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Too Competitive to Care? The Overall Explanatory Power of Personality for Occupational Gender Segregation

Thomas Buser
University of Amsterdam,
Tinbergen Institute and IZA@LISER

IZA@LISER NETWORK
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Abstract

A large literature in behavioral and labor economics is concerned with documenting gender differences in personality traits, preferences and skills, as well as the explanatory power of these differences for gender gaps in occupational choice and career success. These studies usually focus on a single trait or personality classification, such as competitiveness, risk preferences, or the Big Five personality inventory. In this paper, I instead ask how much of gender differences in occupational sorting can be statistically explained by a comprehensive range of trait and preference measures jointly. I combine detailed indicators of economic preferences and personality traits elicited in a representative Dutch survey panel and link them to career outcomes for which large gender gaps are observed: the underrepresentation of women in management and math-intensive occupations, and the underrepresentation of men in teaching and caring occupations and the public sector. Correcting for measurement error, differences in preferences and personality can statistically explain a large part – typically half or more – of gender differences in occupational sorting. An unanticipated finding is that traits with a "dark" side – such as willingness to play dirty, externalizing behavior or psychopathy – capture a surprisingly large share of these gaps.

JEL classification

J16, J24, D91

Keywords

gender, occupational segregation, personality, economic preferences, competitiveness

Corresponding author

Thomas Buser
t.buser@uva.nl

* This paper uses data from the LISS panel administered by Centerdata (Tilburg University, The Netherlands).

1 Introduction

Even as women have overtaken men in educational attainment and as wage gaps have narrowed, occupational gender segregation remains a persistent feature of developed labor markets (Blau et al., 2013; Goldin, 2014). Women remain heavily underrepresented in supervisory positions (Haegele, 2024), in upper management (Bertrand and Hallock, 2001), and in entrepreneurship (Rietveld and Patel, 2022; Guzman and Kacperczyk, 2019), and they are scarce in math-intensive and technical occupations (Kahn and Ginther, 2018; Card and Payne, 2021); men, in turn, are scarce in teaching and caring occupations (Reeves, 2022; Block et al., 2018; Burbano et al., 2024) and in the public sector (Gomes and Kuehn, 2026). Because occupation and industry now account for a large share of the measurable gender wage gap (Blau and Kahn, 2017; Cortes and Pan, 2018; Fluchtmann et al., 2024), understanding why men and women sort into different careers is central to understanding gender inequality in the labor market. Men's growing absence from caring and teaching work matters too: persistent shortages of teachers, nurses and other health and care workers in many countries, together with the rapid growth of employment in these sectors, make it increasingly important to understand why men sort out of the very occupations where labor is most in demand (Reeves, 2022).

A large literature in behavioral and labor economics seeks to explain gender gaps in the labor market through gender differences in economic preferences and personality (Croson and Gneezy, 2009; Bertrand, 2011, 2020; Niederle, 2016; Lozano et al., 2022; Chowdhury and Peter, 2026). Men and women differ on average along many traits that plausibly matter for careers. Economists have documented that men are more willing to compete (Niederle and Vesterlund, 2007, 2011; Buser, 2026b), more risk tolerant (Croson and Gneezy, 2009; Dohmen et al., 2011; Falk and Hermle, 2018), and less prosocial (Falk and Hermle, 2018). Personality psychologists have shown robust differences in the Big Five personality traits (Weisberg et al., 2011; Gensowski et al., 2021) – women tend to be more agreeable and conscientious, men tend to be more emotionally stable – and in "dark" traits – men tend to score higher on psychopathy and manipulativeness, and lower on honesty-humility (Buser, 2025). Vocational interests differ strongly along a "things versus people" dimension: men have a relative preference for working with things, women for working with people (Su et al., 2009; Kuhn and Wolter, 2022). Personality traits and economic preferences are, in turn, robust predictors of educational attainment, occupational choice and earnings (Mueller and Plug, 2006; Almlund et al., 2011; Buser et al., 2024; Flinn et al., 2025). Some traits on which men and women differ have been shown to correlate with choices that generate occupational segregation. Competitiveness, for example, predicts the choice of more prestigious and math-intensive education paths, management positions and income (Buser et al., 2014, 2017, 2022, 2024), and agreeableness and neuroticism negatively predict income (Mueller and Plug, 2006; Flinn et al., 2025). The typical study in this literature isolates the explanatory power of a *single* trait or personality classification for a *single* gap. The resulting estimates are informative but typically modest in magnitude: measured competitiveness, for example, accounts for on the order of 10–20% of the gender gaps in study choice or career outcomes (Buser et al., 2014, 2024), and Flinn et al. (2025) find that gender differences in the Big Five traits can explain around 19% of the gender wage gap.

Reviews of the field have drawn a correspondingly cautious conclusion. Assessing the quantitative evidence, Blau and Kahn (2017) judge that psychological attributes "account for a small to moderate portion of the gender pay gap, considerably smaller than . . . occupation and industry effects"; Bertrand (2011) similarly considers the evidence that laboratory gender differences in preferences translate into labor-market outcomes to be "far from conclusive."[1] Other reviews concur in treating measured trait differences as one channel among several rather than the dominant one, and emphasize that the link between experimental preference measures and real-world sorting remains to be firmly established (Azmat and Petrongolo, 2014; Shurchkov and Eckel, 2018; Niederle and Vesterlund, 2011; Cortes and Pan, 2018; Lozano et al., 2022).

The single-trait focus of much of this literature may, however, systematically understate the overall importance of personality. Different traits and preferences overlap partially at best – each captures a distinct way in which men and women differ on average – and each is measured with error. When gender differences are spread across many such partially independent dimensions, the explanatory power of personality *as a whole* can be much larger than the contribution of any trait considered in isolation, for two reasons: a study that measures one trait omits the independent contributions of the others, and measurement error attenuates the contribution of the trait it does measure. The aim of this paper is to estimate this overall explanatory power. Rather than asking how much of one gap one trait explains, I ask how much of gender differences in a wider set of career outcomes can be statistically accounted for by gender differences across a comprehensive battery of preferences and personality traits measured in the same individuals.

I use a nationally representative Dutch survey panel (LISS) that contains an unusually rich set of preference and personality measures together with detailed indicators of occupational choice and professional achievement. The battery spans measures that psychologists

[1] Note that occupation is itself a choice: if personality shapes occupational sorting, then psychological attributes and the occupation effects they are compared against are not competing explanations, but potentially the same channel measured at different stages.

and economists have developed, many of which show robust gender differences: preferences for competition, risk seeking and challenge seeking; social preferences such as altruism, trust, reciprocity, third-party punishment and moral universalism; the Big Five and grit; "dark" traits such as Machiavellianism, psychopathy, narcissism, (low) honesty-humility, externalizing behavior, and willingness to compete unfairly; and preferences for math and the disposition to engage in cognitive effort. I link these to the career outcomes that display some of the widest remaining gender gaps in Western labor markets: holding a management or supervisory position, being an entrepreneur, working in a STEM occupation, working in a teaching or caring occupation, and working in the public sector. Because traits are measured with error, ordinary least squares understates this share through attenuation bias; I therefore also report estimates that correct for measurement error using obviously-related instrumental variables (ORIV; Gillen et al., 2019).

The headline finding is that the overall explanatory power of personality is much larger than single-trait estimates would suggest. Correcting for measurement error, gender differences in the measured traits statistically account for roughly half or more of the conditional gender gaps in working in a caring or teaching occupation (48%), the public sector (66%), management (55%), supervisory positions (74%) and entrepreneurship (close to 100%, though the number of entrepreneurs in the data is small and this share is therefore imprecisely estimated), and about 60% of the gender gap in income among singles. The one large gap that the measured traits explain only modestly is the STEM gap (around 18%), which appears to be driven by a narrower set of dispositions, most notably a gender difference in stated preference for mathematics.

These results have a direct methodological implication: studies that isolate the explanatory power of personality one trait at a time will tend to underestimate how much of occupational segregation is associated with gender differences in personality overall. The caring and teaching occupations are a case in point: gender differences in the full set of measured traits account for 48% of the gender gap, yet no single group of traits – competitiveness, social preferences, the Big Five and grit, the dark traits, or cognition – accounts for more than 19% on its own.

Apart from estimating the overall explanatory power of personality, I also identify the most influential traits for each outcome. An unanticipated result is that some of the traits that carry the most explanatory power are non-standard traits that have been largely ignored by the gender economics literature – willingness to play dirty, externalizing behavior, negative reciprocity and psychopathy. In general, traits that – clearly or potentially – have a "dark" side capture a surprisingly large share of many of the gaps. At the same time, the results reinforce the large literature on the gender difference in willingness to compete by showing that its explanatory power has been understated: once measurement error is accounted for, competitiveness and related traits carry more weight than previous estimates suggest.

These results also speak to a broader puzzle. A growing body of work documents a "gender-equality paradox": average gender differences in personality, preferences and academic inclinations tend to be *larger*, not smaller, in richer and more gender-equal countries (Schmitt et al., 2008; Costa et al., 2001; Falk and Hermle, 2018; Stoet and Geary, 2018; Mac Giolla and Kajonius, 2019). While the interpretation of this pattern is contested (Richardson et al., 2020; Klinowski and Niederle, 2025), it suggests that as material and institutional barriers to women's careers have fallen, dispositional differences may have become relatively more important in shaping who does what. My results are consistent with this view: in a rich and gender-equal country, gender differences in measured personality can account for a large part of the occupational segregation that persists despite the closing of the education gap. It is important to emphasize that the analyses in this paper are purely correlational. However, they still indicate that the *ceiling* for the extent to which gender differences in personality can explain gender differences in occupational sorting is higher than previously thought.

2 Data

I use data from the Dutch LISS (Longitudinal Internet Studies for the Social sciences) panel, an ongoing online survey panel that has been operating since late 2007. It is based on a true probability sample of households drawn from the population register by Statistics Netherlands. The panel members answer yearly "core" questionnaires covering, for instance, work, education, and personality. On top of these, researchers can pay to field questionnaires on the panel, which can then be linked to all other data available on the respondents. All LISS data, including researcher-run questionnaires, are publicly available.

The comprehensive set of preference and personality measures used in this study was assembled from the core personality module and a series of one-off questionnaires fielded between 2021 and 2024; I link these to occupational data from the core modules. I restrict the analysis sample to respondents aged between 25 and 65, the ages over which occupational careers are typically observed, and to respondents for whom all trait measures are available. Appendix Table A2 compares this analysis sample to the full LISS sample in the same age range; the two are very similar in terms of age, gender composition, education, employment and income.

The main outcome measures are six binary indicators of occupational sorting. *Caring or teaching occupation* and *STEM occupation* are based on the four-digit ISCO-08 occupation code of the respondent's most recent job. The caring or teaching indicator covers health and education occupations: medical doctors, nurses, paramedical and care professionals and associate professionals, teachers at all levels, and related care workers.[2] *STEM occupation* covers science, engineering and information-technology professionals and associate professionals.[3] *Manager* and *Supervisor* are based on the Work and Schooling core module, which asks respondents to classify their profession. "Manager" equals one if a respondent ever indicated holding a "higher supervisory profession" (e.g. manager, director, owner of a large company, supervisory civil servant) over the years they participated in the panel; "Supervisor" additionally includes "intermediate supervisory or commercial" professions (e.g. head representative, department manager, shopkeeper), so that managers are a subset of supervisors. *Entrepreneur* equals one if a respondent ever indicated being a "director of a limited liability or private limited company" or a "majority shareholder director" (and therefore excludes those who merely designate themselves as self-employed or independent professionals). *Public sector* equals one if the respondent's most recent job was in the public sector.[4]

I additionally look at gender differences in income, which is defined as monthly gross income in euros and is taken from the background data. In the analyses I consider it separately for respondents living without and with a partner, because the gender gap in personal income differs starkly between the two.

I connect occupational sorting to an extensive range of personality traits and economic preferences, which I organize into five groups.

Competition, risk and challenge seeking. Competitiveness is measured through the detailed questionnaire of Buser and Oosterbeek (2023), which is largely based on Urbig et al. (2021), and the single general item validated by Buser et al. (2024). This yields measures of the enjoyment of competition, the use of competition for self-development, the desire to win, and general competitiveness. The same questionnaire elicits general challenge seeking, self-efficacy (Chen et al., 2001), and general willingness to take risk through the single-item measure of Dohmen et al. (2011). Buser et al. (2024) and Buser and Oosterbeek (2023) show that competitiveness and challenge seeking are strong predictors of income and supervisory positions in the LISS data.

Social preferences. I use the items from the preference survey module of Falk et al. (2023) to measure negative reciprocity, positive reciprocity, trust, altruism, and willingness to punish someone who treats others unfairly (third-party punishment). I complement these with a measure of moral universalism (Enke et al., 2022), the relative weight a respondent

[2]ISCO codes 2200-2269, 2300-2359, 2634, 2635, 3221-3258, 3412, 5311, 5312, 5320, and 5330.

[3]ISCO codes 2100-2166, 2500-2530, 3100-3155, 3500-3521.

[4]Because all core modules are elicited yearly, I replace missing values with those from adjacent years where possible.

places on the welfare of distant versus close others.

Big Five and grit. The core personality module elicits the Big Five traits (Goldberg et al., 2006): extraversion, agreeableness, conscientiousness, emotional stability, and openness. I add grit, measured through the Short Grit Scale of Duckworth and Quinn (2009).

Dark traits. I measure the Dark Triad – Machiavellianism (a tendency to manipulate and exploit others), psychopathy (lack of empathy and remorse), and narcissism (excessive self-love and entitlement) – through the short scale of Jonason and Webster (2010), and honesty-humility (the sixth HEXACO trait capturing sincerity, fairness, greed avoidance and modesty) through the inventory of Lee and Ashton (2004). I also include a retrospective index of externalizing behavior in childhood (Buser, 2026a), and two measures of willingness to engage in unfair competition validated by Buser and Sangi (2025): willingness to play dirty and, conversely, an aversion to rule-breaking. Buser and Sangi (2025) show that willingness to play dirty predicts supervisory and management positions, as well as working in the private (vs the public) sector in the LISS data. Buser (2026a) shows that childhood misbehavior predicts later life supervisory and management positions, entrepreneurship, and working in the private sector in the LISS data.

Cognition. I measure the disposition to engage in cognitive effort through a short need-for-cognition scale (Cacioppo and Petty, 1982; Lins de Holanda Coelho et al., 2020) and a stated preference for mathematics.[5]

The battery is designed to span the trait families for which the literature documents robust gender differences; it is broad but not exhaustive – it does not cover, for example, time preferences or locus of control.

Appendix Figure A1 shows the full matrix of pairwise correlations between the (standardized) trait measures. Appendix Table A3 lists, for each trait, the number of underlying survey items and the construction of the two measures used for the measurement-error correction strategy (ORIV) described below.

Table A1 in the appendix reports, for each variable, the mean for men and women and the gender difference.

3 Empirical strategy

For each career outcome y_i I start with the conditional gender gap, estimated by ordinary least squares as

$$y_i = \beta \, \text{male}_i + \mathbf{x}_i' \gamma + \varepsilon_i, \tag{1}$$

[5]Preference for math is elicited through the degree of agreement with four items: "I like math", "Math is fun", "I'm good at math", and "I don't have any talent for math".

where male_i is an indicator for being male and $\mathbf{x}_i$ contains dummies for the six education levels and for age in years. The coefficient β measures the gender gap in the outcome that remains after accounting for education and age. I then add a vector of trait measures $\mathbf{t}_i$,

$$y_i = \tilde{\beta}\,\text{male}_i + \mathbf{t}_i'\delta + \mathbf{x}_i'\gamma + u_i, \tag{2}$$

and summarize the explanatory power of the traits by the percentage reduction in the absolute gender coefficient,

$$\%\ \text{explained} = \frac{|\beta| - |\tilde{\beta}|}{|\beta|}. \tag{3}$$

This is the share of the conditional gender gap that is statistically accounted for by gender differences in the included traits. A value of one means the gender gap disappears once the traits are controlled for, and a negative value means the gap widens. I add the traits both group by group – competition, social preferences, Big Five and grit, dark traits, and cognition – and all together.

I report three sets of estimates. The first applies equations (1)–(3) directly, using the constructed trait indices. Because each index is an imperfect, noisy measure of an underlying disposition, measurement error attenuates the trait coefficients and therefore *understates* the explained share (Gillen et al., 2019). I address this in two complementary ways. First, I replace the constructed indices with the full set of underlying survey *items*, which exploits all item-level variation. For example, instead of including the extraversion measure, I include the underlying questions individually. Second, I use the obviously-related instrumental variables (ORIV) approach of Gillen et al. (2019). For each trait, I construct two measures from independent subsets of the underlying items. The ORIV approach then uses the two measures as instruments for each other, which eliminates the uncorrelated part of the measurement error in the two measures.[6] Because many traits are strongly correlated (see Appendix Figure A1), the coefficients on individual traits or items in the joint specifications are not separately interpretable; I therefore focus throughout on the gender coefficient and the share of the gap that remains after controlling for different sets of trait measures, which is well identified.

The explained share is a nonlinear function of two coefficients estimated on the same

[6]For traits that are measured by multi-item scales (e.g. the Big Five traits), each of the two measures consists of the average of half of the items in the scale. For some traits (trust, negative reciprocity, challenge seeking) I have exactly two survey items. For the single-item measures of risk seeking and general competitiveness, I use two separate elicitations. Finally, for a few single-item measures I only have a single elicitation and can therefore not instrument them (altruism, positive reciprocity, third-party punishment). The ORIV regressions stack two copies of the data, one for each assignment of the two measures; reported sample sizes refer to the number of respondents and standard errors are clustered at the respondent level.

sample, which makes analytical inference difficult. To quantify its sampling uncertainty, I compute bootstrap confidence intervals that re-run the entire estimation pipeline – including the standardization of the traits and the ORIV first stages – within each of 999 resamples drawn with replacement and stratified by gender; Appendix Table A4 reports the resulting confidence intervals.

An important caveat that applies throughout is that all these analyses are correlational. If controlling for personality explains gender gaps in sorting, this does not mean that personality differences are the ultimate cause of occupational sorting. Traits and careers may be jointly determined. A specific version of this concern is that the traits are measured in 2021–2024 while several career outcomes are observed over a longer window, so that careers could in part shape the measured traits; the high rank-order stability of personality in adulthood (Cobb-Clark and Schurer, 2012) limits, but does not eliminate, this concern. The estimates are still informative with respect to the *ceiling* for the extent to which gender differences in personality can explain gender differences in occupational sorting. At the same time, the battery does not span all of personality and the ORIV correction only removes the part of the measurement error that is uncorrelated across the two partial measures, so the estimates can also be read as a *lower* bound on the explanatory potential of personality as a whole. Moreover, the analyses presented in this paper cannot say anything about the origins of the gender differences in personality, which may be innate or products of gendered socialization.

4 Results

I begin by visualizing the size of the gender gaps that the rest of the section seeks to explain. Figure 1 shows the gaps in the career outcomes. In the analysis sample, 35% of women but only 12% of men work in a caring or teaching occupation, while 19% of men but only 3% of women work in a STEM occupation. Men are more than twice as likely as women to have held a management position (18% versus 8%) and to have been an entrepreneur (2.7% versus 1.1%), and are substantially more likely to have held a supervisory position (36% versus 23%). Women, in turn, are considerably more likely to work in the public sector (40% versus 28%). To make these gaps comparable across occupations, the figure expresses each binary outcome as the deviation of the occupation's sex composition from the sex ratio in the sample: the STEM workforce is 37 percentage points more male than the sample, the caring and teaching workforce is 24 percentage points less male, and the management, supervisory and entrepreneurial workforces are between 12 and 22 percentage points more male.

Figure 2 shows that gender differences in the measured traits are equally pervasive and, for several traits, large. Men score substantially higher on every facet of competitiveness and

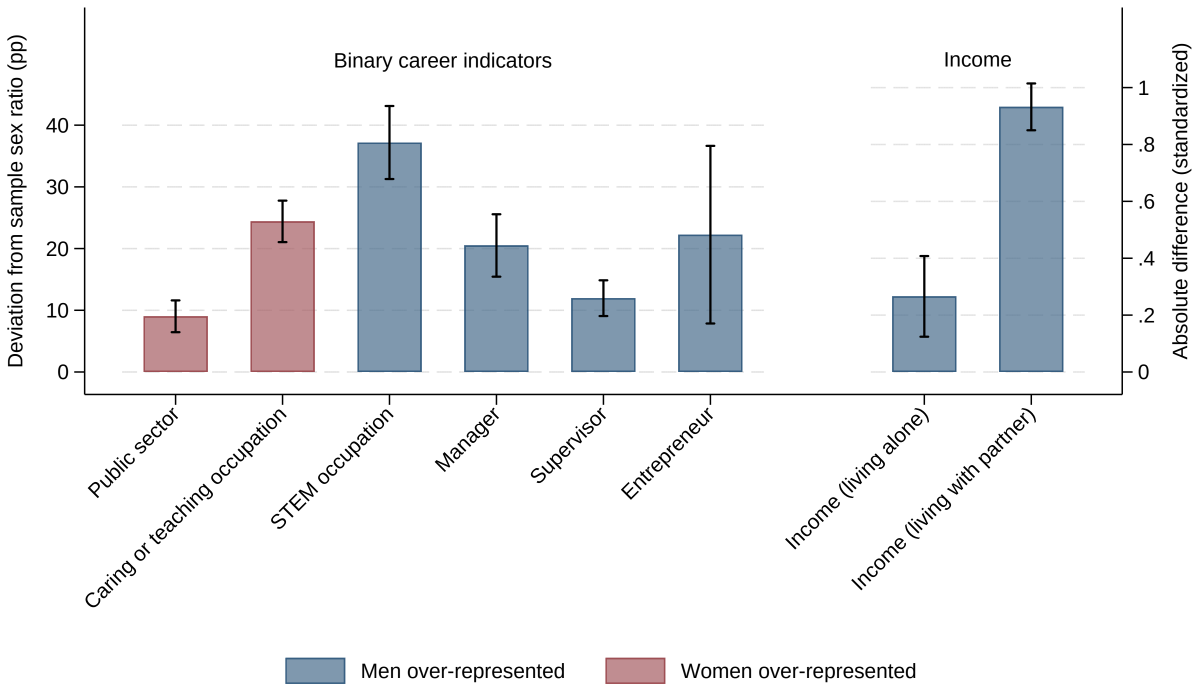

Figure 1: Gender differences in occupational outcomes. Bars show, for each binary career indicator, the deviation of the occupation's sex composition from the sample sex ratio, in percentage points (left axis), and the standardized gender difference in income (right axis), estimated from regressions of each outcome on a gender indicator for respondents aged 25–65. Navy bars denote outcomes in which men are over-represented, maroon bars outcomes in which women are over-represented. Capped lines are 95% confidence intervals.

on risk taking, on negative reciprocity and third-party punishment, on the dark traits (Machiavellianism, psychopathy, narcissism, externalizing behavior and willingness to play dirty), and on the cognitive measures, especially the stated preference for mathematics (a gap of half a standard deviation). Women score substantially higher on agreeableness, honesty-humility, conscientiousness, altruism, universalism and aversion to rule-breaking. The pattern mirrors the broad regularities documented in the personality literature (Schmitt et al., 2008; Weisberg et al., 2011; Muris et al., 2017; Su et al., 2009; Croson and Gneezy, 2009; Niederle, 2016): men tilt toward agentic, competitive and "thing-oriented" dispositions and women toward communal, prosocial and "people-oriented" ones.

For a trait to help explain a gender gap in a career outcome, it must both (i) differ between men and women and (ii) predict the outcome. Figure 2 documents that the first condition applies. Almost all traits exhibit a statistically significant gender difference. For a few traits – the different aspects of competitiveness, risk taking, negative reciprocity, emotional stability, psychopathy, honesty-humility, externalizing, willingness to play dirty,

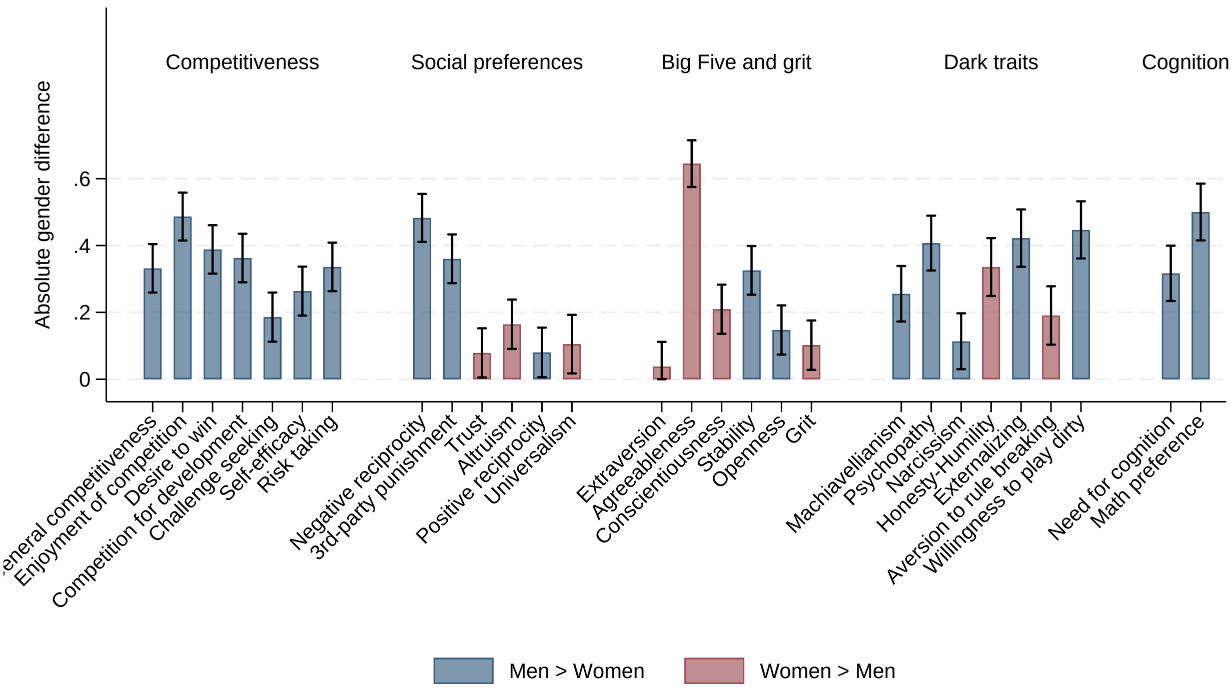

Figure 2: Gender differences in personality and preferences. Bars show the absolute standardized gender difference in each trait, estimated from regressions on a gender indicator for respondents aged 25–65. Navy bars denote traits on which men score higher, maroon bars traits on which women score higher. Capped lines are 95% confidence intervals.

need for cognition, and math preference – the difference is close to 0.4 standard deviations. For agreeableness it even reaches 0.6 standard deviations.

The second condition is documented in Appendix Figure A2, which shows that many traits are strongly associated with at least some career outcomes conditional on education and age. Competitiveness and related traits positively predict supervisory positions and entrepreneurship and negatively predict working in a caring or teaching occupation and the public sector. The same applies to negative reciprocity and willingness to punish others for wrong-doing. The Big Five traits predict career sorting in intuitive ways: agreeableness predicts working in a caring or teaching occupation and the public sector, extraversion and openness predict supervisory positions and entrepreneurship. Most "dark" traits positively predict supervisory positions and entrepreneurship and negatively predict working in a caring or teaching occupation. The same applies to need for cognition and preference for math. Correlations of personality traits with working in a STEM occupation follow less of a neat pattern. The strongest positive predictors are need for cognition, preference for math, openness, and psychopathy, the strongest negative predictors are agreeableness and extraversion.

Table 1 reports the main results. For each outcome it shows, for the three estimation approaches – OLS with the constructed trait indices, OLS with the individual survey questions, and ORIV – the gender coefficient and the share of the conditional gender gap explained by each trait group and by all traits jointly. Bootstrap confidence intervals for the explained shares are reported in Appendix Table A4.

Table 1: Explanatory power of gender differences in personality for occupational sorting

	Baseline	Competitiveness	Social preferences	Big 5 & grit	Dark traits	Cognition	All
Caring or teaching occupation (N = 1,592)							
OLS							
Male	-0.240***	-0.222***	-0.221***	-0.210***	-0.209***	-0.219***	-0.161***
SE	(0.020)	(0.021)	(0.021)	(0.021)	(0.021)	(0.020)	(0.024)
Share explained	—	0.07	0.08	0.12	0.13	0.09	0.33
OLS (individual questions)							
Male		-0.216***	-0.221***	-0.190***	-0.180***	-0.217***	-0.134***
SE		(0.021)	(0.021)	(0.023)	(0.023)	(0.021)	(0.026)
Share explained		0.10	0.08	0.21	0.25	0.10	0.44
ORIV							
Male		-0.208***	-0.208***	-0.201***	-0.193***	-0.216***	-0.124***
SE		(0.022)	(0.021)	(0.022)	(0.023)	(0.021)	(0.026)
Share explained		0.13	0.13	0.16	0.19	0.10	0.48
Public sector (N = 1,711)							
OLS							
Male	-0.125***	-0.104***	-0.101***	-0.121***	-0.093***	-0.098***	-0.069***
SE	(0.023)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.027)
Share explained	—	0.17	0.19	0.03	0.25	0.21	0.45
OLS (individual questions)							
Male		-0.099***	-0.100***	-0.112***	-0.084***	-0.095***	-0.065**
SE		(0.024)	(0.024)	(0.026)	(0.026)	(0.024)	(0.030)
Share explained		0.21	0.20	0.10	0.33	0.24	0.48
ORIV							
Male		-0.099***	-0.090***	-0.102***	-0.083***	-0.095***	-0.043
SE		(0.025)	(0.024)	(0.025)	(0.025)	(0.024)	(0.030)
Share explained		0.20	0.28	0.19	0.34	0.24	0.66
STEM occupation (N = 1,579)							
OLS							
Male	0.167***	0.173***	0.169***	0.150***	0.169***	0.148***	0.141***
SE	(0.015)	(0.017)	(0.016)	(0.016)	(0.017)	(0.015)	(0.017)
Share explained	—	-0.04	-0.02	0.10	-0.01	0.11	0.15
OLS (individual questions)							
Male		0.171***	0.170***	0.153***	0.171***	0.147***	0.141***
SE		(0.017)	(0.016)	(0.018)	(0.017)	(0.015)	(0.019)
Share explained		-0.02	-0.02	0.08	-0.03	0.12	0.15
ORIV							
Male		0.174***	0.170***	0.147***	0.171***	0.145***	0.137***
SE		(0.017)	(0.016)	(0.017)	(0.018)	(0.015)	(0.019)
Share explained		-0.04	-0.02	0.12	-0.03	0.13	0.18
Manager (N = 1,825)							
OLS							
Male	0.099***	0.080***	0.092***	0.094***	0.081***	0.084***	0.071***
SE	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)	(0.016)	(0.018)
Share explained	—	0.19	0.07	0.05	0.19	0.15	0.28
OLS (individual questions)							
Male		0.078***	0.092***	0.079***	0.078***	0.081***	0.066***
SE		(0.016)	(0.015)	(0.017)	(0.018)	(0.015)	(0.020)
Share explained		0.21	0.07	0.20	0.21	0.18	0.33
ORIV							
Male		0.059***	0.093***	0.085***	0.073***	0.080***	0.044**
SE		(0.016)	(0.016)	(0.017)	(0.018)	(0.016)	(0.020)
Share explained		0.41	0.06	0.14	0.26	0.19	0.55

	Baseline	Competitiveness	Social preferences	Big 5 & grit	Dark traits	Cognition	All
Supervisor (N = 1,825)							
OLS							
Male	0.146***	0.106***	0.124***	0.139***	0.113***	0.119***	0.088***
SE	(0.021)	(0.021)	(0.022)	(0.023)	(0.022)	(0.022)	(0.024)
Share explained	—	0.27	0.15	0.05	0.23	0.19	0.40
OLS (individual questions)							
Male		0.105***	0.124***	0.109***	0.102***	0.116***	0.076***
SE		(0.022)	(0.022)	(0.024)	(0.024)	(0.022)	(0.027)
Share explained		0.28	0.15	0.25	0.30	0.21	0.48
ORIV							
Male		0.069***	0.118***	0.123***	0.098***	0.112***	0.038
SE		(0.022)	(0.022)	(0.023)	(0.024)	(0.022)	(0.027)
Share explained		0.53	0.19	0.16	0.33	0.23	0.74
Entrepreneur (N = 1,711)							
OLS							
Male	0.016**	0.008	0.011	0.013	0.013*	0.012*	0.005
SE	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)	(0.008)
Share explained	—	0.49	0.29	0.21	0.20	0.23	0.69
OLS (individual questions)							
Male		0.008	0.011	0.011	0.014*	0.012*	0.004
SE		(0.007)	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)
Share explained		0.50	0.34	0.33	0.14	0.26	0.78
ORIV							
Male		0.002	0.010	0.012	0.012	0.012*	0.000
SE		(0.007)	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)
Share explained		0.86	0.40	0.25	0.23	0.26	0.98
Income (living alone) (N = 500)							
OLS							
Male	670***	484***	655***	540***	588***	558***	447***
SE	(149)	(140)	(146)	(144)	(138)	(143)	(149)
Share explained	—	0.28	0.02	0.19	0.12	0.17	0.33
OLS (individual questions)							
Male		438***	654***	620***	629***	489***	366**
SE		(132)	(146)	(149)	(156)	(141)	(186)
Share explained		0.35	0.02	0.08	0.06	0.27	0.45
ORIV							
Male		385***	626***	530***	551***	529***	271
SE		(144)	(142)	(139)	(139)	(140)	(173)
Share explained		0.42	0.07	0.21	0.18	0.21	0.59
Income (living with partner) (N = 1,229)							
OLS							
Male	1,886***	1,746***	1,836***	1,904***	1,843***	1,745***	1,694***
SE	(89.4)	(87.8)	(90.5)	(100)	(94.4)	(89.1)	(105)
Share explained	—	0.07	0.03	-0.01	0.02	0.07	0.10
OLS (individual questions)							
Male		1,705***	1,850***	1,693***	1,807***	1,728***	1,571***
SE		(89.8)	(90.5)	(104)	(107)	(89.8)	(121)
Share explained		0.10	0.02	0.10	0.04	0.08	0.17
ORIV							
Male		1,665***	1,843***	1,851***	1,813***	1,707***	1,564***
SE		(92.6)	(93.5)	(101)	(100)	(90.0)	(121)
Share explained		0.12	0.02	0.02	0.04	0.09	0.17

Note: each panel reports, for one career outcome, the male coefficient, its standard error, and the share of the baseline conditional gender gap explained (equation 3), for three estimation approaches: OLS with the constructed trait indices, OLS with the underlying individual survey questions, and ORIV. Columns add traits one group at a time and, in the last column, all together. All regressions control for education and age and use the sample of respondents aged between 25 and 65. N refers to the number of respondents; the ORIV regressions stack two copies of the data and cluster standard errors at the respondent level. Standard errors are robust; $*p < 0.10$; $**p < 0.05$; $***p < 0.01$.

Three patterns stand out. First, the joint explanatory power of personality for gender differences in occupational sorting is large. Taking the measurement-error-corrected ORIV estimates, gender differences in the measured traits jointly statistically account for 48% (bootstrap 95% CI [32%, 66%]) of the conditional gender gap in working in a caring or teaching occupation, 66% [31%, 98%] of the gap in public-sector employment, 55% [27%, 93%] of the gap in holding a management position, and 74% [46%, 99%] of the gap in supervisory positions. For income, the traits explain 59% [−12%, 97%] of the gender gap among respondents living without a partner, though only 17% [7%, 28%] among those living with a partner, consistent with the household division of labor playing a much larger role in the latter (Kleven et al., 2019; Bertrand, 2020). The point estimate for entrepreneurship suggests that the traits account for essentially all (98%) of the gap. But this gap, although large in relative terms, is estimated from a small number of entrepreneurs in the data. Consequently, the explained share is very imprecisely estimated: the percentile CI is uninformative ([−400%, 98%]), the bootstrap median is 66% with an interquartile range of 41–85%, and the remaining ORIV coefficient is 0.000 with a 95% CI of $[-0.017, 0.017]$ against a baseline gap of 0.016. The traits thus plausibly account for much of the entrepreneurship gap, but the gap is too small in absolute terms for a precise statement. The one large occupational gap that the measured traits explain only modestly is the STEM gap (18% [1%, 35%]).

Second, no single group of traits dominates across outcomes. For the gender gap in caring and teaching occupations and in public sector employment, explanatory power is spread quite evenly across all five trait groups. Explanatory power for the gender gaps in supervisory and management positions and entrepreneurship is more concentrated in competitiveness and risk seeking. But even here, other trait groups – in particular the dark traits – provide substantial additional explanatory power.

Third, correcting for measurement error matters a great deal. The naive OLS estimates using the constructed indices explain considerably less – for example 28% rather than 55% of the management gap, 40% rather than 74% of the supervisory gap, and 45% rather than 66% of the public-sector gap. Replacing the indices with the underlying survey items (the "individual questions" rows) recovers part of this attenuation, and the ORIV correction

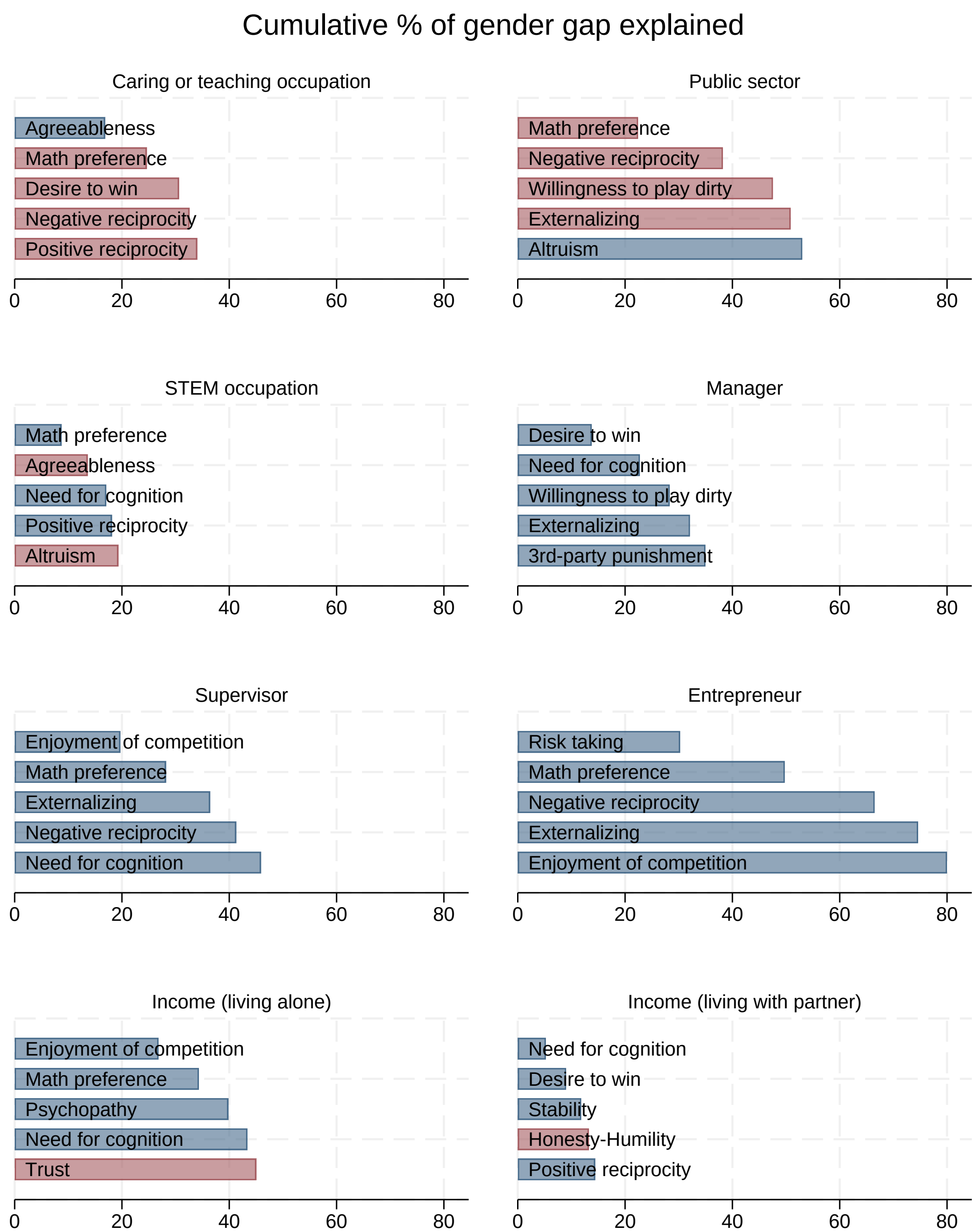

Figure 3: Traits that explain the most of each gender gap. For each outcome, bars show the cumulative percentage of the conditional gender gap explained by the five most influential traits selected by forward selection, as they are added one at a time in order of marginal contribution. Results are based on OLS regressions with dummy controls for education level and age-in-years for the sample aged between 25 and 65; the cumulative shares are therefore not corrected for measurement error. Navy bars denote traits positively associated with the outcome, maroon bars traits negatively associated with it.

recovers more.[7]

This supports the conclusion that the literature underestimates the explanatory power of personality and preferences for gender differences in career sorting due to a combination of three factors: looking at only a subset of relevant traits, looking at only a subset of relevant gender gaps in the labor market, and failing to account for measurement error.

The analyses presented so far demonstrate the overall explanatory potential of personality but make it hard to identify the traits that matter most for each outcome. To achieve this, I use a forward selection algorithm that first selects the trait whose inclusion leads to the largest drop in the gender gap conditional on basic controls, then the trait that leads to the largest additional drop conditional on the first trait and controls, and so on. Figure 3 shows the cumulative share of the gender gap in each outcome that is explained by the five most important traits.

Traits that show up repeatedly are competitiveness (desire to win and enjoyment of competition), preference for math and need for cognition, externalizing behavior, willingness to play dirty, and reciprocity (both positive and negative). Moreover, risk taking has the most explanatory power for the gender gap in entrepreneurship. The large gender differences in these traits (see Figure 2) can explain much of the gender gaps in occupation and – for people living without a partner – income. Appendix Figure A3 extends the exercise to the ten most influential traits for each outcome. It is important to keep in mind that traits within each trait group are often strongly correlated (e.g. the different aspects of competitiveness). Which of these strongly correlated traits gets picked is somewhat random. Appendix Table A7 reports how often each trait is among the ten selected when the selection is re-run within bootstrap resamples.[8]

The high frequency with which competition-related traits are selected supports the large literature that documents the explanatory power of gender differences in willingness to compete for gender gaps in the labor market (see Croson and Gneezy (2009); Niederle (2016); Lozano et al. (2022); Chowdhury and Peter (2026); Buser (2026b) for surveys), although previous studies, by using noisier measures and not correcting for measurement error, have underestimated the explanatory potential. The relevance of women's preference for working with "people" and men's preference for working with "things" – which is loosely proxied here

[7] All regression analyses presented so far control for level of education, but this is itself potentially influenced by personality. Appendix Table A5 shows results without the education control (conditioning on age only). The explained shares are virtually unchanged.

[8] Appendix Table A6 also reports bootstrap confidence intervals for the cumulative explained shares, rerunning the entire selection within each resample, next to a placebo benchmark in which the same selection algorithm is run after randomly permuting the block of trait values across respondents; the placebo quantifies how much "explained" share pure selection noise can generate, and the actual shares exceed it by a wide margin.

by math preference and need for cognition – is well-established too (Lippa, 1998; Su et al., 2009). However, some of the frequently selected traits are novel and surprising. Using the LISS data, Buser and Sangi (2025) already established that willingness to play dirty predicts leadership positions and working in the private sector – but also lower self-esteem and worse social connections – above general willingness to compete. I show here that the large gender difference in willingness to play dirty can statistically explain gender differences in labor market sorting. Also using the LISS data, Buser (2026a) shows that childhood misbehavior (externalizing) predicts later-life leadership and entrepreneurship – but also antisocial and illicit behavior (see Papageorge et al. (2022) and Del Bono et al. (2024) for further studies that establish a positive correlation between childhood externalizing and later-life labor market success). Boys are more likely to misbehave than girls, and I show here that this can statistically explain gender gaps in labor market sorting. Finally, Falk and Hermle (2018) – using a global dataset – have established that women are more positively reciprocal and less negatively reciprocal in most countries, but the link of reciprocity with labor market sorting (and gender gaps in labor market sorting) has remained underexplored.

5 Conclusion

A large literature documents gender differences in economic preferences and personality and asks how much they explain of gender gaps in the labor market, in particular gender differences in occupational sorting. These studies typically focus on one trait and a limited set of outcomes at a time and have tended to find modest explanatory power. In this paper I ask a different, complementary question: what is the *overall* explanatory power of gender differences in personality and economic preferences for gender gaps in occupational sorting. That is, I estimate how much of the most-widely discussed gender gaps in occupational sorting – the underrepresentation of women in leadership positions and STEM, the underrepresentation of men in teaching and caring occupations – can be statistically accounted for by combining a comprehensive battery of preference and personality measures elicited in a single representative panel. The main finding is that personality matters much more than previous studies indicated. Once measurement error is corrected for, gender differences in the measured traits account for roughly half or more of the conditional gender gaps in working in a caring or teaching occupation, the public sector, management positions, supervisory positions, and entrepreneurship. Only the STEM gap is left mostly unexplained.

Explanatory power is distributed across many personality dimensions, each only partially captured by other traits and each measured with error. Studies that focus on a single trait or classification therefore understate the role of personality overall, both because they omit other relevant traits and because of measurement error in the traits they do consider. Estimating the joint explanatory power, and correcting for measurement error, reveals both that personality differences can account for a substantial part of occupational segregation and that many different traits matter. Buser (2025) establishes an analogous result for gender differences in voting and political ideology: a thorough battery of personality measures can explain a much larger proportion of political gender gaps than any individual trait or classification in isolation.

A further, unanticipated, result is that some of the traits that carry the most explanatory power are non-standard traits that have received relatively little attention in the gender economics literature – willingness to play dirty, externalizing behavior, negative reciprocity and psychopathy. For many outcomes, traits that – clearly or potentially – have a "dark" side capture a surprisingly large share of the gender gap. My results indicate that if we want to know why men are overrepresented in managerial positions and underrepresented in teaching and caring occupations, we are – perhaps unfortunately – better off looking at gender differences in the dark sides of personality than at traits such as grit, conscientiousness, or social skills that the labor economics literature typically focuses on. Two qualifications are in order: I investigate selection into positions and occupations, not performance in them. Also, the dark traits may partly proxy for assertive or agentic dimensions that are not fully captured by other personality measures. The fact that non-standard and recently defined traits such as willingness to engage in dirty competition (Buser and Sangi, 2025) are often amongst the most influential also raises the possibility that there are further personality dimensions that are important but hitherto ignored. At the same time, my results reinforce the large literature on the gender difference in willingness to compete by showing that its explanatory power for gender gaps in leadership positions is large once measurement error is accounted for.

It is important to keep in mind that the findings are descriptive and correlational. The measured traits may themselves be shaped by the same gendered socialization that shapes occupational choices, and traits and careers plausibly influence each other in either direction. What the results do show is that the ceiling for the explanatory power of gender differences in personality is high and that the persistence of occupational segregation in a rich, gender-equal country coincides with, and is statistically accounted for by, large gender differences in personality. This connects to the broader "gender-equality paradox" – the finding that gender differences in personality and preferences are largest in the most developed and gender-equal countries (Falk and Hermle, 2018; Stoet and Geary, 2018; Schmitt et al., 2008). As the human-capital and institutional barriers that once kept many people out of certain occupations have receded, dispositional differences may have become relatively more important in shaping who does what. To the extent that dispositions now drive sorting, policies aimed solely at removing the remaining formal barriers may leave much of occupational segregation in place. How occupations are structured and rewarded, and how gendered traits form in the first place, then become the relevant margins.

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Appendix

Table A1: Descriptive statistics and gender differences (analysis sample, ages 25–65)

	Men	Women	Difference	N
Career outcomes				
Caring or teaching occupation	0.116	0.350	-0.234***	2,407
STEM occupation	0.186	0.031	0.155***	2,385
Manager	0.175	0.075	0.100***	2,833
Supervisor	0.363	0.225	0.139***	2,833
Entrepreneur	0.027	0.011	0.016***	2,669
Public sector	0.277	0.402	-0.125***	2,669
Monthly gross income (EUR)	3,688	2,235	1,452***	2,709
Competitiveness (standardised)				
Competitiveness (general)	0.18	-0.15	0.33***	2,870
Enjoyment of competition	0.27	-0.22	0.49***	2,846
Desire to win	0.21	-0.18	0.39***	2,844
Competition for development	0.20	-0.16	0.36***	2,845
Challenge seeking	0.10	-0.08	0.19***	2,851
Self-efficacy	0.14	-0.12	0.26***	2,847
Risk taking	0.18	-0.15	0.34***	2,869
Social preferences (standardised)				
Negative reciprocity	0.26	-0.22	0.48***	2,831
Third-party punishment	0.20	-0.16	0.36***	2,831
Trust	-0.04	0.04	-0.08**	2,868
Altruism	-0.09	0.07	-0.16***	2,831
Positive reciprocity	0.04	-0.04	0.08**	2,829
Universalism	-0.06	0.05	-0.10**	2,009
Personality (standardised)				
Extraversion	-0.02	0.02	-0.04	2,853
Agreeableness	-0.35	0.29	-0.65***	2,853
Conscientiousness	-0.11	0.09	-0.21***	2,853
Emotional stability	0.18	-0.15	0.33***	2,853
Openness	0.08	-0.07	0.15***	2,853
Grit	-0.06	0.05	-0.10***	2,835
Dark traits (standardised)				
Machiavellianism	0.14	-0.12	0.26***	2,210
Psychopathy	0.22	-0.19	0.41***	2,210
Narcissism	0.06	-0.05	0.11***	2,209
Honesty-Humility	-0.18	0.16	-0.34***	2,011
Externalizing	0.23	-0.20	0.42***	2,011
Aversion to rule-breaking	-0.10	0.09	-0.19***	2,014
Willingness to play dirty	0.24	-0.21	0.45***	2,014
Cognition (standardised)				
Need for cognition	0.17	-0.15	0.32***	2,208
Math preference	0.27	-0.23	0.50***	2,014

Note: the table reports means for men and women and the gender difference (men minus women). Career outcomes are in natural units (shares, or euros for income); trait measures are standardized to mean zero and unit standard deviation in the analysis sample, so their differences are in standard deviations. Stars denote the significance of the difference: *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

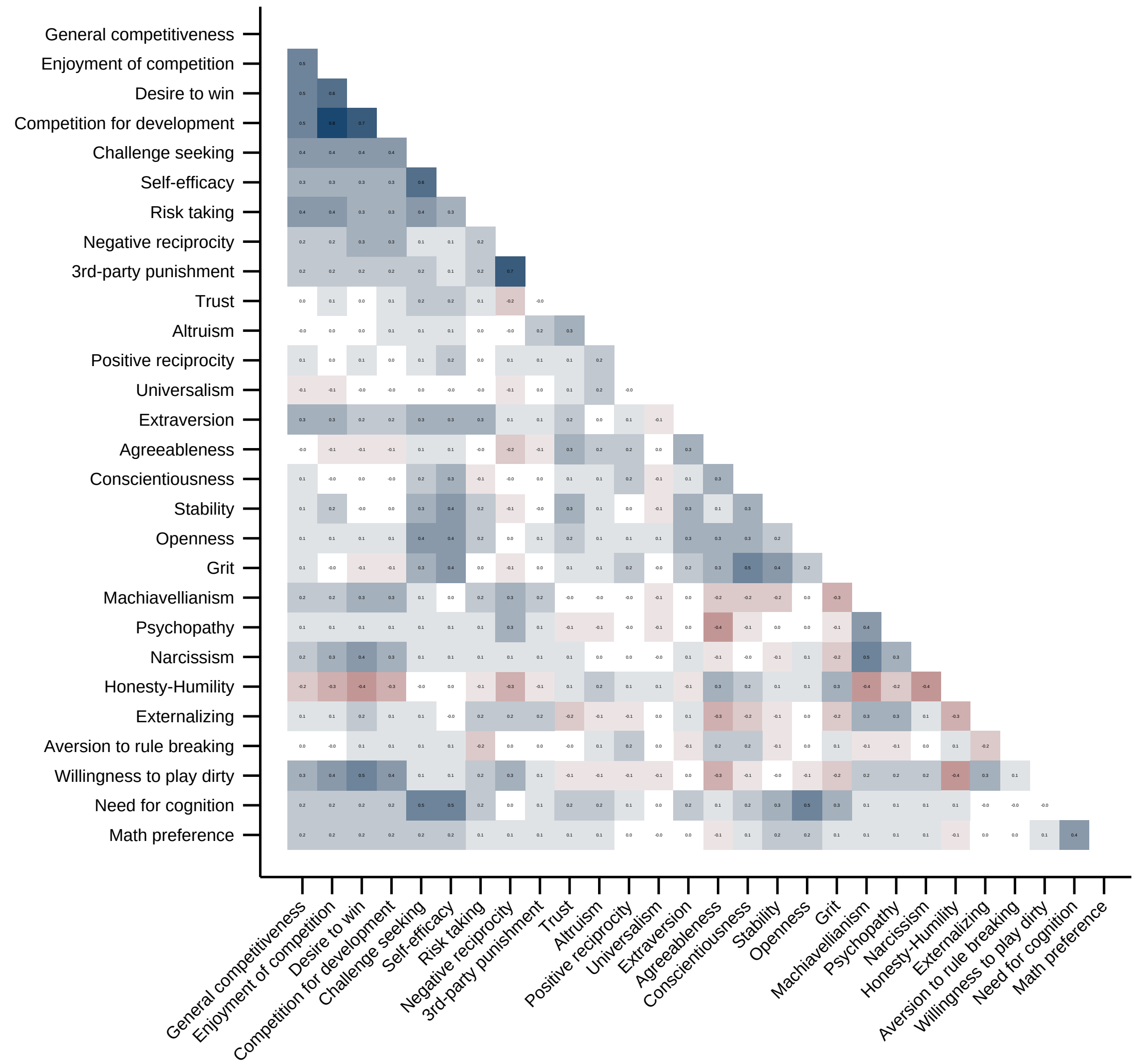

Figure A1: Pairwise correlations between the trait measures. Entries are Pearson correlations between the standardized trait indices for respondents aged 25–65.

Table A2: Analysis sample versus full LISS sample

	Analysis sample	Full LISS, ages 25–65
Age (mean)	49.2	47.2
Share female	0.53	0.55
Education: Primary	0.04	0.03
Education: Secondary (vocational)	0.14	0.13
Education: Secondary (academic)	0.08	0.08
Education: Vocational	0.31	0.30
Education: Higher vocational	0.29	0.30
Education: University	0.14	0.16
Has occupation code	0.86	0.83
Monthly gross income (EUR)	2,851	2,890
N	1,843	2,870

Note: the analysis sample consists of respondents aged 25–65 with non-missing values for all 27 trait indices. The comparison column covers all LISS respondents aged 25–65 in the estimation data. Education shares are computed among respondents with a non-missing education level.

Table A3: Construction of the trait measures and the ORIV split

	Items	ORIV split (measure 1 / measure 2)
Competitiveness		
Competitiveness (general)	1	two elicitations (2021 / 2017 wave)
Enjoyment of competition	4	2 / 2
Desire to win	5	3 / 2
Competition for development	4	2 / 2
Challenge seeking	2	1 / 1
Self-efficacy	4	2 / 2
Risk taking	1	two elicitations (2021 / 2017 wave)
Social preferences		
Negative reciprocity	2	1 / 1
Third-party punishment	1	not instrumented
Trust	2	1 / 1
Altruism	1	not instrumented
Positive reciprocity	1	not instrumented
Universalism	2	1 / 1 (domestic / global elicitation)
Big Five and grit		
Extraversion	10	5 / 5
Agreeableness	10	5 / 5
Conscientiousness	10	5 / 5
Emotional stability	10	5 / 5
Openness	10	5 / 5
Grit	10	5 / 5
Dark traits		
Machiavellianism	4	2 / 2
Psychopathy	4	2 / 2
Narcissism	4	2 / 2
Honesty-Humility	10	5 / 5
Externalizing	8	4 / 4
Aversion to rule-breaking	4	2 / 2
Willingness to play dirty	3	1 / 2
Cognition		
Need for cognition	6	3 / 3
Math preference	4	2 / 2

Note: for each trait, the table reports the number of underlying survey items and how the items are divided into the two measures used in the ORIV estimation. "Two elicitations" means the same single item was elicited in two different survey waves. Traits marked "not instrumented" rest on a single elicitation of a single item and enter the ORIV specifications uninstrumented.

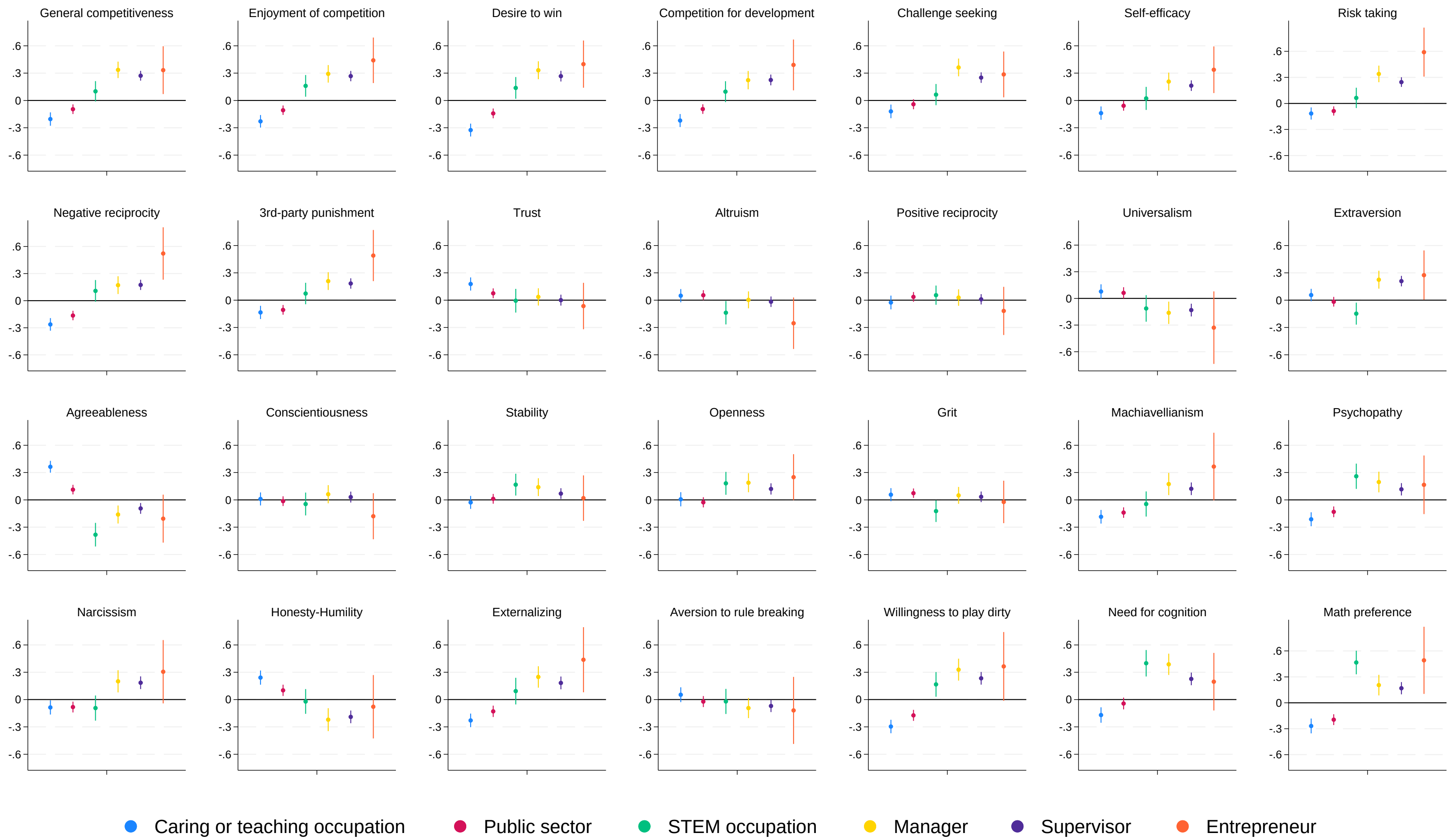

Figure A2: Associations between each trait and each career outcome. Each panel plots the coefficients from regressions of the (mean-scaled) career outcomes on one standardized trait, controlling for education and age, for respondents aged 25–65.

Table A4: Bootstrap confidence intervals for the explained shares (all traits)

	Share explained, all traits				ORIV share	Remaining
	OLS	Questions	ORIV	ORIV − OLS	median [IQR]	gap (ORIV)
Caring or teaching occupation	0.33	0.44	0.48	0.16	0.49 [0.44, 0.55]	-0.124
	[0.21, 0.45]	[0.29, 0.62]	[0.32, 0.66]	[0.08, 0.26]		[-0.175, -0.070]
Public sector	0.45	0.48	0.66	0.21	0.65 [0.52, 0.80]	-0.043
	[0.21, 0.85]	[0.14, 0.90]	[0.31, 0.98]	[-0.09, 0.38]		[-0.102, 0.021]
STEM occupation	0.15	0.15	0.18	0.02	0.18 [0.12, 0.23]	0.137
	[0.03, 0.28]	[-0.02, 0.31]	[0.01, 0.35]	[-0.07, 0.11]		[0.099, 0.177]
Manager	0.28	0.33	0.55	0.27	0.56 [0.45, 0.68]	0.044
	[0.09, 0.53]	[0.06, 0.66]	[0.27, 0.93]	[0.14, 0.47]		[0.004, 0.084]
Supervisor	0.40	0.48	0.74	0.34	0.74 [0.64, 0.86]	0.038
	[0.21, 0.64]	[0.21, 0.80]	[0.46, 0.99]	[0.17, 0.51]		[-0.016, 0.091]
Entrepreneur	0.69	0.78	0.98	0.29	0.66 [0.41, 0.85]	0.000
	[-2.18, 0.98]	[-2.24, 0.97]	[-4.00, 0.98]	[-1.88, 0.43]		[-0.017, 0.017]
Income (living alone)	0.33	0.45	0.59	0.26	0.54 [0.35, 0.76]	271
	[0.00, 0.72]	[-0.29, 0.96]	[-0.12, 0.97]	[-0.30, 0.56]		[-155, 716]
Income (living with partner)	0.10	0.17	0.17	0.07	0.17 [0.14, 0.21]	1,564
	[0.03, 0.17]	[0.06, 0.27]	[0.07, 0.28]	[0.02, 0.13]		[1,321, 1,813]

Note: point estimates are the in-sample shares of the conditional gender gap explained by all traits jointly (equation 3), as in Table 1. Brackets are percentile 95% confidence intervals over 999 bootstrap replications, drawn with replacement and stratified by gender; the full estimation pipeline, including the standardization of the traits and the ORIV first stages, is re-run within each replication. The ORIV − OLS column reports the within-replication difference between the ORIV and OLS shares. Because the share is a ratio, its percentile interval becomes erratic when the baseline coefficient is small relative to its sampling noise (entrepreneurship, income among singles); the last two columns therefore additionally report the median and interquartile range of the ORIV share across replications and the *remaining* ORIV gender coefficient in levels, a statistic that remains well-behaved in those cases.

Table A5: Robustness: dropping the education controls

	Baseline male coef.	Share explained, all traits		
	(age controls only)	OLS	Questions	ORIV
Caring or teaching occupation	-0.248***	0.31	0.45	0.46
Public sector	-0.123***	0.41	0.48	0.64
STEM occupation	0.166***	0.16	0.15	0.18
Manager	0.105***	0.33	0.34	0.55
Supervisor	0.143***	0.42	0.48	0.74
Entrepreneur	0.019**	0.66	0.76	0.87
Income (living alone)	673***	0.39	0.51	0.64
Income (living with partner)	1,954***	0.13	0.19	0.18

Note: as the all-traits columns of Table 1, but controlling for age only. Education is potentially itself an outcome of the traits; dropping it tests whether conditioning on education drives the explained shares. Standard errors are robust; $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A6: Cumulative explained share of the selected traits: bootstrap and placebo

	Five selected traits		Placebo (permuted traits)	
	Cumulative %	Bootstrap 95% CI	Mean	95th percentile
Caring or teaching occupation	34.0	[26.3, 46.1]	1.4	2.3
Public sector	53.0	[33.9, 88.2]	2.8	4.8
STEM occupation	19.3	[12.0, 31.7]	1.5	2.5
Manager	35.0	[28.2, 66.0]	2.2	3.7
Supervisor	45.9	[34.2, 78.7]	2.2	3.6
Entrepreneur	80.0	[49.5, 100.0]	7.1	12.2
Income (living alone)	45.0	[27.8, 93.9]	6.9	12.5
Income (living with partner)	14.4	[10.9, 20.4]	0.9	1.6

Note: the first two columns report the in-sample cumulative percentage of the conditional gender gap explained by the five forward-selected traits (as in Figure 3) and its 95% percentile interval over 199 bootstrap resamples in which the entire selection is re-run. The placebo columns run the same selection algorithm after randomly permuting the block of trait values across respondents (jointly, preserving the trait-trait correlations but severing any true link to gender and outcomes) in each of 199 permutations; they report the mean and the 95th percentile of the resulting spurious cumulative shares.

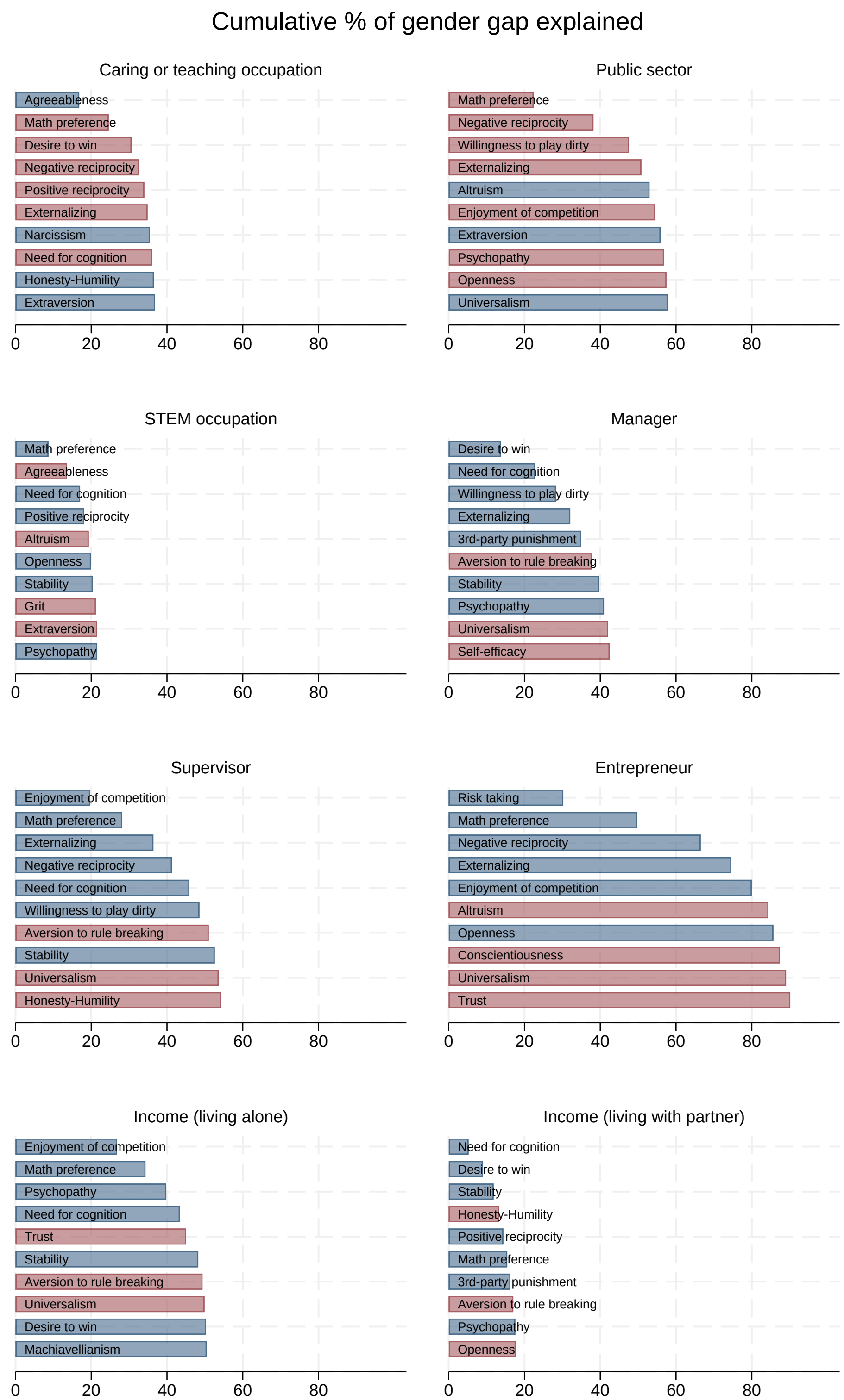

Figure A3: Traits that explain the most of each gender gap (ten traits). As Figure 3, but showing the cumulative share explained by the ten most important traits for each outcome.

Table A7: Stability of the forward selection across bootstrap resamples

	Most frequently selected traits (% of bootstrap draws in which selected)
Caring or teaching occupation	Agreeableness (100), Math preference (99), Positive reciprocity (98), Desire to win (87), Negative reciprocity (68), Need for cognition (65), Externalizing (60), Willingness to play dirty (51), Extraversion (51), Narcissism (47)
Public sector	Math preference (100), Willingness to play dirty (95), Negative reciprocity (89), Altruism (73), Externalizing (71), Extraversion (67), Enjoyment of competition (54), Psychopathy (52), Openness (41), Risk taking (37)
STEM occupation	Math preference (99), Need for cognition (96), Positive reciprocity (94), Altruism (88), Agreeableness (84), Openness (77), Stability (76), Grit (65), Extraversion (60), Psychopathy (43)
Manager	Need for cognition (100), 3rd-party punishment (91), Willingness to play dirty (84), Externalizing (70), Aversion to rule breaking (69), Desire to win (64), Stability (60), Psychopathy (59), Risk taking (57), Universalism (52)
Supervisor	Need for cognition (99), Math preference (87), Externalizing (86), Enjoyment of competition (84), Willingness to play dirty (69), Aversion to rule breaking (66), 3rd-party punishment (64), Universalism (62), Stability (61), Risk taking (58)
Entrepreneur	Risk taking (67), Math preference (66), Negative reciprocity (52), Externalizing (51), Openness (50), Enjoyment of competition (49), Trust (48), Challenge seeking (45), Conscientiousness (42), 3rd-party punishment (42)
Income (living alone)	Enjoyment of competition (97), Psychopathy (73), Math preference (72), Need for cognition (70), Stability (65), Aversion to rule breaking (59), Trust (59), Universalism (47), Grit (42), Self-efficacy (37)
Income (living with partner)	Stability (99), Need for cognition (98), Positive reciprocity (97), Math preference (86), Desire to win (80), Honesty-Humility (76), 3rd-party punishment (65), Aversion to rule breaking (61), Psychopathy (47), Openness (45)

Note: the ten-step forward selection of Appendix Figure A3 (over all 27 traits, OLS, controls for education and age) is re-run within each of 199 bootstrap resamples stratified by gender. For each outcome, the table lists the ten traits most frequently among the ten selected, with the percentage of resamples in which they are selected in parentheses.