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(Not just) Intelligence stratifies the occupational hierarchy: Ranking 360 professions by IQ and non-cognitive traits

Tobias Wolfram *

Faculty of Sociology, Bielefeld University, Bielefeld, Germany

A R T I C L E I N F O

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A B S T R A C T

Occupational sorting, the process of individuals actively selecting into and being selected for different occupations, has significant implications for social stratification and inequality. The psychometric view of occupational differentials in ability emphasizes the importance of intelligence for occupational sorting, as it acts as a necessary condition to enter and remain in certain professions due to their high cognitive demand. The resulting cognitive stratification of the occupational hierarchy leads to strong associations between occupational mean IQ and sociological measures of occupational status and pay. Past research has been criticized for lack of representativeness and small sample sizes. In this study, we both confirm the psychometric view in a large representative sample and extend it to a set of nine non-cognitive traits. We show that the psychometric view holds (on a weaker level) for multiple non-cognitive traits, and using small-area estimation, we provide precise mean estimates and rankings of intelligence and non-cognitive traits for 360 occupations, including rare professions. Keywords: Social Stratification, Occupation, Non-Cognitive Traits.

Occupation is a significant aspect of adult life (Lambert & Griffiths, 2018), with individuals spending 60,000 to 80,000 h working over a period of 30 to 40 years, shaping both their economic prospects and personal identity. Career choice is often central to an individual's self-concept and personal fulfillment (Banks et al., 1992), while also providing insights into their skills, earning potential, and social status (Hauser & Warren, 1997). As a result, occupation is a fundamental facet of modern society that has been widely studied across various disciplines.

Since the earliest days of modern psychometrics, researchers have quantified the cognitive differences between occupations, creating comprehensive lists of mean occupational cognitive ability (i.e. Gottfredson, 1997; Harrell & Harrell, 1945; Yerkes, 1921) and studying cognitive ability levels of particular professions (i.e. Jordan, 1932; McManus, Smithers, Philippa Partridge, & Keeling, and Peter R Fleming., 2003; Scharfen & Memmert, 2019; Wai, 2013). A recent study (Usher et al., 2021) for example investigated the mean cognitive ability of aerospace engineers and neurosurgeons, professions colloquially seen as the epitome of cognitive demand, and found virtually no significant differences, neither between both occupations nor to the general population - a result that generated substantial public interest.[1]

The great resonance to this finding might be due to its counter intuitive nature, given that theory and previous work strongly suggest otherwise: The effect of individual level cognitive ability on virtually every life outcome is well established (Ritchie, 2015; Warne, 2020). A rich literature links socioeconomic outcomes, such as income (Murray, 1998), social class (Strenze, 2007) and education (Deary, Strand, Smith, & Fernandes, 2007) to cognitive ability. It affects job performance on all levels of complexity, training success in military and civilian contexts as well as leadership and creativity (Kuncel & Hezlett, 2010; Schmidt & Hunter, 1998, 2004). Such performance differences remain, even if investments are undertaken to provide adequate training, and they do not vanish with growing on-the-job experience (Gottfredson, 1997). On an aggregate level, mean occupational IQ is highly correlated with measures of occupational complexity (Zisman & Ganzach, 2023). This implies that intelligence is an important driving force of occupational sorting, leading to visible occupational cognitive stratification - a hypothesis that has been investigated for more than 100 years - and that

* Corresponding author.
E-mail address: twolfram.eisenach@gmail.com.

[1] Being read more than 80,000 times in less than three weeks after publication and picked up by more than hundred news outlets, this paper is one of the top 0.1% most read non-COVID-19 related articles published in the British Medical Journal in the past decade, of a total of almost 25,000 publications, based on month with highest traffic per publication measured by sum of full text and PDF access.

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the result of Usher et al. (2021) might be an artifact, driven by selectivity issues in their non-probability sampling design, which substantially overrepresents individuals with finished tertiary education.

The psychometric view of occupational differentials in ability (Hauser, 2010, from here shortened to *psychometric view*), most famously associated with the works of Jensen (1980, 1998) and Gottfredson (1985, 1986, 1997, 2003), emphasizes the role cognitive ability plays in occupational stratification. This insistence is based on multiple findings: Intelligence "clusters"[2] within occupations, mean occupational cognitive ability differences are substantial and strongly associated with occupational status measures and income. Furthermore, with higher occupational mean cognitive ability, intra-occupational variation decreases. This phenomenon has often been interpreted by proponents of the psychometric view as intelligence acting as a necessary condition to enter and remain in certain professions due to their high cognitive demand.

The psychometric view represents an important puzzle piece within the broader discourse on the mechanisms of social stratification: Here, proponents of the social advantage and disadvantage thesis (SAD, coined by Saunders, 1997) argue for the importance of sociostructural factors (in particular family background) in the stratification process (i.e. Bourdieu, 1987; Bowles & Gintis, 2002b; Bukodi & Goldthorpe, 2018). This perspective is criticized by advocates of the meritocratic thesis, who stress that in modern industrial societies, merit (typically defined as ability plus effort) is the most important determinant of social and economic position (i.e. Herrnstein & Murray, 1995; Marks, 2013, 2022; Saunders, 1997). Within western societies, differences in cognitive ability in adulthood are not associated with rearing environments provided by parents (Bouchard, Lykken, McGue, Segal, & Tellegen, 1990; Willoughby, McGue, Iacono, & Lee, 2021), but instead mostly due to genetic differences (Bouchard, 2014; Plomin & Deary, 2015). In this sense, a strong influence of cognitive ability on occupational sorting can be viewed as evidence for the importance of individual ability in contrast to social (dis-)advantage for stratification processes. Independent of their social starting point individuals therefore "gravitate" (Wilk, Desmarais, & Sackett, 1995) through their career towards occupations whose cognitive demands closely match their own, largely unchangeable abilities.

Two main strands of criticism of the psychometric view can be identified: First, the validity of its results has been drawn into question. Sociologists (Hauser, 2010; Huang, 2013) suspect a lack of representativity and replicability of central findings and conclude that intelligence played an overall much smaller role in occupational stratification than previously claimed. New results like the aforementioned absence of occupational differences in cognitive ability found by Usher et al. (2021) lend credence to such arguments.

Second, accumulating evidence indicates that the focus the psychometric view places on cognitive ability might ignore a wide range of non-cognitive traits (i.e. dimensions of personality, risk aversion or self control) that have been shown to influence occupational sorting (i.e. Almlund, Duckworth, Heckman, & Kautz, 2011; Barrick, Mount, & Gupta, 2003; Dohmen, 2014; Heckman, Stixrud, & Urzua, 2006; Holland, 1997) and that can be considered to fall under the umbrella of ability + effort. So far, it has, however, not been investigated to what extent the findings of the psychometric view on cognitive ability and occupation might also translate to non-cognitive traits. Therefore, the potential of an *extended psychometric view*, taking both cognitive and non-cognitive traits into account, to give a better estimate of the role that individual differences play in occupational sorting, remains to be explored.

[2] Any mention of "clustering" used in this paper refers to the grouping of individuals into different occupations based on certain traits or characteristics, and should not be associated with any statistical cluster analysis method. The term is used in a broader sense to refer to the general concept of grouping individuals into occupations based on certain criteria or characteristic.

Table 1.1
Share of variance in cognitive ability associated with occupation in the literature.

Publication	Population	Share
Stewart (1947)	White enlisted US men (WW2)	0.51
Jensen (1980)	US workforce, collected from late 40s to late 60s	0.47
Gottfredson (1997)	Job Applicants (US, 1983–1992)	0.31
Hauser (2010)	1957 Wisconsin Highschool Graduates (US, first job)	0.22
Hauser (2010)	1957 Wisconsin Highschool Graduates (US, 1975–1977 job)	0.20
Hauser (2010)	1957 Wisconsin Highschool Graduates (US, 1992–1993 job)	0.19
Hunt and Madhyastha (2012)	Job Applicants (US, unclear timeframe)	0.31
Huang (2013)	Extension of Gottfredson's (1997) applicant data (US, 1983–2002)	0.24
Huang (2013)	Repeated observations of NLSY79 panelists (US, 1983–2002)	0.20
Huang (2013)	Repeated observations of WLS panelists (US, first job to 1993)	0.18

This article provides a comprehensive investigation into the existence and size of the stratification and segregation of occupation by cognitive ability and non-cognitive traits. In contrast to past studies, we leverage a recent, large and representative UK sample for this purpose. This allows us to make three central contributions to the literature: a) Using small area estimation methods from survey statistics (Rao & Molina, 2015), we are able to provide representative and precise mean occupational cognitive ability estimates for a total of 360 occupational groups, even in cases where the number of respondents available per occupation seems prohibitively small. Furthermore, we b) thoroughly empirically evaluate the validity of the psychometric view on the importance of cognitive ability for occupational stratification. Lastly, we c) extend both a) and b) to a set of nine non-cognitive traits (the Big Five, risk-taking, delayed gratification, selfi-efficacy and overall mental health), to test the validity of an extended psychometric view.

1. Occupation and cognition

1.1. *The psychometric view of occupational differentials in ability*

Due to the large samples required, the first studies that provided job level estimates of cognitive ability relied on military data: At the request of personnel officers, Yerkes (1921) tested 18,423 soldiers during the last months of World War I using the Army Alpha and Army Beta test and constructed the first intelligence estimates for 68 occupations based on interviews in which they stated their pre-war professions, later improved and extended to 96 occupational designations (Fryer, 1922). Early on, researchers stressed the importance of the occupational sorting by intelligence apparent in these data for social stratification research (Kornhauser, 1925).

With the advent of World War II new data became available: Harrell and Harrell (1945) reported estimates for 74 occupations using information on 18,782 white Air Force recruits, shortly followed by much more detailed reports on 227 occupations based on 83,618 enlisted white army recruits, collected by Stewart (1947). Being based on male samples of ethnically homogeneous (white) soldiers, these estimates, though intuitively sensible in their findings, could not be considered representative for the working US population.

Still, these studies showed sizable clustering of cognitive ability within occupation (see Table 1.1. In general, all mentions of occupational clustering, between-occupational variation, etc. refer to the share of total variance in an outcome variable (i.e. cognitive ability) that can be explained by a categorical occupational grouping variable, which is equivalent to the intra-class correlation coefficient (ICC). By taking the square-root, one obtains a measure of correlation between occupation and the outcome variable as sometimes used in the literature (i.e. Hauser, 2010).

Results for civil populations proved to be even more difficult to obtain: Using U.S. Department of Labor data (US Department of Labor, 1970), Jensen analyzed cognitive test results of 39,600 US workforce participants clustered in 444 occupations (Jensen, 1980, 339ff) and showed that almost half of the variation in cognitive ability occurs between occupations. Later, Gottfredson (1997) presented estimates for 72 professions. Here, 31% of the total variation was explained by between-occupation differences. Using newer data from the same source, Hunt and Madhyastha (2012) found that a measure of general cognitive ability derived from expert-rated occupational skills (Peterson, Mumford, Borman, Jeanneret, & Fleishman, 1999, see also Data & Methods below) correlated strongly ($r = 0.56$, implying again 31% of the variation explained) with individual level intelligence. However, both analyses were based on a commercial dataset of job applicants, not actual employees, again putting the representativity of the data used in question.

In addition, high correlations between occupational mean cognitive ability and sociological metrics of occupational status and prestige in the range of 0.8 to 0.9 have been reported early on (i.e. Canter, 1956; Counts, 1925). These findings became integrated into canonical treatments of the literature on occupation and cognitive ability (i.e. Gottfredson, 2003; Jensen, 1980). Hunt and Madhyastha (2012) confirmed these results and report a correlation between occupational complexity (highly correlated with mean occupational cognitiv ability, Zisman & Ganzach, 2023) and median salary of 0.73.

Finally, another finding of the literature concerns the spread within the occupational intelligence distribution: First identified by Harrell and Harrell (1945), the variation of cognitive ability within occupation becomes smaller with increasing occupational mean ability. This implies, that while jobs with low cognitive demands overall attract applicants with matching cognitive ability, they will (i.e. due to incomplete information, viewing a position as a stepstone, etc.) also draw individuals of higher intelligence levels than required, resulting in high within-occupation variation. In contrast, with increasing occupational mean intelligence, cognitive job demands rise to a level that only a diminishing share of the population is capable to satisfy, therefore reducing the variance. “A certain threshold level of intelligence is a necessary but not sufficient condition for success in most occupations” (Jensen, 1980, 344).

This overall tradition of research has subsequently been coined the psychometric view of occupational differentials in ability (Hauser, 2002, 2010; Huang, 2013). It concludes that intelligence is a) heavily clustered by occupation, b) its variance decreases with the mean and c) mean occupational cognitive ability shows strong associations with sociological measures of occupational status and pay.

1.2. Potential mechanisms

The psychometric view has provided insights into the cognitive differences that exist among occupational groups, but the underlying mechanisms driving these differences remain unclear. From a sociological perspective, associations of mean occupational cognitive ability and measures of occupational status and salary, align well with a “modified-functionalist” (Gottfredson, 1985) framework: Here, social stratification can be viewed as a cultural adaption by which complex societies assure that the most qualified individuals (defined by their relevant abilities) ascend to the most important positions by providing incentives in the form of monetary compensation and status (Davis & Moore, 1945), therefore driving occupational sorting.

This process can be further understood by examining individual-level mechanisms proposed by the gravitational hypothesis (McCormick, DeNisi, & Shaw, 1979; McCormick, Jeanneret, & Mecham, 1972): According to this hypothesis, individuals self-select into occupations based on their abilities, interests, and values, while organizations use cognitive ability in relation to occupational complexity as a criterion in staffing decisions (Wilk et al., 1995). The level of cognitive aptitude required for successful performance varies across occupations, and individuals tend to gravitate towards jobs that match their abilities and preferences: A poor match between an individual’s abilities and the complexity of their job can motivate them to seek out or gravitate towards a better match, potentially leading to greater career stability (Wilk & Sackett, 1996). Tying the micro and macro levels together, Ganzach (2011) demonstrated that these shifts not only relate to job complexity but also to compensation, as less intelligent workers tend to move towards lower-paying jobs while more intelligent workers tend to move towards higher-paying jobs.

1.3. Criticism

The psychometric view has been drawn into question by social scientists, who emphasize the lack of representativity of the early military data and in addition argue that the U.S. Department of Labor results Jensen relied on are potentially biased as well: Data were collected “somewhat haphazardly, over a period of years, from the late 1940s to the late 1960s, and in ‘samples’ of highly variable size, definition, and quality” (p. 28, Hauser, 2002). Hauser (2002, 2010) and Huang (2013) provide instead two alternative data sources (Wisconsin Longitudinal Study, WLS and National Longitudinal Survey of Youth, NLSY79) and find much weaker occupational clustering by ability (a comparison of the various estimates in the literature is displayed in Table 1.1) and small to no associations between mean occupational intelligence and within-occupation variation.

These datasets, though, are in themselves questionable with respect to their representativeness of the population: The WLS used in (Hauser, 2002, 2010), a sample of 10,317 respondents, is restricted to men and women that graduated from Wisconsin high schools in 1957, and therefore truncated with respect to cognitive ability by excluding high school dropouts. It furthermore represents only a geographically selective part of the US population and due to the small sample size, ability estimates can only be constructed for 65 large occupational clusters. The NLSY79 proposed by Huang (2013) comprises less than 13,000 participants born between 1957 and 1964, whose repeated observations had to be pooled to obtain a sample large enough to be analysed.

Whether the high estimates of occupational clustering in the earlier literature or the lower values found in newer studies are closer to the truth and if the association between occupational means and intra-occupational variance truly exists, remains therefore to be tested in a large and population-representative dataset, as the one used in this study.

2. Occupation and non-cognitive traits

Occupational stratification can be argued to be a realization of a diverse range of measurable psychological traits, rather than just intelligence. Labor economists (i.e. Dohmen, 2014; Heckman et al., 2006), as well as vocational and industrial/organizational psychologists (i.e. Barrick et al., 2003; Holland, 1997) stress the role of personality and other non-cognitive factors for selecting into occupations. For example, strong correlations have been found between personality factors and the selection of white collar occupations (Ham, Junankar, & Wells, 2009), as well as the tendency of risk-taking graduates to choose high-earning occupations with higher employment risks (Fouarge, Kriechel, & Dohmen, 2014). Distinctive profiles of personality traits can be identified for various jobs (Lounsbury et al., 2012; Lounsbury, Steel, Gibson, & Drost, 2008), even using nonstandard data sources, like social media postings (Kern, McCarthy, Chakrabarty, & Rizoiu, 2019). In line with the gravitational hypothesis, individuals aligning with these profiles achieve higher wages (John & Thomsen, 2014) and are on average more productive (Barrick & Mount, 1991).

Conflict theoretic sociologists (i.e. Bowles & Gintis, 1976, 2002a) have emphasized the significance of non-cognitive traits in the labor market, giving them more importance than cognition. Specifically, work habits that enable effective individual and organizational performance, such as the ability to conform to rules and procedures, adherence to external authority (for jobs with low complexity), and initiative guided by internalized behavioral norms (at higher work complexity levels), are deemed crucial. Additionally, focus, energy, and efficiency are thought to be universally valued (Farkas, 2003). As such, socialization processes within the family and education system are presumed to shape non-cognitive traits, enabling employers to exert control over their employees.

Nonetheless, a plethora of twin studies reveals minimal to no systematic impact of the rearing environment, but substantial genetic influences on various non-cognitive traits, including personality (Briley & Tucker-Drob, 2017), self-perceived ability (Greven, Harlaar, Kovas, Chamorro-Premuzi, & Plomin, 2009), achievement motivation (Klassen, Eifler, Hufer, & Riemann, 2018), and self-control (Willems, Boesen, Li, Finkenauer, & Bartels, 2019). Molecular genetic evidence further corroborates this notion: Buser, Ahlskog, Johannesson, Oskarsson, et al. (2022) provide evidence that individuals with different genetic predispositions sort into diverse study majors and occupations, with a partially causal effect, as evidenced by sibling comparisons. The authors identify three different psychological dimensions in the genome along which occupations are stratified: A combination of risk seeking, extraversion, openness to experience and mental stability ("daring"); a combination of cognitive skills, maths skills and self-control ("analytical", combining cognitive and non-cognitive traits), as well as an "emotional" component, which brings together high pro-sociality with low mental stability and low self-control.

While previous studies have established the compelling significance of non-cognitive traits in occupational stratification, a comprehensive evaluation has yet to be conducted to compare occupational clustering and hierarchies in relation to these factors vis-à-vis cognitive ability. The undertaking of such an assessment has been hindered by several impediments, including the need for accurate measurement of the traits in question, intelligence, and occupational information for a large pool of respondents, which proved to be prohibitively challenging until now.

3. Data & methods

3.1. Understanding society

The analysis is based on *Understanding Society*, an ongoing longitudinal survey of more than 40,000 UK households that started in 2009 (Buck & McFall, 2011). Interviews are carried out face-to-face and a complex stratified sampling design is employed to ensure representativity for the population of the United Kingdom (Benzeval et al., 2020).

Occupation: We operationalize occupation using the 2010 Standard Occupational Classification (SOC2010) (Elias, Birch, et al., 2010), which distinguishes 9 major, 25 sub-major, 90 minor and 369 unit groups. In some years, occupations of a subset of respondents were only measured using the previous SOC2000 system (Elias, McKnight, Davies, & Kinshott, 2000). In these cases, SOC2000 was mapped to SOC2010 using a crosswalk.[3] For each cognitive and non-cognitive trait, occupation from the same wave was used. If occupational information was missing in a particular wave, information from the most recent wave (either preceding or following) was used. Overall, valid occupation measures are available for 56,096 respondents, spanning 367 SOC2010 unit groups.

Cognitive Ability: Respondents aged 16 or older were asked to participate in a range of tests of cognitive ability as part of wave 3 of the survey. Data were collected from January 2011 to April 2013. Five cognitive domains were assessed, including verbal declarative memory through immediate and delayed word recall tasks; fluid reasoning with a select subset of number series from the Woodcock-Johnson III Tests of Cognitive Abilities; numeric ability using everyday problems that required arithmetic operations (quantitative reasoning tasks in the terminology of Carroll, 1993); working memory using a sequential subtraction task; and verbal semantic fluency by asking participants to name as many animals as possible within one minute.[4] A detailed overview of all tests can be found in (McFall, 2013). Utilizing the scores of all 5 tests (adjusted by age and a squared term of age), a general factor of cognitive ability was extracted by means of exploratory factor analysis using the psych-package (Revelle, 2017) in R. To guard against floor- and ceiling effects, factor scores were rank-normalized and scaled to the conventional values of the IQ-scale (mean = 100 and standard deviation = 15), including respondents outside of the labor force or without occupational information. A comparison of both rank-normalized and raw distributions is given in Figs. A.1 and A.2.

Table 3.1
Descriptive statistics of used cognitive and non-cognitive measures.

Wave	Trait	N[1]	Mean	SD	Alpha	Omega
1	Willingness to take Risks	26,018	0.14	0.90	–	–
3	Big 5: Agreeableness	28,725	−0.03	0.94	0.57	0.59
3	Big 5: Conscientiousness	28,724	0.05	0.91	0.54	0.58
3	Big 5: Extraversion	28,723	0.04	0.95	0.6	0.62
3	Big 5: Neuroticism	28,727	0.01	0.94	0.7	0.71
3	Big 5: Openness	28,691	0.08	0.94	0.66	0.67
3	Cognitive Ability	29,036	100.97	14.34	0.75	0.71
4	Overall Mental Health	27,682	0.05	0.99	0.9	0.91
5	Delayed Gratification	26,977	0.01	0.98	0.57	0.58
5	Generalized Self Efficacy	26,953	0.06	0.95	0.91	0.91

[1] Cases with information on both the respective trait and occupation.

Non-Cognitive Traits: Data on multiple non-cognitive traits is available in Understanding Society through various waves. We construct scores from exploratory factor analysis for the big five personality traits based on the items of the BFI-15 inventory (Lang, John, Lüdtke, Schupp, & Wagner, 2011), overall mental health as measured by the 12-item General Health Questionnaire (GHQ-12, Goldberg & Williams, 1988), delayed gratification using seven items[5] from the Delayed Gratification Inventory (DGI-10, Hoerger, Quirk, & Weed, 2011), self-efficacy using the 10 item Generalized selfi-efficacy Scale (Schwarzer & Jerusalem, 1995) and willingness to take risks based on a single item assessing subjective risk preferences ("Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?"). All measures are again constructed on the complete set of respondents, rank-normalized and afterwards restricted to the working population. A comparison of both rank-normalized and raw distributions is given in Figs. A.1 and A.2.

An overview of all constructs is given in Table 3.1: For each trait 26,000 to 29,000 observations with information on occupation and the respective variable are available. Reliability of the constructs as measured by Cronbach's Alpha and McDonald's Omega varies. For cognitive ability, alpha reliability was estimated as a weighted linear combination of all subtests (Nunnally & Bernstein, 1994) and Omega using the hierarchical Omega (Zinbarg, Yovel, Revelle, & McDonald, 2006).

[3] Available at https://github.com/dncnbrn/SOCmapping.

[4] To guard against biases, we removed veterinarians from the sample as their score on this test exceeded all other occupations by a significant margin for obvious reasons.

[5] We removed three items ("I try to consider how my actions will affect other people in the long-term.", "I do not consider how my behaviour affects other people.", "I have given up physical pleasure or comfort to reach my goals.") that showed no loading on a joint factor.

3.2. Occupational status measures

Information on the International Index of Socioeconomic Status (ISEI, Ganzeboom, De Graaf, & Treiman, 1992), Standard International Occupational Prestige Scale (SIOPS, Ganzeboom & Treiman, 1996) and occupational median pay was collected. ISEI and SIOPS scores are provided by Ganzeboom and Treiman (2010), who used the less granular ISCO-08 scale, so a mapping from ISCO to SOC2010[6] was employed. In cases where no 1:1 matching was possible, weighted means of the ISEI and SIOPS scores were calculated. Information on mean occupational pay was estimated using data from the Labour Force Survey (LFS) and the Annual Survey of Hours and Earnings (ASHE) according to the method described by Barnes (2019).

3.3. Small area estimation

As can be seen in Fig. A.3, the number of respondents per occupation is unequally distributed for all traits: One fifth of all occupations have (depending on the trait in question) less than 13–17 observations, 10% less than 8–9 observations. Direct estimation of occupational means with such a small number of respondents would lead to very imprecise estimates.

We solve this problem by utilizing small area estimation (SAE). SAE is a subfield of survey statistics aimed at providing reliable measurements for disaggregated geographic (small area) or demographic (small domains) subgroups with small sample size, where direct estimation would result in high uncertainty. Modern SAE solves this issue by "borrowing strength" (Ghosh & Rao, 1994) from external auxiliary information about the area/domain and combining it with a direct estimator (Rao & Molina, 2015), therefore drastically increasing precision of estimates.

3.3.1. The Fay-Herriot model

A commonly used approach in the SAE-literature is the Fay-Herriot (FH) model (Fay & Herriot, 1979), which we apply to generate precise cognitive and non-cognitive mean estimates for m occupations. In the terminology of Jiang and Lahiri (2006) we have a two-level Bayesian model of the form

$$\text{Level 1}: y_i^{Direct}|\theta_i \overset{ind}{\sim} N(\theta_i, \psi_i), i = 1, \ldots, m;$$
$$\text{Level 2}: \theta_i \overset{ind}{\sim} N(x_i{}'\beta, \sigma_u^2), i = 1, \ldots, m.$$

Here θ_i denotes the true parameter of interest, in our case the mean estimate for occupation i. However, we only observe a noisy direct estimate y_i^{Direct} with a sampling variation, ψ_i, which is equated with the sampling variance ($Var(y_i^{Direct})$). We obtain y_i^{Direct} by computing means of cognitive ability and non-cognitive traits for each occupation, with each observation being again weighted using design weights (Lynn, Kaminska, et al., 2010). For estimation of $Var(y_i^{Direct})$, a nonparametric bootstrap is applied.

Level 2 links θ_i to a vector of known auxiliary variables x_i (see below) that are associated with θ_i through a vector of coefficients, β. Remaining variance of θ_i, that is not captured by $x_i{}'\beta$, is expressed in σ_u^2. Given x_i, $Var(y_i^{Direct})$ and y_i^{Direct} for a vector of m occupations, estimates of σ_u^2 and β are obtained using maximum likelihood theory.

Finally, the fitted model is used to construct Empirical Best Linear Unbiased Predictions (EBLUPs, Robinson, 1991) of θ_i for each occupation:

$$\widehat{\theta}_i^{EBLUP} = \gamma_i y_i^{Direct} + (1-\gamma_i) x_i{}'\widehat{\beta}.$$

The EBLUP estimate for a particular occupational mean is therefore a composite of the direct estimator y_i^{Direct} and the predicted mean given the auxiliary variables $x_i{}'\widehat{\beta}$, weighted by a factor γ_i. It is determined by the strength of the association of the auxiliary variables with the outcome and the degree of uncertainty in the direct estimate ψ_i:

$$\gamma_i = \frac{\widehat{\sigma}_u^2}{\psi_i + \widehat{\sigma}_u^2}.$$

For direct estimates of occupations with a large number of observations, differences between $\widehat{\theta}_i^{EBLUP}$ and y_i^{Direct} will therefore be small, while noisy direct estimates will be shrunk towards $x_i{}'\widehat{\beta}$, especially if a strong relationship between x and θ exists.

The uncertainty of the EBLUP[7] can be quantified using either analytical means or bootstrapping. Robust variants of the FH-model exist to guard against potential bias if distributional assumptions are violated (Warnholz, 2016) and are used accordingly in the analysis.

3.3.2. Auxiliary variables

The FH-model requires external auxiliary information about each occupation. We utilize data of the US O*NET system for this purpose: O*NET (Peterson et al., 1999) is an extensive database, containing detailed information on abilities, skills, interests and knowledge required for different jobs, according to the verdict of experts. We collect data on 20 abilities (enduring attributes of the individual that influence performance) and their importance for occupations rated on scales from 0 to 7. The same is done for 18 skills (meaning capacities that facilitate learning or the more rapid acquisition of knowledge). 9 different types of interests (preferences for work environments) are further available, as well as 33 knowledge indicators, encompassing sets of principles and facts relevant to the respective occupation. As O*NET is extremely granular, data on 1575 different jobs were collected and mapped to SOC2010 occupations following a crosswalk provided by the LMI For All API.[8] If multiple O*NET jobs were related to a single SOC2010 entry, the mean was computed. In total, 360 occupations could be mapped.

3.4. Estimating occupational clustering

Univariate: To maximize the number of respondents, we estimate the degree of occupational clustering for each trait separately. For this, we apply linear models with the respective trait as the dependent variable and occupation as a random effect on the individual level. The share of variance explained by the random effect denotes our measure of interest.[9] In order to obtain standard errors, a nonparametric bootstrap ($n = 50$) is used.

Multivariate: Analyzing each trait separately can underestimate the true extent to which cognitive and non-cognitive traits are relevant for occupational stratification depending on the correlation structure of all variables in question (Del Giudice, Marco, & Irwing, 2012). We calculate an estimate of the multivariate occupational clustering by cognitive and non-cognitive traits using 1 - Wilk's Lambda, a multivariate generalization of the within-group variance (Wang, Bridgeford, Wang, Vogelstein, & Caffo, 2020). Unfortunately, due to the longitudinal nature of Understanding Society, complete information on all traits is only available for a fraction of respondents. We restrict ourselves to

[6] Accessible at https://www.ons.gov.uk/file?uri=/methodology/classificationsandstandards/standardoccupationalclassificationsoc/soc2010/ug201002soc2010toisco08v2_tcm77-283163.xls

[7] As the EBLUP minimizes the mean squared error, we technically no longer look at a variance or standard error or but instead at the MSE, whose square root can for all intents and purposes be treated as a standard error.

[8] Accessible via http://api.lmiforall.org.uk

[9] Each observation is weighted according to the calibrated design weights provided by Understanding Society (Lynn et al., 2010). To correct for measurement error we apply Spearman's attenuation correction using McDonald's Omega as a reliability measure (correction using Cronbach's Alpha led to very similar results), as done in previous studies (most notably Hauser, 2010; Jensen, 1980).

Table 4.1
Proportion of variance of cognitive ability and non-cognitive traits associated with occupation.

	Overall	By Sex		By Age	
		Male	Female	Older Half	Younger Half
Cognitive Ability	0.241*** (0.006)	0.29*** (0.009)	0.241*** (0.007)	0.304*** (0.009)	0.236*** (0.009)
Big 5: Agreeableness	0.089*** (0.004)	0.101*** (0.005)	0.088*** (0.005)	0.147*** (0.007)	0.115*** (0.006)
Big 5: Conscientiousness	0.071*** (0.004)	0.122*** (0.006)	0.095*** (0.006)	0.109*** (0.006)	0.122*** (0.007)
Big 5: Extraversion	0.067*** (0.004)	0.101*** (0.006)	0.082*** (0.004)	0.104*** (0.006)	0.11*** (0.005)
Big 5: Neuroticism	0.085*** (0.004)	0.09*** (0.005)	0.067*** (0.004)	0.117*** (0.006)	0.109*** (0.005)
Big 5: Openness	0.096*** (0.004)	0.146*** (0.008)	0.111*** (0.006)	0.157*** (0.007)	0.111*** (0.005)
Delayed Gratification	0.093*** (0.005)	0.139*** (0.009)	0.117*** (0.006)	0.131*** (0.008)	0.133*** (0.008)
Generalized Self Efficacy	0.069*** (0.003)	0.094*** (0.005)	0.077*** (0.004)	0.095*** (0.005)	0.096*** (0.005)
Overall Mental Health	0.036*** (0.002)	0.062*** (0.003)	0.05*** (0.003)	0.068*** (0.004)	0.056*** (0.003)
Willingness to take Risks	0.059*** (0.003)	0.074*** (0.004)	0.067*** (0.003)	0.108*** (0.004)	0.071*** (0.004)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

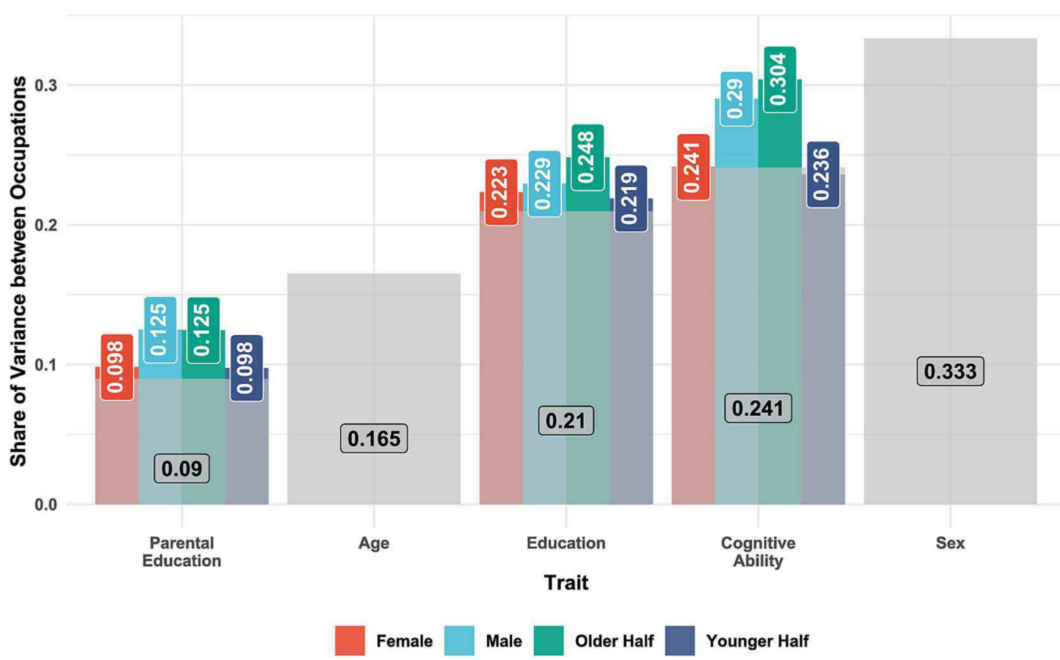

Fig. 1. Share of variance of cognitive ability and sociodemographic variables associated with occupation.

intelligence and the dimensions of the big five, all of which were part of wave 3 and therefore answered by a large overlapping set of respondents, resulting in 27,532 cases.

4. Analysis

4.1. Occupational clustering of cognitive ability and non-cognitive traits

Estimates for occupational clustering for both non-cognitive traits and intelligence are displayed in Table 4.1. For cognitive ability, roughly a quarter of the total variance (24.1%) can be attributed to between-occupation differences. Homogenizing samples for sex and age show substantially stronger clustering for men (29%, compared to 24.1% for women) and older participants (30.4% compared to 23.6% for the younger half). Significant effects are found for each non-cognitive outcome (strongest for gratification delay, openness and agreeableness, weakest for mental health). Once more, homogenizing for age and sex increases the estimates in nearly all cases, with higher values obtained for men than for women. To make sure that non-cognitive clustering is not just an artifact driven by correlations between non-cognitive traits and cognitive ability, we residualized all non-cognitive outcomes for cognitive ability. As shown in Table A.1, this only marginally reduced clustering. Still, no single non-cognitive trait is as strongly associated with occupational sorting as cognitive ability.

It is instructive to compare the estimated degree of occupational clustering by cognitive ability to the sociodemographic occupational

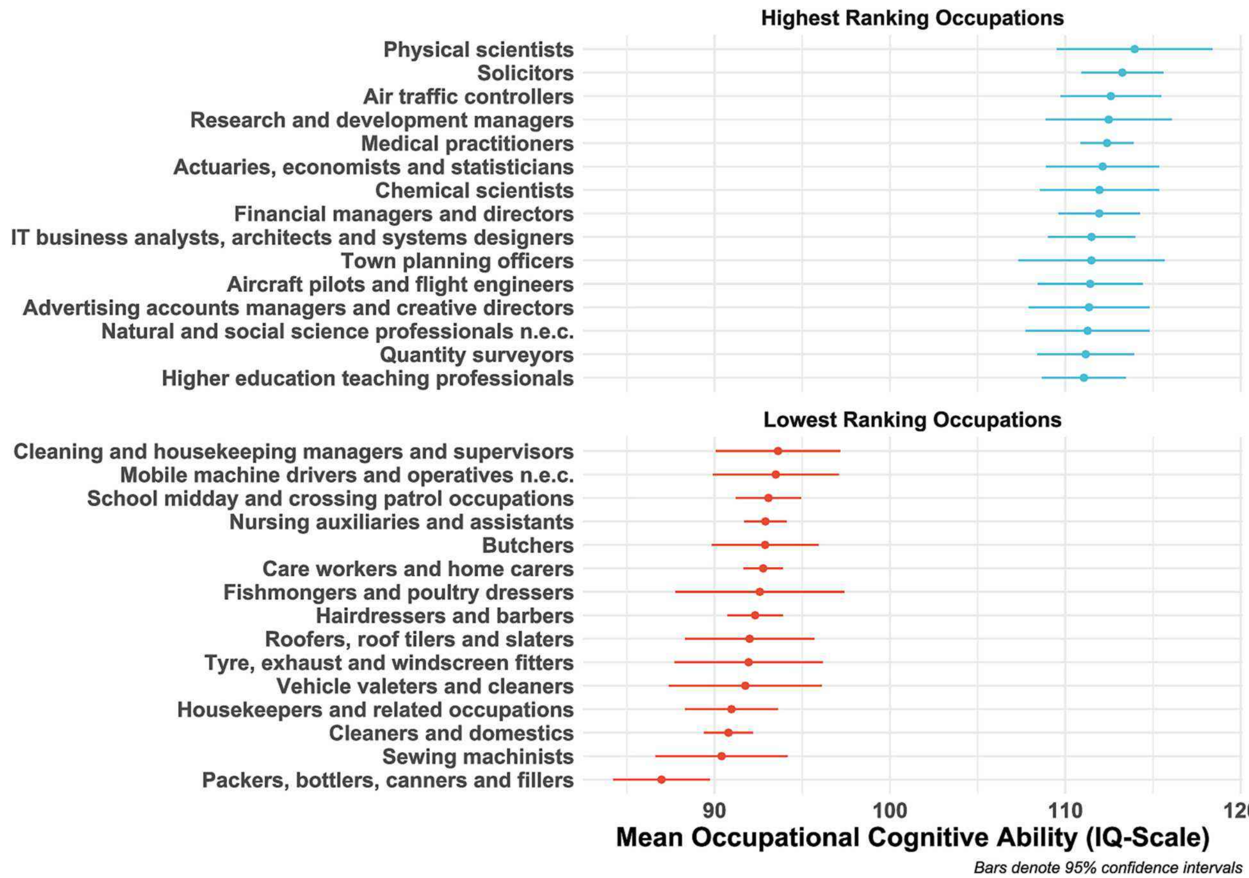

Fig. 2. Top highest and lowest ranking occupations for cognitive ability.

clustering observed in everyday life, such as by age (Brinton & Ngo, 1993; Humpert, 2012), sex (Charles, 2003; Haveman & Beresford, 2012), and education (Bernardi & Ballarino, 2016). As depicted in Fig. 1, individuals within occupations tend to share similar age, sex, and educational backgrounds. Intelligence, on the other hand, displays more pronounced clustering than any sociodemographic factors except for sex. In contrast to the social advantage and disadvantage thesis, parental socioeconomic status, which is measured by the highest level of parental education, demonstrates only slight clustering within occupations.

Multivariately, we estimate 1- Wilk's Lambda (correcting by the mean reliability of the involved constructs) for cognitive ability and the five dimensions of the Big Five as 0.498, indicating that personality and cognition exhibit a strong joint clustering within occupation.

4.2. Constructing precise mean estimates using small area estimation

In line with the aforementioned low observational count (Fig. A.3), precision of direct estimates is low for many occupations. We fit FH models (as implemented in the R emdi-package; Kreutzmann et al. (2019)) using the O*NET auxiliary variables, a best subset of which is chosen by forward-selection for each outcome. Measurement-error corrected *adj.* R^2 values (Lahiri & Suntornchost, 2015) of the fitted models indicate sizable associations between auxiliary variables and the (non-)cognitive traits, ranging from 0.23 (overall mental health) to 0.8 (cognitive ability), as shown in Table A.2.[10] Model-based and direct estimates are highly correlated as shown in Fig. A.5.[11] However, as expected, precision of the model-based estimates is substantially higher (Fig. A.7): The median standard error of the FH-EBLUP is between 23.6% (cognitive ability) and 56% (overall mental health) smaller than that of the direct estimate, for 25% of the observations, the reduction amounts to between 37.5% (cognitive ability) and 67.3% (overall mental health). A full overview is given in Table A.4.

Cognitive mean estimates: For cognitive ability, results for the 15 highest and lowest scoring occupations are shown in Fig. 2 and exhibit a high face validity: Cognitive demanding professions like lawyers, engineers, scientists and statisticians are found at the top, while manual jobs like packers and cleaners are at the bottom.

Similarly, top and bottom positions for non-cognitive traits are intuitively sensible, as the selection in Fig. 3 and the full overview in Fig. A.9 indicate. The complete rankings, including direct and model-based estimates and their uncertainty for all available SOC2010 occupations are given in appendix B. In addition, we converted the model-based estimates to the International Standard Classification of Occupations (ISCO-08) using the crosswalk provided by the ONS.[12] Both SOC2010 and ISCO-08 model-based estimates are available in a supplementary excel table.

[10] Residual diagnostics indicated a violation of the normality assumption for some of the models. We mitigate this issue by fitting a robustified version of the Fay-Herriot model with bootstrapped MSE (Warnholz, 2016)

[11] Furthermore, as a robustness check, we verify that the rank-normalization of our traits of interest did not substantially alter results, as can be seen in Figure A.6.

[12] Available at https://www.ons.gov.uk/economy/environmentalaccounts/datasets/truncatedproportionalconversionbetweenisco08andruksocclassifications

Fig. 3. Top 5 highest and lowest ranking occupations non-cognitive traits (selection), n.e.c = not else classified.

4.3. Associations between occupational trait means and status measures

In order to test if an association between mean occupational intelligence and measures of occupational status exists, we computed correlations between the occupational trait estimates from the small area models and ISEI, SIOPS and median income. The obtained coefficients indicate strong associations between mean occupational cognitive ability and both dimensions of occupational status, as well as income for the small area estimates as shown in Fig. 4. Similar effects are found for delayed gratification, selfi-efficacy, openness, conscientiousness and risk preferences. Notably, the associations with delayed gratification are almost as high as those with intelligence. Very small or even negative correlations exist between the three measures and the remaining other non-cognitive traits, overall mental health, neuroticism, agreeableness and extraversion. Analyses using direct instead of model-based estimates lead to similar results (Fig. A.8).

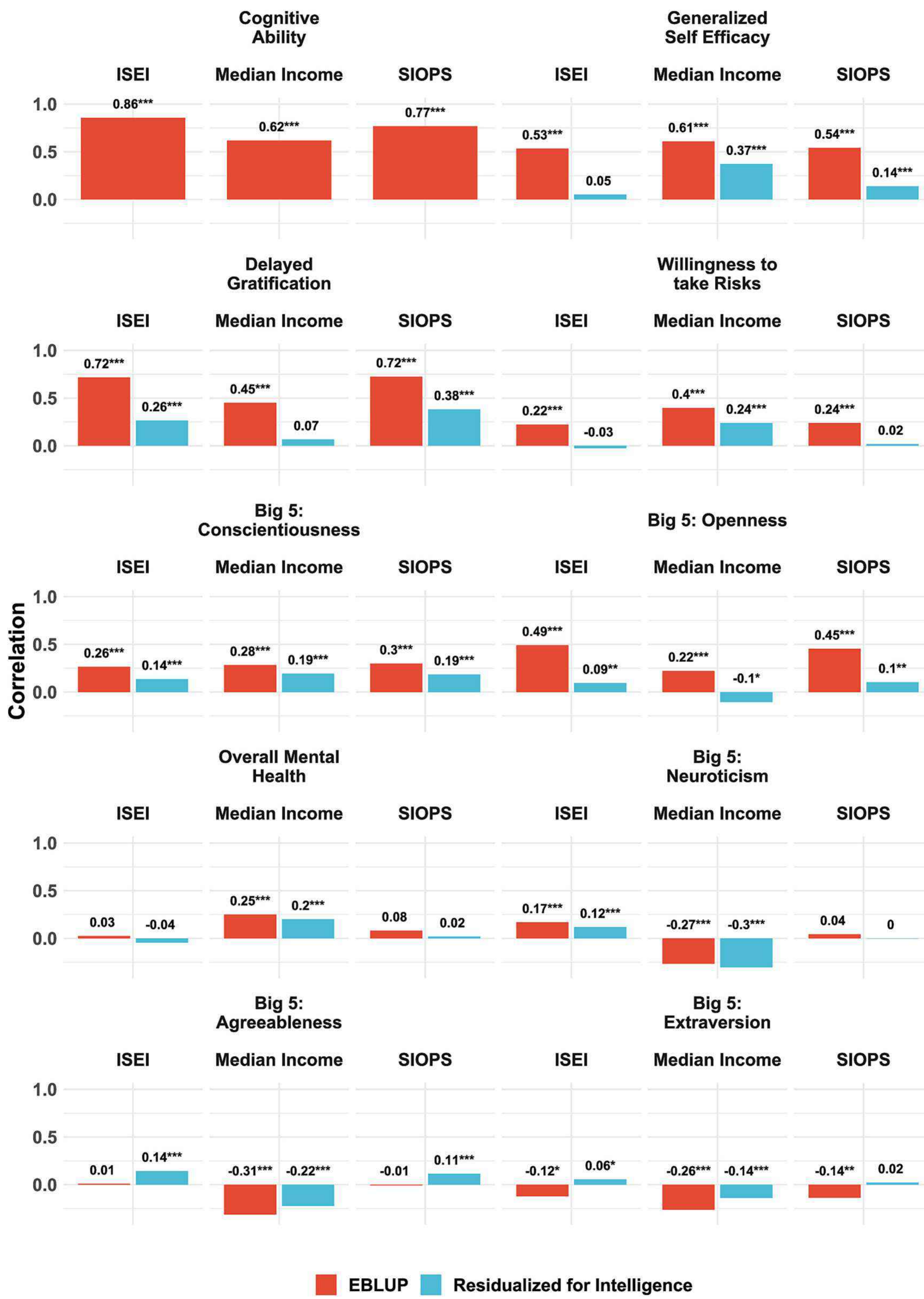

Fig. 4. Correlation of cognitive ability and non-cognitive traits with occupational status, prestige and income, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

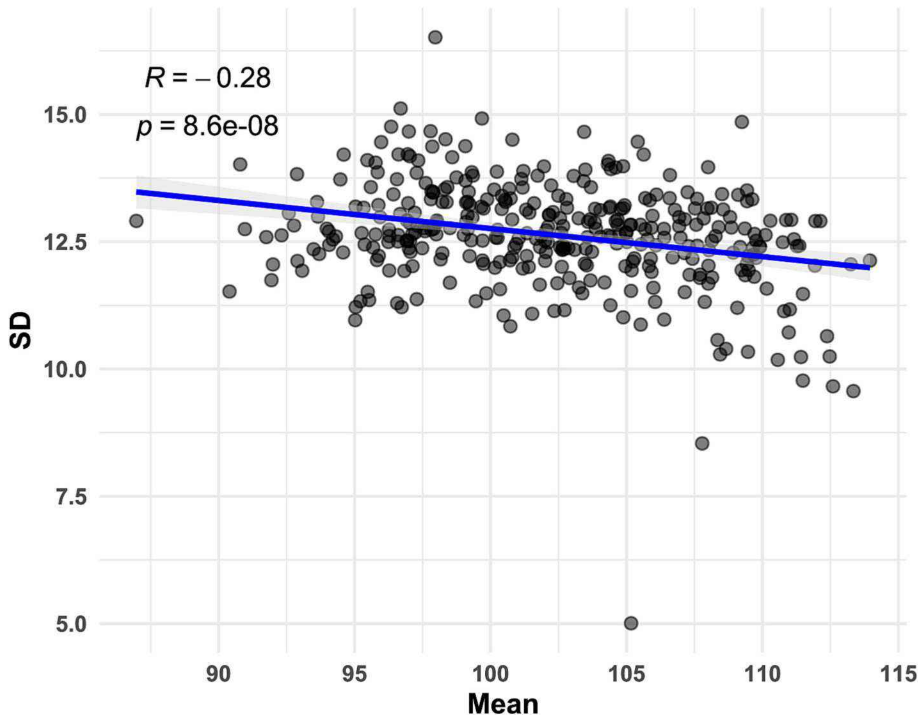

Fig. 5. Correlation of between-occupation mean and within-occupation standard deviation (cognitive ability).

4.4. Within-occupation variation as a function of between-occupation means

To investigate the association between intra-occupational variance and occupational means, we looked at the correlation between the model-based occupational mean estimates and the respective within-occupation standard deviation. As the latter is highly variable (especially for professions with small N), we again use the Fay-Herriot approach to stabilize estimates of standard deviations using the same approach as for the means. As shown in Table A.3 associations with the auxiliary variables are again substantial, correlations between model-based and direct estimates are high (Fig. A.10) and standard errors significantly reduced (Fig. A.7).

Fig. 5 displays correlations *between mean and SD* for cognitive ability, which are moderate (−0.28). Again, we find similar patterns for non-cognitive traits: Fig. 6 indicates significant associations between occupational means and standard deviations for all traits with the exception of agreeableness. The correlation for intelligence is even surpassed by that for mental health (−0.4) and extraversion (0.5). However, while all other effects are also observable in the association of direct estimates of mean and SD, this is not the case for these two traits (Table A.5). Furthermore, especially for agreeableness and conscientiousness, but to a lesser degree also for risk taking, openness, self-efficacy, neuroticism and extraversion, we observe floor and ceiling effects in the trait distribution (as shown in Fig. A.7) that might slightly bias these results upwards, away from null.

5. Discussion

In the present study, we constructed estimates of mean cognitive ability for more than 360 occupations using small area estimation and external auxiliary information from O*NET. The general structure of the constructed ranking is intuitively sensible and exhibits high face validity. This is the first time in roughly thirty years that such a ranking has been made available for cognitive ability, and to our knowledge the first time that it is based on a representative sample. We also use the same approach to provide estimates for nine non-cognitive traits, which exhibit high face-validity as well. As researchers commonly categorize professions according to the SOC2010 classification, our constructed data are easily transferable to other studies, for example as a useful proxy or imputation measure for cognitive ability and non-cognitive traits.

Using this data, we investigated the importance of cognition for occupational sorting. We found strong variation in cognitive ability between professions: The difference between the highest and lowest mean intelligence estimates amounts to almost two standard deviations (physical scientists, with 114 vs. packers, bottlers, canners and fillers, with 87) and aligns well with past rankings (i.e. Gottfredson, 1997). Roughly a quarter of the variation in cognitive ability occurs between occupations, for men and older participants it is close to one third.

By comparing occupational sorting based on intelligence to sorting based on sociodemographic factors, which are visible in everyday life, we show that incumbents within occupations tend to be more similar with regards to their intelligence than they are in terms of age and years of education, however not sex, stressing the importance of horizontal stratification by sex-specific occupational choice (Steinmetz, 2011). Occupational sorting by parental socioeconomic status is in contrast very weak.

Clustering for non-cognitive traits is statistically significant, but smaller: For all studied traits, less than 10% of the variance is attributable to occupation and the difference between lowest and highest occupational mean scores range from 0.49 (mental health) to 1.47 (openness) SD, with most traits being close to one SD.

We also analysed the association of both cognitive and non-cognitive occupational mean estimates with measures of occupational status and prestige, as well as income. Again, we find the strongest associations for intelligence, though multiple non-cognitive traits, in particular delay of gratification, self-efficacy, openness to experience, conscientiousness and risk preferences, also show sizable effects.

Lastly, we studied the relationship between occupational mean

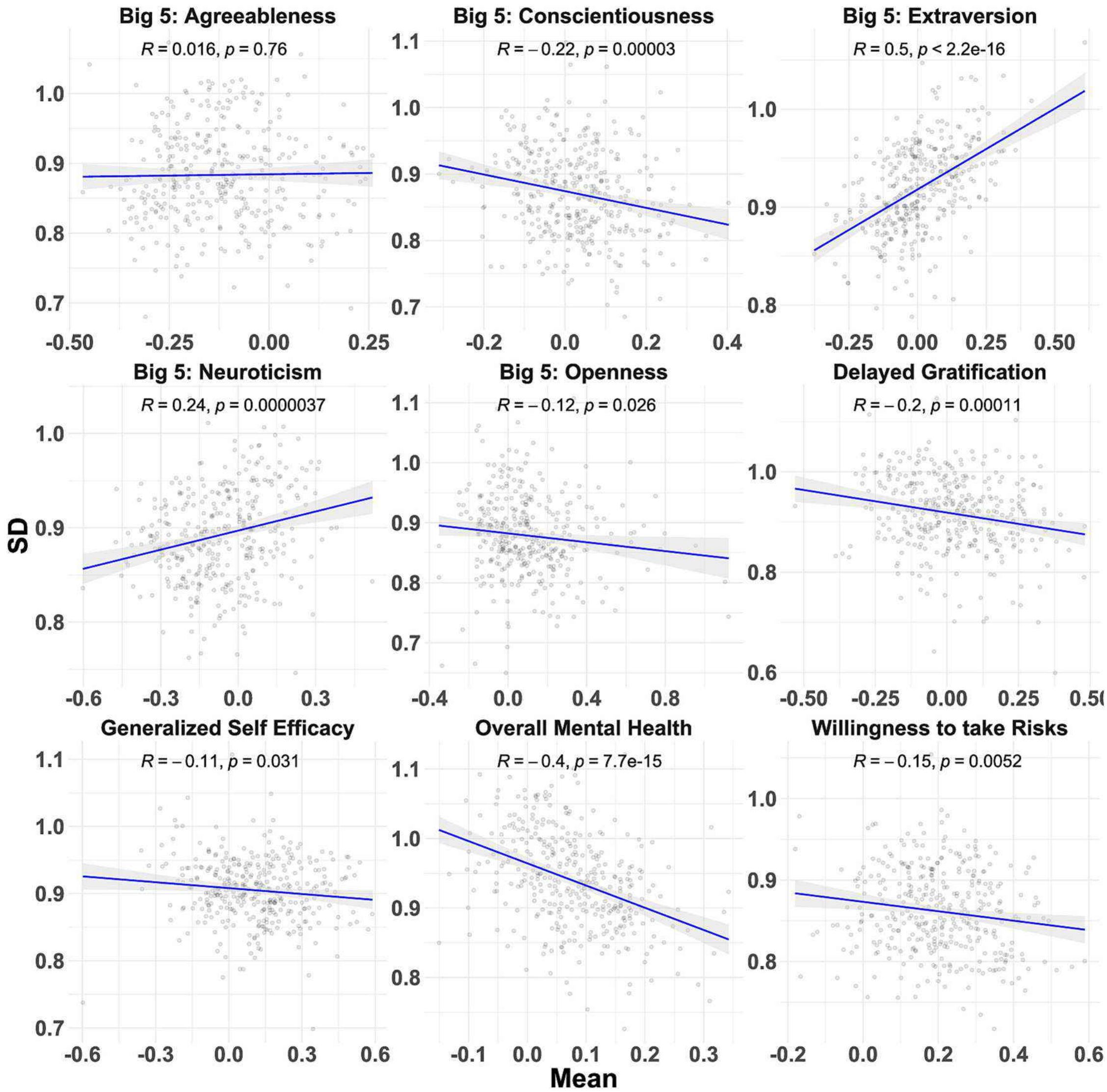

Fig. 6. Correlation of between-occupation mean and within-occupation standard deviation (non-cognitive traits).

estimates of cognitive and non-cognitive skills and their respective within-occupation variation. We found significant associations between means and standard deviation for all traits (with the exception of agreeableness), the strongest for cognitive ability and mental health, and weaker, but still notable, ones for most other non-cognitive factors. These findings do not just align with the interpretation of intelligence as a necessary but not sufficient condition for selection into and persistence within a profession, but they further imply that similar processes might also be at work for various other traits. *Positive* associations between mean and standard deviations were observed for neuroticism and especially extraversion, meaning that the opposite of these two traits, high levels of mental stability and the ability to work without extended human interaction, are selected for. Although there is not always a clear preference order of the extremes of a trait distribution for non-cognitive factors, as opposed to intelligence, certain traits such as high extraversion, high introversion, high willingness to take risks, and very low willingness to take risks may fill specific niches in the labor market. It is worth noting that for none of the studied traits is there a pattern where both extremely high and extremely low occupational mean scores are linked with a lower standard deviation. However, due to potential floor and ceiling effects and partially divergent findings between the FH model and direct estimates, we regard the association between occupational mean and standard deviation for non-cognitive traits as less robust and more in need of external replication than for cognitive ability.

Our results generally confirm the psychometric view of occupational differentials in ability that emphasizes the role of cognition on occupational sorting and stratification. Nevertheless, while our estimates of the share of variance in cognition associated with occupation are substantially higher than the lower extremes of estimates reported in previous research (down to 0.18), they are also significantly lower than the strong clustering reported in older datasets (up to 0.51 as found by Stewart, 1947). It is unclear how to explain this discrepancy. It might result from a lack of representativity of past samples, as previously claimed (Hauser, 2010). Differences between the USA, from which most data used in prior studies stems, and UK, the population used in this analysis, are also a potential factor, as well as the reliability of our intelligence measure (even though we corrected for that). It is also possible that differences in job composition and changes in occupational structure over time might play a role in explaining the observed discrepancy, as older studies may include a greater proportion of jobs, which are less prevalent today, for example in manufacturing. It should also be mentioned that differences in occupational clustering found in the literature might be artificially inflate by solely focusing on explained variation as the target metric - taking the square-root and analysing the correlation between occupation and cognitive ability instead, the differences between our current estimate of roughly 24% occupational clustering for cognitive ability and the 47% reported by Jensen (1980) for the US workforce do not seem that much off ($r = 0.49$ vs $r = 0.68$).

However, another potential cause could be temporal changes in social stratification processes: If the role of cognition diminishes over time, this could indicate a weakening of meritocratic dynamics in potential favor of the promulgation of social advantages. Larger follow-up studies (i.e. using multigenerational register data combined with military intelligence tests) could investigate this phenomenon further over a longer time period and would provide an excellent testing ground of the gravitational hypothesis.

Such a design would also guard against the problem of reverse causality: Because the collection of information on occupation and psychological traits occurred at the same time, there is a possibility that career decisions had an impact on the characteristics of the respondents examined (Woods, Wille, Chia-huei, Lievens, & De Fruyt, 2019), therefore increasing occupational clustering over time. While a plausible case could perhaps be made in case of the association between mental health and income, we do not consider this to otherwise strongly affect our results, as while empirical evidence on this topic is scarce (Smallfield & Kluemper, 2022), what exists points to only minor effects of occupation on personality (Wu, Wang, Parker, & Griffin, 2020) and intelligence over time (Lane, Windsor, Andel, & Luszcz, 2017; Smart, Gow, & Deary, 2014). Furthermore, the rank order stability of cognitive ability and personality after adolescence is well documented (Bleidorn et al., 2022; Rönnlund, Sundström, & Nilsson, 2015).

Furthermore, the importance of non-cognitive traits should not be underestimated: The predictions of the psychometric view are, though often on a weaker level, confirmed for non-cognitive factors, effects that are robust to controlling for cognitive ability. In addition, covariance patterns of cognitive ability and non-cognitive traits seem to jointly form particular profiles that strongly cluster within occupations, underscoring the large role that individual differences play in the labor market. Although non-cognitive factors have a significantly smaller role in the central conclusions of the psychometric view, they do suggest this perspective's scope is much more comprehensive than initially thought, even by its main proponents.

Declaration of Competing Interest

The Author declares no competing interest.

Data availability

The data that has been used is confidential.

Acknowledgements

The Author thanks Laura Wartschinski for advice concerning webscraping and Felix Tropf, Nico Büttner, Mirko Ruks and Maik Hamjediers for feedback on earlier drafts of this text.

Appendix A. Additional figures & tables

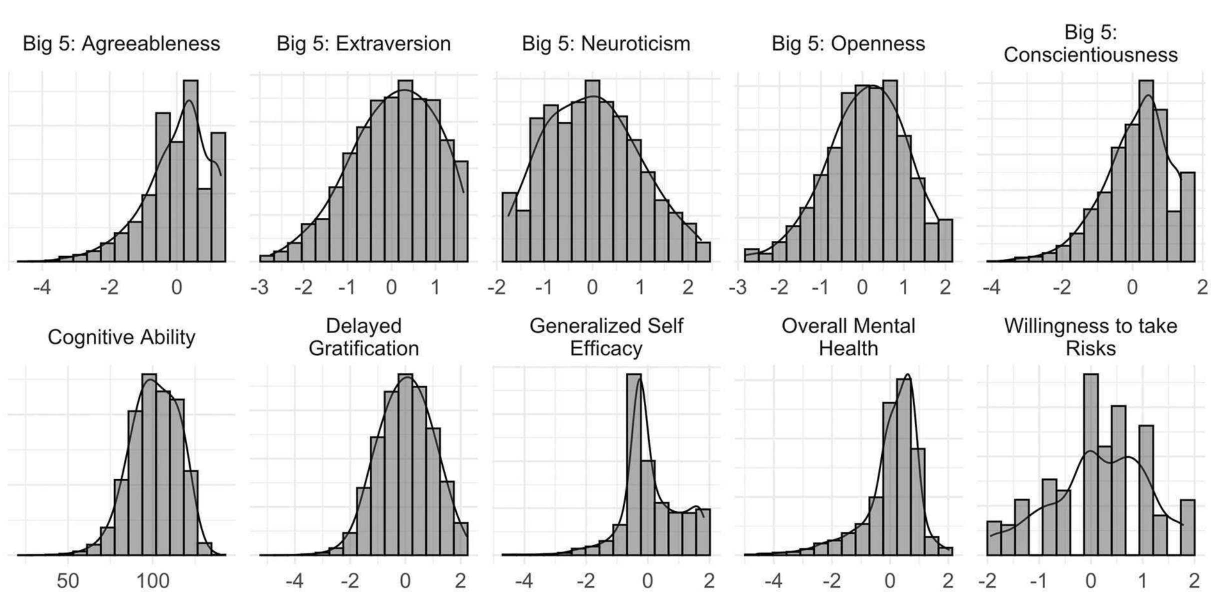

Fig. A.1. Distribution of non-rank-normalized traits in sample.

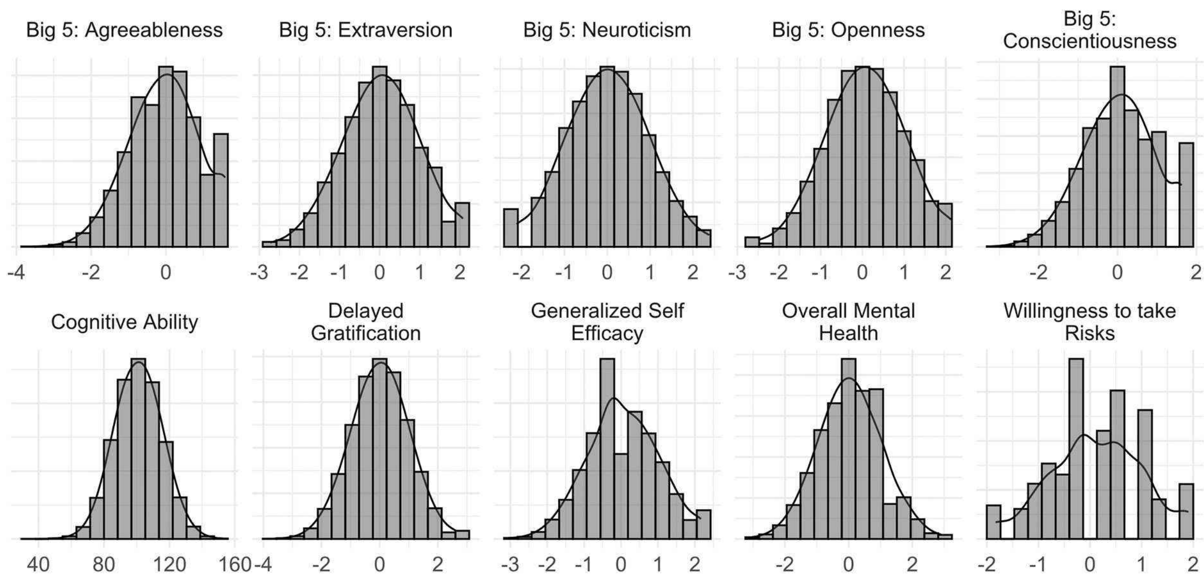

Fig. A.2. Distribution of rank-normalized traits in sample.

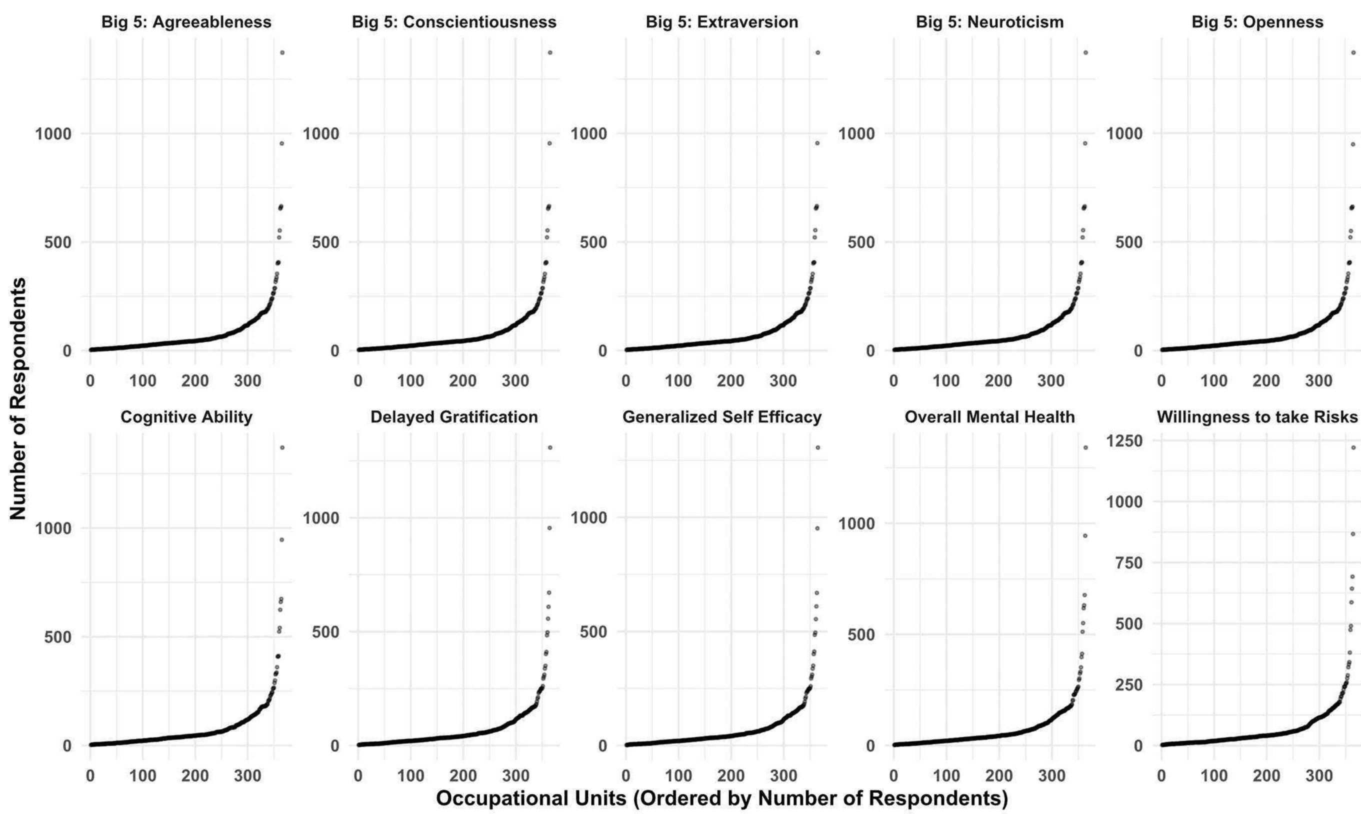

Fig. A.3. Distribution of observations over occupational units.

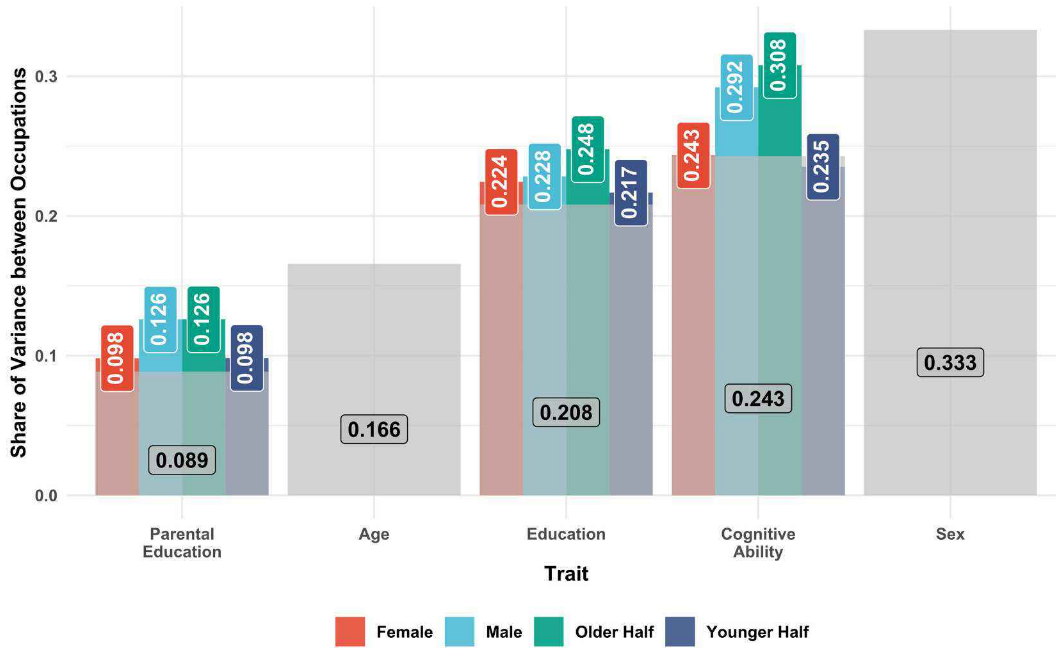

Fig. A.4. Share of variance of cognitive ability and sociodemographic variables associated with occupation (non-rank-normalized).

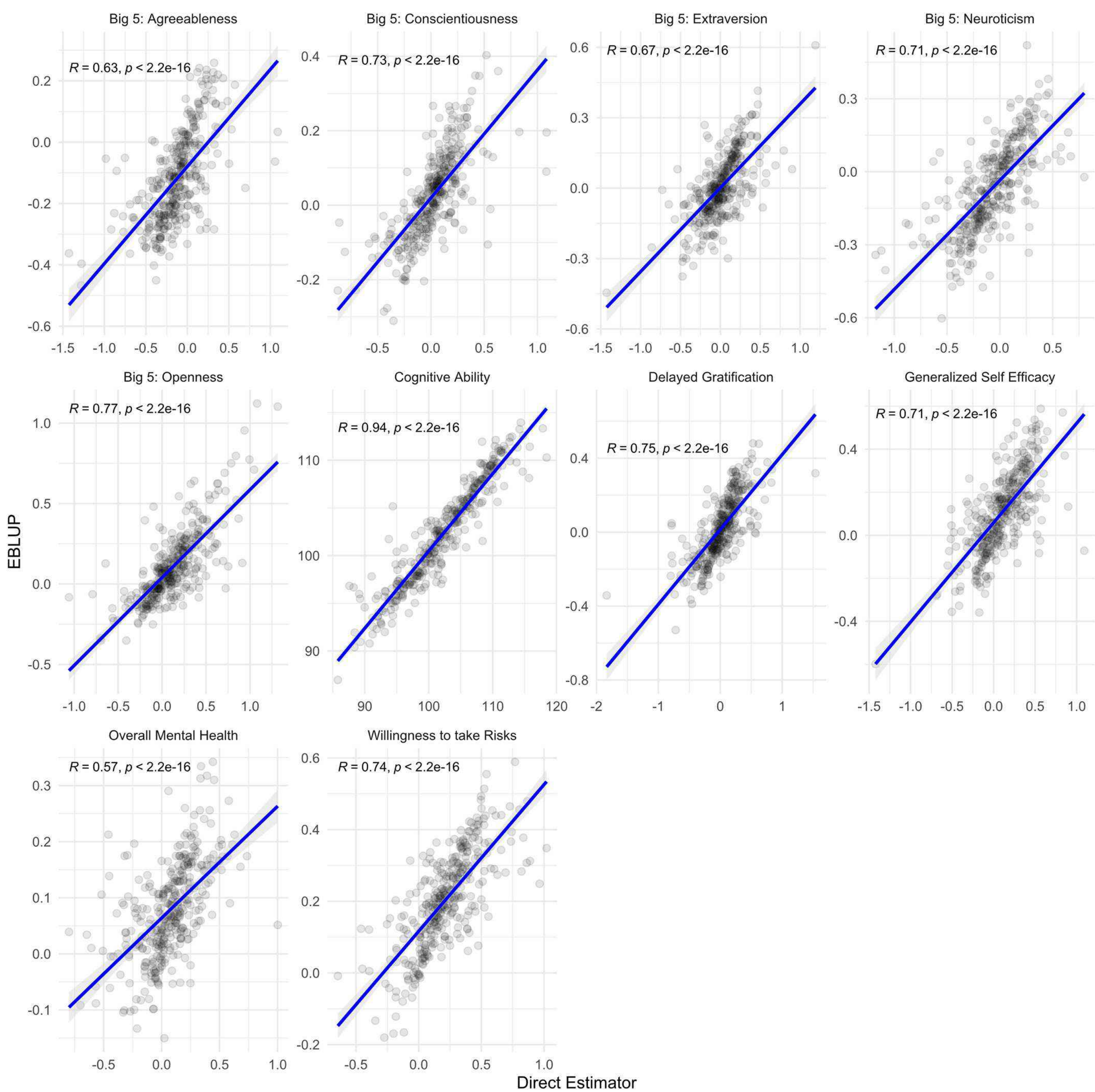

Fig. A.5. Association of direct and model-based estimates (mean).

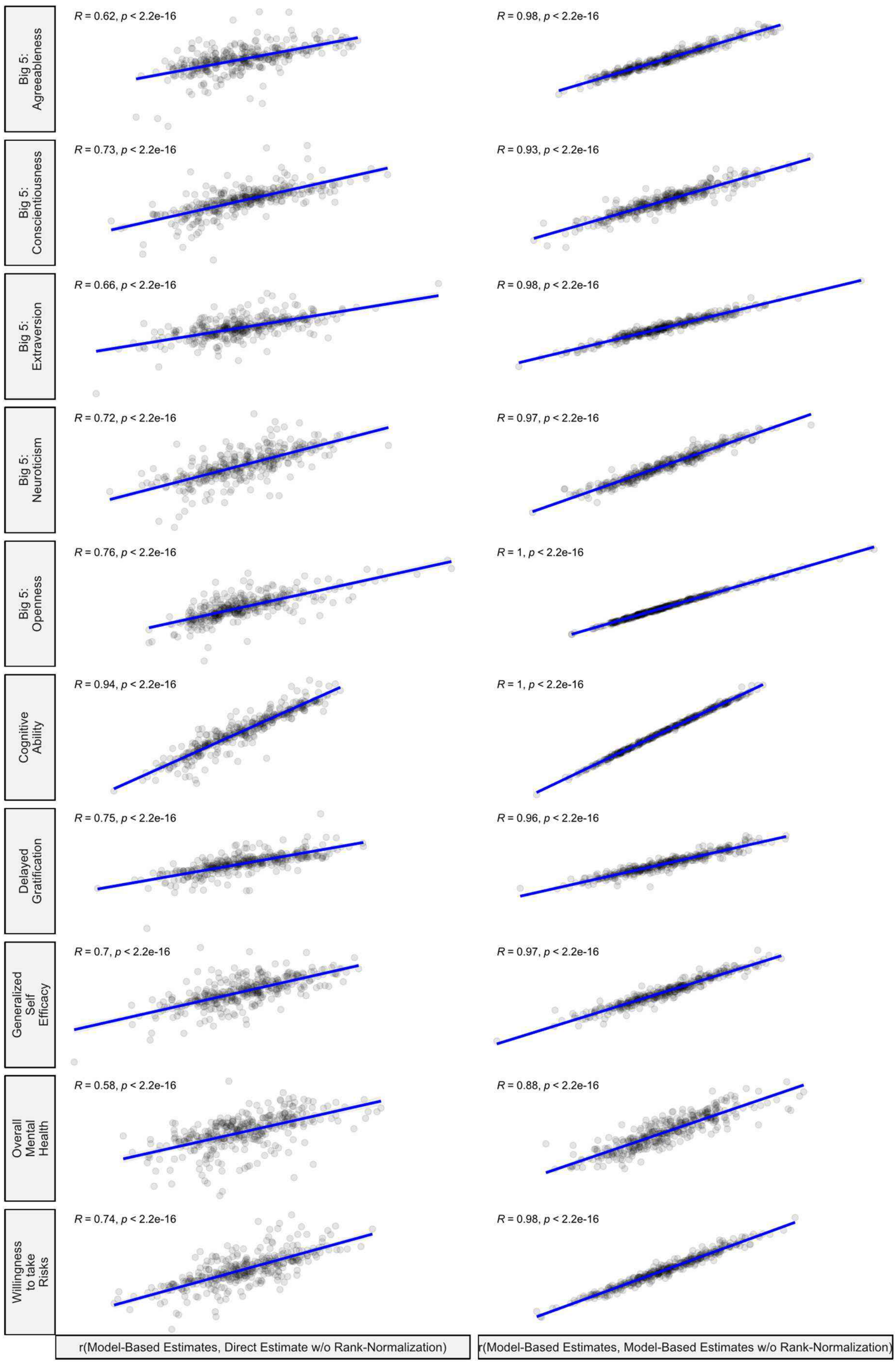

Fig. A.6. Association between model-based estimates and direct estimates/model-based estimates without rank-normalization.

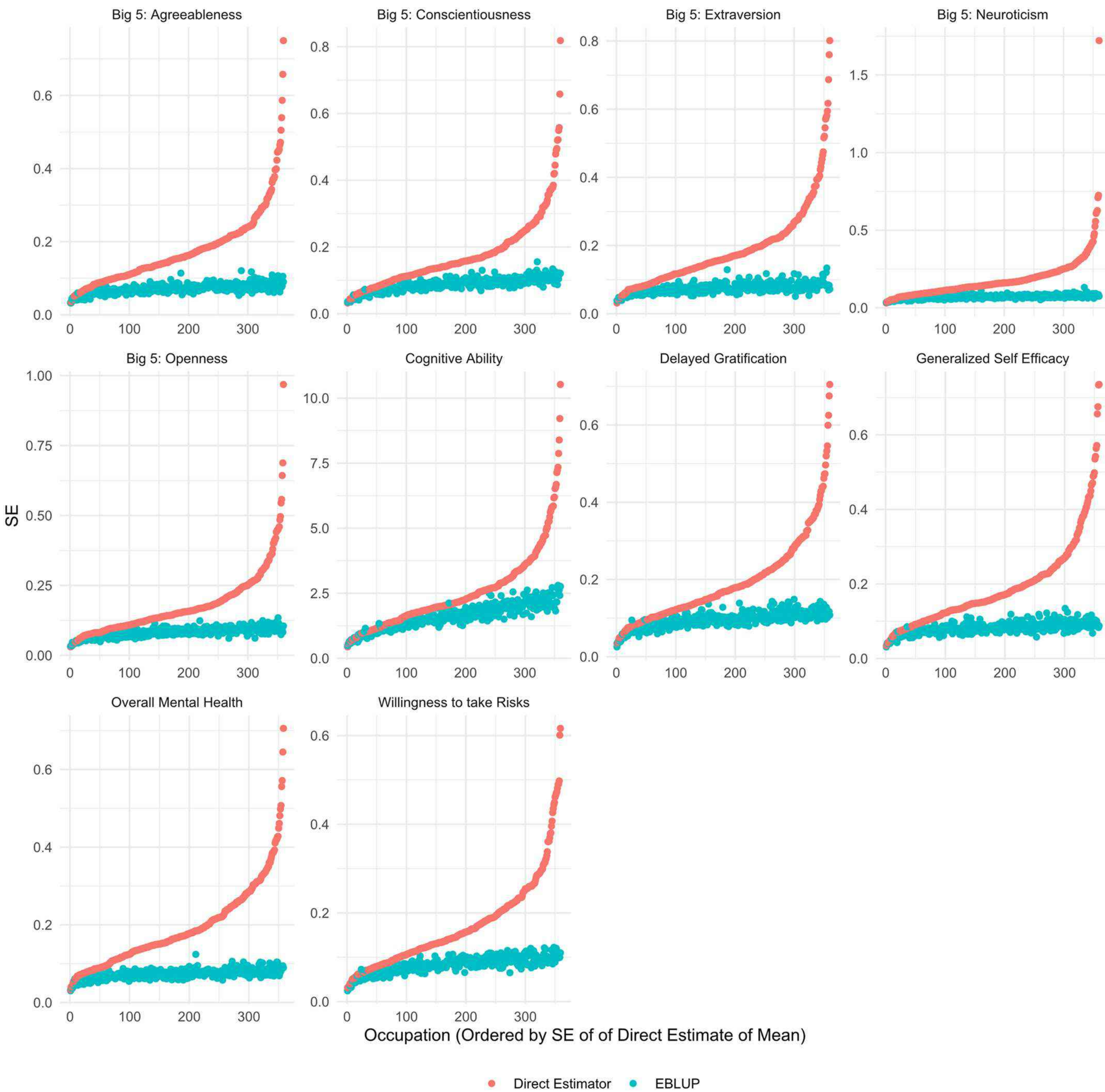

Fig. A.7. Comparison of SEs for direct and model-based estimation of means.

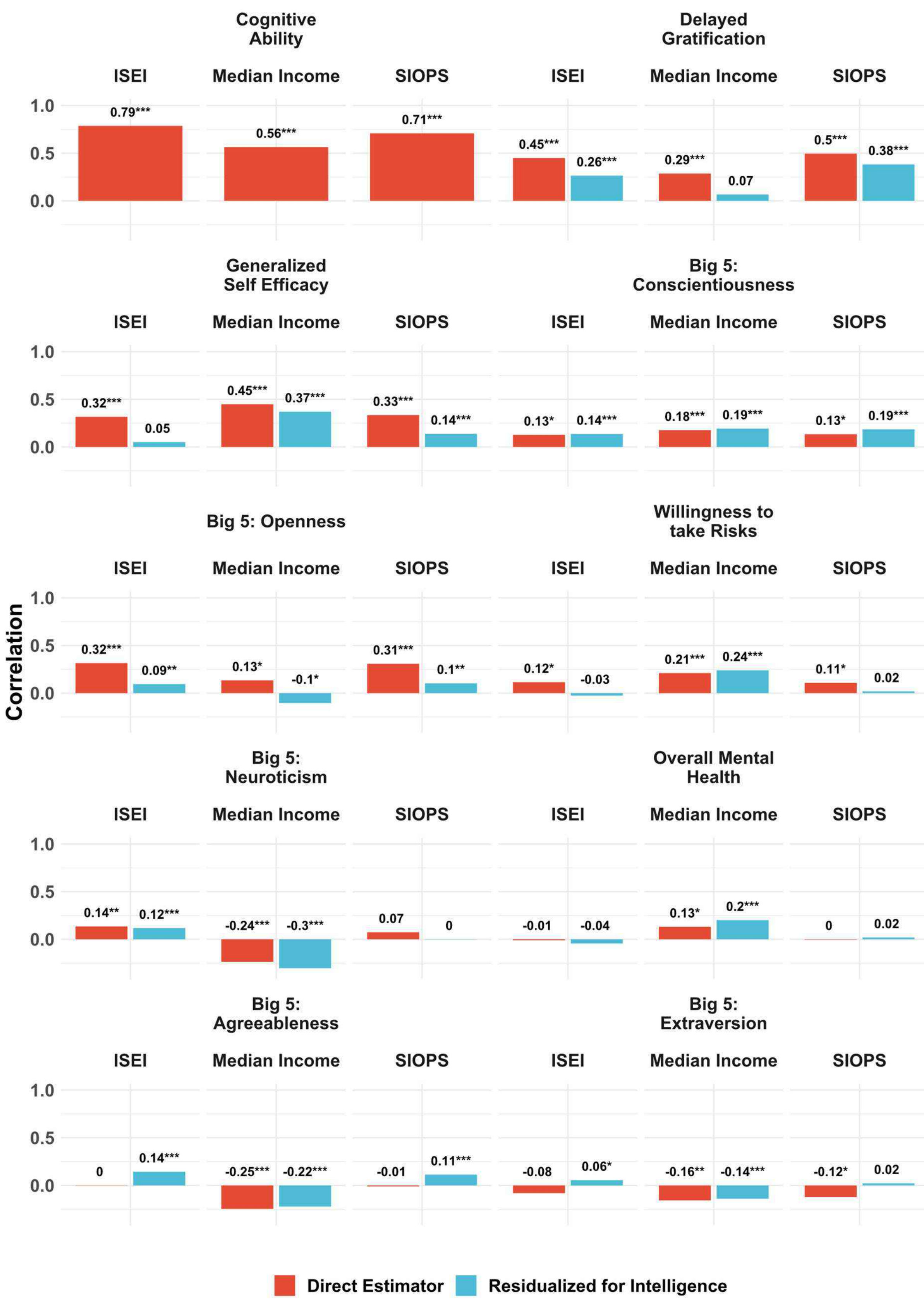

Fig. A.8. Correlation of direct estimates of cognitive ability and non-cognitive traits with occupational status, prestige and income, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

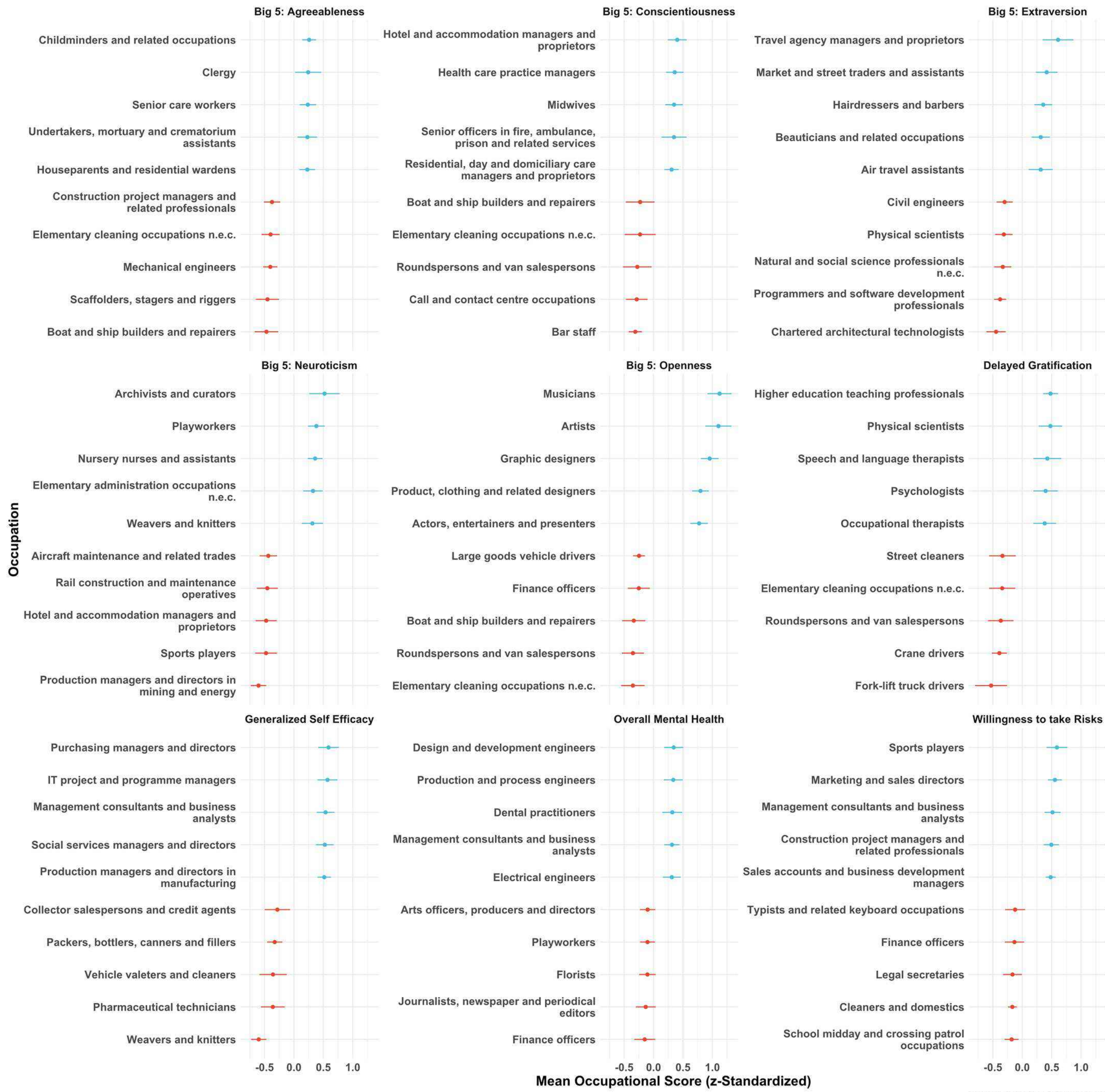

Fig. A.9. Top 5 highest and lowest ranking occupations (all non-cognitive traits), n.e.c = not else classified.

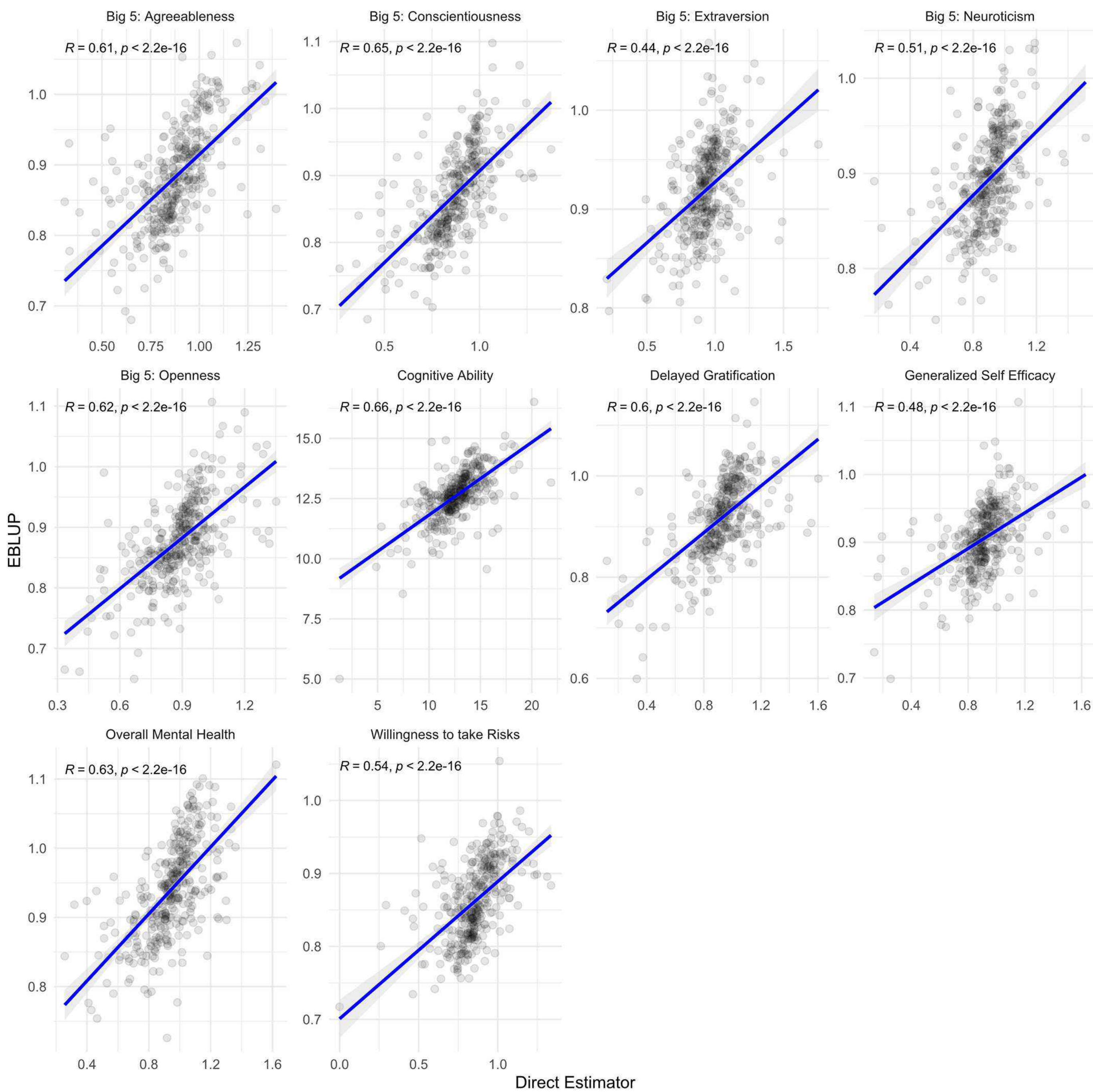

Fig. A.10. Association of direct and model-based estimates (SD).

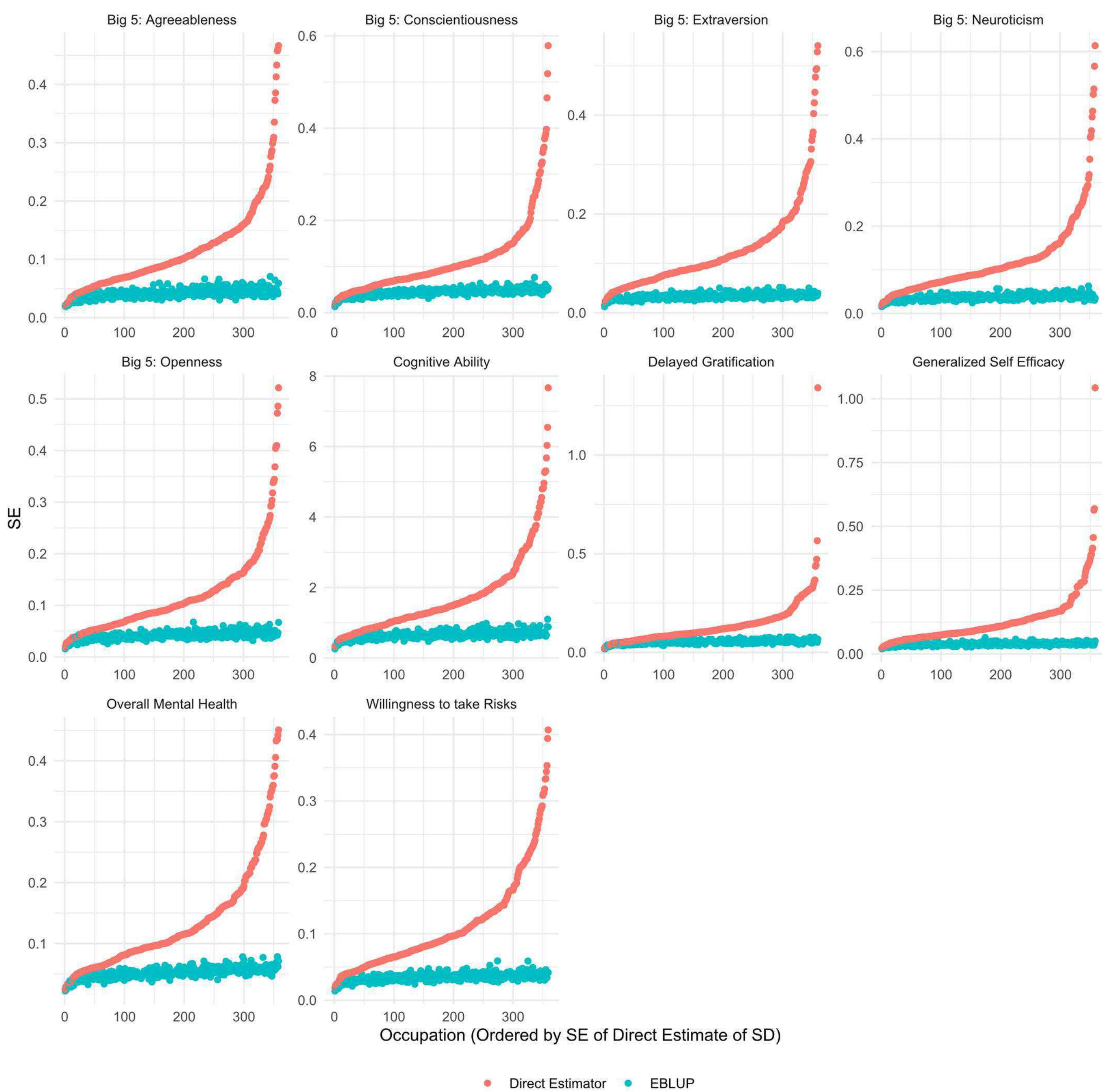

Fig. A.11. Comparison of SEs for direct and model-based estimation of SDs.

Table A.1
Proportion of variance non-cognitive traits associated with occupation (residualized for cognitive ability).

	Overall	By Sex		By Age	
		Male	Female	Older Half	Younger Half
Big 5: Agreeableness	0.086*** (0.003)	0.105*** (0.006)	0.084*** (0.005)	0.136*** (0.008)	0.118*** (0.005)
Big 5: Conscientiousness	0.074*** (0.004)	0.123*** (0.007)	0.097*** (0.006)	0.109*** (0.008)	0.122*** (0.007)
Big 5: Extraversion	0.067*** (0.004)	0.104*** (0.006)	0.083*** (0.005)	0.104*** (0.006)	0.111*** (0.006)
Big 5: Neuroticism	0.082*** (0.004)	0.09*** (0.004)	0.068*** (0.005)	0.114*** (0.005)	0.108*** (0.005)

(continued on next page)

Table A.1 (*continued*)

	Overall	By Sex		By Age	
		Male	Female	Older Half	Younger Half
Big 5: Openness	0.085***	0.133***	0.105***	0.141***	0.105***
	(0.003)	(0.007)	(0.005)	(0.007)	(0.006)
Delayed Gratification	0.086***	0.142***	0.107***	0.121***	0.145***
	(0.004)	(0.008)	(0.006)	(0.008)	(0.008)
Generalized Self Efficacy	0.062***	0.096***	0.077***	0.092***	0.097***
	(0.003)	(0.006)	(0.004)	(0.005)	(0.005)
Overall Mental Health	0.04***	0.073***	0.054***	0.073***	0.069***
	(0.002)	(0.004)	(0.004)	(0.005)	(0.004)
Willingness to take Risks	0.066***	0.101***	0.078***	0.114***	0.096***
	(0.003)	(0.006)	(0.005)	(0.005)	(0.005)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.2
Variance explained by the auxiliary variables in Fay-Herriot models for mean of each (non-)cognitive trait.

	Abilities	Abilities & Skills	Abilities, Skills & Knowledge	Abilities, Skills, Knowledge & Interests	Best AIC Subset
Big 5: Agreeableness	0.25	0.29	0.30	0.35	0.47
Big 5: Conscientiousness	0.05	0.11	0.10	0.20	0.38
Big 5: Extraversion	0.39	0.43	0.46	0.48	0.60
Big 5: Neuroticism	0.34	0.36	0.49	0.53	0.68
Big 5: Openness	0.46	0.48	0.54	0.62	0.70
Cognitive Ability	0.71	0.72	0.73	0.75	0.80
Delayed Gratification	0.39	0.40	0.41	0.46	0.54
Generalized Self Efficacy	0.39	0.40	0.44	0.51	0.61
Overall Mental Health	−0.04	−0.03	0.00	−0.11	0.23
Willingness to take Risks	0.24	0.27	0.28	0.33	0.49

Table A.3
Variance explained by the auxiliary variables in Fay-Herriot models for SD of each (non-)cognitive trait.

	Abilities	Abilities & Skills	Abilities, Skills & Knowledge	Abilities, Skills, Knowledge & Interests	Best AIC Subset
Big 5: Agreeableness	0.15	0.19	0.23	0.33	0.49
Big 5: Conscientiousness	0.22	0.19	0.22	0.25	0.43
Big 5: Extraversion	−0.01	−0.03	0.01	0.01	0.25
Big 5: Neuroticism	0.09	0.14	0.17	0.20	0.38
Big 5: Openness	0.24	0.38	0.39	0.41	0.54
Cognitive Ability	0.02	0.01	0.14	0.25	0.43
Delayed Gratification	0.02	0.01	0.03	0.22	0.37
Generalized Self Efficacy	−0.01	0.02	−0.03	0.04	0.26
Overall Mental Health	0.12	0.11	0.08	0.15	0.36
Willingness to take Risks	−0.01	0.03	0.02	0.13	0.37

Table A.4
Quantiles of percentage SE-reduction from direct estimator to EBLUP.

	75% Quantile of SE-Reduction	Median of SE-Reduction	25% Quantile of SE-Reduction
Big 5: Agreeableness	0.63	0.53	0.38
Big 5: Conscientiousness	0.54	0.39	0.26
Big 5: Extraversion	0.64	0.52	0.36
Big 5: Neuroticism	0.64	0.53	0.38
Big 5: Openness	0.57	0.44	0.29
Cognitive Ability	0.37	0.24	0.13
Delayed Gratification	0.55	0.41	0.25
Generalized Self Efficacy	0.61	0.49	0.34
Overall Mental Health	0.67	0.55	0.39
Willingness to take Risks	0.56	0.41	0.26

Table A.5
Correlation of mean and standard deviation, direct estimator vs. EBLUP.

	Direct Estimator	EBLUP
Big 5: Agreeableness	−0.03	0.02
Big 5: Conscientiousness	−0.16***	−0.22***
Big 5: Extraversion	0.05	0.5***
Big 5: Neuroticism	0.13**	0.24***
Big 5: Openness	−0.09.	−0.12*
Cognitive Ability	−0.19***	−0.28***
Delayed Gratification	−0.11*	−0.2***
Generalized Self Efficacy	0.01	−0.11*
Overall Mental Health	0.04	−0.4***
Willingness to take Risks	−0.13**	−0.15**

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.intell.2023.101755.

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