in earnings. Similarly, conscientiousness ($\theta = 0.016$, 1.61%) and extraversion ($\theta = 0.003$, 0.30%) are positively correlated with earnings, whereas agreeableness ($\theta = -0.017$, −1.69%) and neuroticism ($\theta = -0.018$, −1.78%) show negative correlations.

To address the potential dependency of effect estimates within the same study, the robust estimation of variance approach was also used. Such dependency can arise from nested effect sizes or multiple measurements collected for the same individuals. The analysis showed that the overall earnings effects remained consistent with the main results across the Big Five personality traits, and no significant changes were observed when considering various within-study effect size correlations.[7] Additionally, four sensitivity analyses were conducted to validate the robustness of the REML results, and these analyses are available in the Supporting Information section.

The summary statistics also reveal significant heteroskedasticity in the results, indicating that the reported personality effects lack consistency across studies. Indeed, the I^2 score demonstrates that over 99% of the total variation across studies can be attributed to between-study variability rather than sampling error. The *Q*-statistic test was also employed to assess whether the effect

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

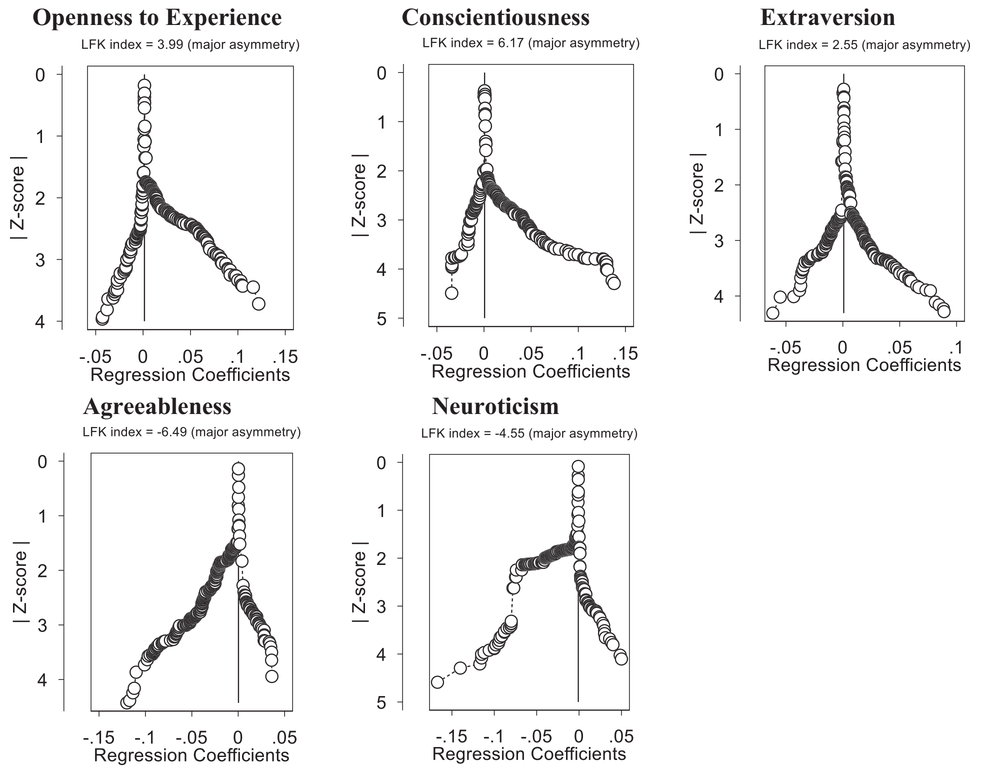

FIGURE 2 Doi plots.

sizes are distributed around the mean, and this test underscores the presence of heterogeneity among the results (*p*-value <0.0001).

4.2 | Publication bias

In this study, Doi plots were employed to visually assess publication bias. Constructing a Doi plot involved serially ranking the reported coefficients of each study. However, unlike the funnel plot, where coefficients are plotted against the sample size, here, coefficients were plotted against a folded normal quantile (*Z*-score).[8]

In the absence of publication bias, studies should be evenly distributed throughout the Doi plot, with an equal number of studies at each level of precision. However, the presence of publication bias is indicated by a disproportionate concentration of studies in either the bottom-right or bottom-left quadrants of the plot. This suggests that studies with larger effect sizes and higher precision are more likely to be published.

The Doi plots presented in Figure 2 reveal an uneven distribution of regression coefficients in the dataset. Moreover, the LFK index surpasses a value of 2 for all Big Five traits, indicating a strong presence of publication bias.

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

TABLE 3 Publication Bias, funnel asymmetry test–precision effect test (FAT–PET).

	O	C	E	A	N
Effect beyond bias (precision effect)	0.015**	0.006	0.000	−0.008**	−0.006
	(0.006)	(0.004)	(0.002)	(0.004)	(0.005)
Standard error (publication bias)	0.302	0.906***	0.386	−0.786***	−1.007***
	(0.201)	(0.255)	(0.231)	(0.229)	(0.275)
Adjusted R^2	0.275	0.358	0.063	0.363	0.366
N	216	231	245	246	245

Note: *A*, agreeableness; *C*, conscientiousness; *E*, extraversion; *N*, neuroticism; *O*, openness to experience. 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.

Table 3 displays the results of the FAT–PET regression using Equation (4), initially without including $X_{i,k}$ covariates. The test confirms the presence of publication bias for conscientiousness, agreeableness, and neuroticism. Consequently, the overall regression coefficients presented in Table 2 were overestimated due to this publication bias. This occurs because studies with statistically significant findings are more likely to be published, leading to potential inaccuracies in estimating the effects of personality traits on earnings.

For example, consider conscientiousness. Without accounting for publication bias, a one standard deviation increase in conscientiousness is associated with a 1.16% increase in earnings. However, the effect drops to 0.60% once publication bias is taken into account.

Although it might appear that personality traits do not exert a significant influence on earnings once publication bias is considered, it is important to approach this conclusion with caution. The apparent insignificance of the coefficients does not necessarily imply that personality traits lack relevance in the labor market. There may be other factors at play that offset one another, making it difficult to determine the overall impact.

To further investigate potential publication bias, four additional tests were conducted in line with recent studies. These tests are particularly useful when significant heterogeneity is present ($I^2 > 80\%$) (Stanley, 2017). The results of these tests are available in the Supporting Information section. All of the methods employed indicate that the semi-elasticities essentially approach zero in magnitude. This suggests that, once publication bias is taken into account, there is minimal-to-no discernible correlation between personality traits and earnings.

4.3 | Heterogeneity

Given the high I^2 value, the next step is to delve into the sources of the observed heterogeneity.[9] The results of Equation (4) estimation are summarized in Table 4, revealing several key insights.

First, it has been confirmed that publication bias is indeed present, aligning with previous tests. This is evidenced by the statistical significance of the standard error coefficients for all Big Five traits at the 1% level.

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

TABLE 4 Explaining heterogeneity in the estimated effects of personality on wages.

	O	*C*	*E*	*A*	*N*
Constant	55.803***	−15.594**	−0.994	−27.385***	−3.629
	(9.039)	(7.416)	(4.695)	(7.204)	(6.400)
Standard error	0.361**	0.838***	0.535***	−0.838***	−1.020***
	(0.176)	(0.150)	(0.128)	(0.148)	(0.161)
Age category	−0.004	0.015**	0.017***	−0.001	0.014**
	(0.013)	(0.008)	(0.004)	(0.007)	(0.006)
Males	−.000	−.000	−0.005**	−0.004	0.009***
	(0.005)	(0.003)	(0.002)	(0.004)	(0.003)
Females	0.003	−0.001	−0.003	0.000	0.001
	(0.005)	(0.004)	(0.002)	(0.004)	(0.003)
Education controlled	−0.020***	−0.002	0.007***	−0.002	0.009***
	(0.005)	(0.004)	(0.002)	(0.004)	(0.003)
Family background controlled	−0.011**	−0.007**	0.000	0.002	0.017***
	(0.005)	(0.003)	(0.002)	(0.003)	(0.003)
Occupation controlled	0.002	−0.013***	−0.005**	0.001	−0.002
	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)
Cognitive ability controlled	−0.004	0.011***	0.001	−0.004	0.002
	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)
Time lag	−0.016*	−0.005	−0.019***	0.024***	−0.004
	(0.009)	(0.006)	(0.004)	(0.005)	(0.005)
UH controlled	−0.020***	−0.007	−0.001	0.007	0.002
	(0.007)	(0.006)	(0.003)	(0.006)	(0.006)
OLS method	−0.024***	−0.009*	−0.001	−0.001	−0.007
	(0.007)	(0 .005)	(0.003)	(0.005)	(0.005)
Use of personality factor scores	0.001	0.008**	0.001	−0.001	0.011***
	(0.005)	(0.003)	(0.002)	(0.004)	(0.004)
Panel data	0.004	0.007*	−0.003	−0.005	−0.023***
	(0.005)	(0.004)	(0.002)	(0.004)	(0.004)
Australia	0.004	0.004	−0.004	−0.013**	0.001
	(0.007)	(0.006)	(0.003)	(0.006)	(0.005)
Asia Pacific	−0.001	0.025***	0.008	0.023***	0.022***
	(0.009)	(0.007)	(0.005)	(0.009)	(0.007)
World (other)	0.036***	−0.003	−0.001	−0.002	−0.005
	(0.007)	(0.006)	(0.004)	(0.005)	(0.005)
Journal	−0.001	−0.004	−0.004*	0.005	0.006
	(0.005)	(0.004)	(0.002)	(0.004)	(0.004)
Pub year (logs)	−7.328***	2.051**	0.132	3.599***	0.477
	(1.188)	(0.975)	(0.617)	(0.947)	(0.841)
N	216	231	245	248	245
R^2	0.494	0.560	0.510	0.527	0.599

Note: *A*, agreeableness; *C*, conscientiousness; *E*, extraversion; *N*, neuroticism; *O*, openness to experience. The approach gives equal weight to each estimate. Standard errors are reported in parentheses and clustered at the study level.
Abbreviation: OLS, ordinary least squares.
*, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Second, the demographic variables shed light on the notion that the returns to personality traits vary throughout an individual's career. Specifically, individuals younger than 35-year old experience more significant effects on their earnings related to conscientiousness and extraversion. In contrast, neuroticism is associated with a greater decline in wages for those over 35-year old.

Furthermore, it appears that gender does not significantly influence the magnitude of most effect sizes. This suggests that, all else being equal, there are no systematic gender-related differences for most personality traits. More precisely, the results indicate that studies exclusively involving male respondents tend to report a smaller effect of neuroticism on earnings and a weaker effect of extraversion on wages compared to studies encompassing both genders.

The third set of variables pertains to an individual's SES and family background. The meta-regression results indicate that studies failing to control for educational attainment tend to overstate the impact of openness to experience on earnings. Furthermore, studies considering education levels tend to report greater positive effects on earnings for individuals displaying extraverted traits, whereas those with neurotic tendencies tend to exhibit weaker effects on their earnings. These findings align with expectations, as openness to experience appears to be the most significant personality trait associated with educational achievement. Conversely, higher levels of neuroticism tend to correlate with lower performance on achievement tests.

The meta-analysis results highlight that an individual's family background can influence the relationship between the Big Five traits and their earnings. Studies omitting factors like parental education and household income may overestimate the effects of openness to experience, conscientiousness, and neuroticism on earnings. This suggests that individuals with higher SES may have greater educational and career aspirations, along with more opportunities for advancement. Additionally, a person's family history can shape their personality development during their formative years, potentially impacting how their personality traits relate to their earnings.

The results of the meta-regression further support the idea that occupation plays a significant role in predicting the variation in reported personality effects on earnings, especially for traits like extraversion and conscientiousness. This underscores the intricate relationship between occupation and the returns associated with personality traits.

Cognitive ability emerges as another factor affecting the impact of personality traits on earnings. The results confirm that when cognitive ability is considered, the effect of conscientiousness on wages becomes even more significant. This finding aligns with prior research suggesting that individuals scoring high in conscientiousness may score lower on cognitive ability tests. Conversely, those with higher cognitive abilities may possess superior intelligence, memory, and attention skills but may not necessarily exhibit the same level of organization or diligence. Nevertheless, an individual's level of conscientiousness can still influence their motivation and engagement with tasks on an IQ test, indirectly affecting their IQ scores. Thus, accounting for cognitive ability is crucial to prevent potential bias from omitted factors.

In addition to what has been mentioned, I assess whether disparities in reported personality effects stem from variations in econometric techniques, data types, or publication characteristics. To commence this assessment, I compare studies that measure personality traits and their corresponding outcomes with and without a time lag. The results consistently demonstrate variations in the effects of openness to experience, extraversion, and agreeableness depending on the time lag employed.

Next, I compare studies employing different econometric techniques. The findings presented in the table indicate that differences in econometric methods do not explain the variations in reported effects for every personality trait. However, it is essential to approach these findings with caution, considering that nearly 80% of the studies in the dataset utilize an OLS approach.

Additionally, the limited sample size in the meta-analysis poses challenges in fully evaluating the extent to which true effects may be influenced by the chosen econometric methods.

The results also indicate that studies using factor scores instead of simple summation or averaging of personality items yield different wage effects for conscientiousness and neuroticism. Comparing studies conducted on American, European, Asian, and Australian populations reveals variations in the impact of personality traits on earnings across different regions and populations. Additionally, the year of publication appears to influence reported effects, with more recent studies reporting higher effects for conscientiousness and agreeableness and lower effects for openness to experience and agreeableness.

Equation (4) was tested with seven different methods to check if the results from the main model were accurate and consistent. The results largely confirm what is found in Table 4, with the discrepancies being negligibly small. The sensitivity tests show that multicollinearity is not overly high. The Supporting Information section provides a more detailed description of the findings.

5 | CONCLUSION

This paper explores the limited yet growing research on the relationship between personality and earnings. There has been an increased interest in studying personality traits as it has been recognized that noncognitive skills play an important role in shaping life outcomes. However, it is still unclear which personality traits have an effect on earnings, to what extent, and how. The complexity of personality traits, influenced by various factors and life events, contributes to this lack of clarity. Therefore, it is crucial to understand whether personality traits affect earnings and what factors explain the different reported effects across studies. The objective of this study was to use meta-analysis techniques to address this uncertainty and determine whether excluding certain explanatory variables from the model leads to a biased estimate of the true effect size.

The results of the meta-analysis reveal that individuals with higher levels of openness to experience and conscientiousness tend to earn more. Although extraversion also has a positive correlation with earnings, it is not as strong. Conversely, individuals with higher levels of agreeableness and neuroticism tend to earn less. In addition, when accounting for publication bias, the influence of these traits on earnings diminishes, especially for conscientiousness, agreeableness, and neuroticism. These key findings are supported by various robustness tests.

This study also aimed to identify the factors contributing to differences in reported effects across studies, given the significant heterogeneity observed in outcomes. The results of the meta-regression analysis identify the factors responsible for variation in the estimated impact of each personality trait between studies. Notably, socioeconomic characteristics emerge as the most significant factors. Specifically, when education is omitted from the model, the effect of extraversion decreases; however, the effects of openness to experience and neuroticism increase. Similarly, excluding family-related variables leads to an increase in the returns associated with openness to experience and conscientiousness, but also an increase in the negative return of neuroticism. Furthermore, accounting for occupation reduces the return associated with conscientiousness, whereas omitting cognitive ability from the model increases the effect of conscientiousness. These results imply that personality traits may be susceptible to omitted variable bias, potentially leading to misleading estimates.

The meta-analysis results suggest several avenues for future research to gain a deeper understanding of the relationship between personality and labor market outcomes. First, a prevalent reliance on self-reported scores in many studies warrants looking for alternative measures, such as informant data or data collected earlier in one's career. This can enrich the analysis of personality trait returns. Additionally, this meta-analysis leans heavily on research from the United States and Europe, emphasizing the need for more studies from other continents to provide valuable insights regarding the generalizability and universality of the findings.

Future studies can substantially benefit from exploring how levels of personality traits interact with socioeconomic factors and delving into the underlying mechanisms of personality formation. It remains unclear whether individuals shape their environments to align with their personalities or if environmental factors can alter their personalities. The role of past interactions in shaping personality is also pivotal, underscoring its importance as a factor to consider in future research. Consequently, further research into personality development is necessary, given its potential impact on the results.

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DATA AVAILABILITY STATEMENT

The datasets generated during and/or analyzed during the current study are available in the Supporting Information section.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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APPENDIX

TABLE A1 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. (2021)	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	The United Kingdom	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	The United States of America	2	2	2	2	2
Denissen et al. (2018)	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

(Continues)

TABLE A1 (Continued)

Study (author(s) and year of publication)	Study title	Country	*O*	*C*	*E*	*A*	*N*
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	The 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	The United States of America	1	1	1	1	1
Fletcher (2013)	The effects of personality traits on adult labor market outcomes: Evidence from siblings	The 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	The 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	The United States of America	2	2	2	2	2
Heineck (2011)	Does it pay to be nice? Personality and earnings in the United Kingdom	The 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 (2014)	Heterogeneous returns to personality: the role of occupational choice	Germany	16	16	16	16	16

(Continues)

TABLE A1 (Continued)

Study (author(s) and year of publication)	Study title	Country	*O*	*C*	*E*	*A*	*N*
Judge et al. (2012)	Do nice guys—and gals—really finish last? The joint effects of sex and agreeableness on income	The 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	The 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 market	Russia	12	12	12	12	12
Mohammed et al. (2021)	Gender differences in earnings rewards to personality traits in wage-employment and self-employment labour markets	Ghana	9	9	9	9	9
Mueller and Plug (2006)	Estimating the effect of personality on male and female earnings	The United States of America	12	12	12	12	12
Nordman et al. (2019)	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	The Netherlands	0	6	6	6	6
Nyhus and Pons (2012)	Personality and the gender wage gap	The Netherlands	4	4	4	4	4
O'Connell and Sheikh (2011)	'Big Five' personality dimensions and social attainment: Evidence from beyond the campus	The United Kingdom	2	2	2	2	2

(Continues)

TABLE A1 (Continued)

Study (author(s) and year of publication)	Study title	Country	*O*	*C*	*E*	*A*	*N*
Osborne Groves (2005)	How important is your personality? Labor market returns to personality for women in the US and UK	The United States of America	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	The 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
Schäfer 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 (2015)	Facial attractiveness and lifetime earnings: Evidence from a cohort study	The United States of America	4	4	4	4	4
Seibert and Kraimer (2001)	The five-factor model of personality and career success	The 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	The Netherlands	1	1	1	1	1
Shanahan et al. (2014)	Personality and the reproduction of social class	The United States of America	1	1	1	1	1

(Continues)

TABLE A1 (Continued)

Study (author(s) and year of publication)	Study title	Country	*O*	*C*	*E*	*A*	*N*
Shi and Moody (2017)	Most likely to succeed: Long-run returns to adolescent popularity	The 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	The United Kingdom	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

Note: *A*, agreeableness; *C*, conscientiousness; *E*, extraversion; *N*, neuroticism; *O*, openness to experience.