CAN COMPETITIVENESS PREDICT EDUCATION AND LABOR MARKET OUTCOMES? EVIDENCE FROM INCENTIVIZED CHOICE AND SURVEY MEASURES

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Abstract—We assess the predictive power of two measures of competitiveness for education and labor market outcomes using a large, representative survey panel. The first is incentivized and is an online adaptation of the laboratory-based Niederle-Vesterlund measure. The second is an unincentivized survey question eliciting general competitiveness. Both measures are strong predictors of income, occupation, level of education, and field of study. The predictive power of the new unincentivized measure is robust to controlling for other traits, including risk attitudes, confidence, and the Big Five personality traits. For most outcomes, the predictive power of competitiveness exceeds that of the other traits.

I. Introduction

A growing literature documents the importance of individual traits such as conscientiousness and grit in determining education and labor market outcomes (Heckman & Rubinstein, 2001; Heckman et al., 2006; Mueller & Plug, 2006; Borghans et al., 2008; Almlund et al., 2011). We contribute to this literature by focusing on competitiveness, a trait emerging from the experimental economics literature. A number of recent studies indicate that individual preferences for competition are strongly associated with educational choices and early labor market outcomes (Buser et al., 2014; Reuben et al., 2015).[1] These studies follow a large literature based on laboratory experiments documenting individual heterogeneity in competitiveness (Gneezy et al., 2003; Niederle & Vesterlund, 2007). In particular the gender gap in competitiveness found in the laboratory has attracted much interest because of its potential to explain gender differences in education and labor market outcomes (Bertrand, 2011).

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[1]Buser et al. (2014) and Buser et al. (2017) show that an incentivized measure of competitiveness predicts specializing in more prestigious and math-heavy subjects for Dutch and Swiss students from the pre-university track of secondary school. Reuben et al. (2015) show the same for the starting salaries and industry choices of MBA graduates. Other studies find that competitiveness predicts participating in a competitive high school entrance exam (Zhang, 2012), investment choices of entrepreneurs (Berge et al., 2015), choosing an ambitious college track in high school (Almås et al., 2016), future salary expectations of undergraduate students (Reuben et al., 2017), and career choices at the vocational education level (Buser et al., 2022). See Lozano et al. (2022) for a survey of this literature.

Studies that explore the relevance of individual competitiveness for shaping careers typically link choices in incentivized experiments conducted in a laboratory or classroom setting to subsequent career choices and outcomes.[2] This makes data collection expensive and logistically cumbersome. As a consequence, most studies use relatively small samples of students (or other selective groups that can be physically captured in one spot) and link the experimental data to short- or medium-term outcomes. To take this literature forward, we elicit competitiveness through two measures that can be administered outside the laboratory setting. The first measure is incentivized and is an adaptation of the setup of the original Niederle-Vesterlund experiment such that it can be administered online. The second measure is an unincentivized survey question and is based on the approach of Dohmen et al. (2011) and Falk et al. (2016) for other economic preferences.

This allows us to make the following main contributions. First, we show that willingness to compete as measured by an incentivized choice experiment strongly predicts earnings and occupation conditional on education level, as well as education level and college major choice in a representative sample. Second, we show that our unincentivized survey question predicts the same outcomes in the same sample. Third, we show that our survey measure of competitiveness predicts these outcomes over and above other unincentivized trait measures that the education economics literature has typically focused on, including risk seeking, confidence, and the Big Five personality traits, indicating that competitiveness is a separate influential trait that is not captured by these other, more traditionally used traits.

Our new, validated questionnaire measure will enable researchers in all social science fields to measure competitiveness in large-scale surveys, opening new avenues for exploring individual and group differences, their origins, and their consequences for career choices and labor market outcomes. The measure is inspired by the seminal work of Dohmen et al. (2011) on risk preferences and consists of the question "How competitive do you consider yourself to be?"

[2]These studies commonly measure competitiveness using the design of Niederle and Vesterlund (2007), where participants choose between piece-rate and tournament incentives for their performance in a real-effort task. Competitiveness is then measured as the choice for tournament incentives conditional on prior performance on the task (and, sometimes, measures of confidence and risk attitudes). This literature has focused mainly on gender differences. Niederle and Vesterlund (2007) find that men are much more likely to compete than women. Their result has been replicated many times (see, e.g., Croson & Gneezy, 2009; Niederle & Vesterlund, 2011; and Niederle, 2016 for surveys), including in field settings (Flory et al., 2015; Samek, 2019; Buser et al., 2023).

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where respondents pick a number on a scale from zero to ten. We included this measure, as well as an incentivized choice experiment based on the design of Niederle and Vesterlund (2007), in two of the monthly rounds of an online survey panel that is representative of the Dutch population. The survey question was included in one of the waves in 2017 and was sent to all members of the panel. The incentivized measure was included in one of the waves in 2018 and was sent to a random subsample of the respondents of the survey question. Because a full year and several unrelated survey rounds passed between the two waves, it is unlikely that participants in the incentivized experiment were aware of the connection between the experiment and the survey question.

Eliciting our competitiveness measures in this panel allows us to leverage the rich information that has already been collected from the panel participants. Besides data on education and labor market outcomes, the data set also contains information about many individual traits such as confidence, self-esteem, and the Big Five personality traits (extraversion, agreeableness, conscientiousness, stability, and openness). To this, we added a measure of risk preferences (Dohmen et al., 2011). We can therefore investigate whether competitiveness predicts education and labor market variables on top of these other traits. Moreover, we can compare the predictive power of competitiveness to that of the other personality traits. These data also allow us to validate our survey question not only by computing its correlation with the incentivized choice at the individual level but also by checking whether both measures predict relevant career outcomes in a similar way.

Several papers in psychology have developed scales to measure aspects of competitiveness (Griffin-Pierson, 1990; Ryckman et al., 1990; Smither & Houston, 1992; Houston et al., 2002; Newby & Klein, 2014). None of these has been widely adopted, and none has, to our knowledge, been linked to education or labor market outcomes in a large sample. Houston et al. (2015) correlate their competitiveness scale with occupational interests in a sample of 149 undergraduate students, finding a positive correlation with the corresponding O*NET rating of the occupation's level of competition.[3] In economics, Bönte and Piegeler (2013) use the Eurobarometer 283 survey on entrepreneurship, which contains an unincentivized measure of competitiveness.[4] They show that this measure is positively correlated with entrepreneurship. Bönte et al. (2017) elicit both an incentivized measure of competitiveness and several unincentivized questions taken from different competitiveness scales from the psychology literature. In a sample of 186 students, they find a significant correlation between incentivized and self-reported competitiveness. They relate both to interest in a managerial career and find a significant correlation with a subset of the self-reported measures, but not with the incentivized choice. Fallucchi et al. (2020) conducted a validation exercise to obtain a survey measure of preference for competition in a sample of 90 students from the University of Luxembourg. Of the eight survey questions they included, the statement "Competition brings the best out of me" correlates highest with an incentivized competition choice elicited two weeks later.[5]

We elicit both our incentivized measure and our unincentivized measure of competitiveness in a large and representative sample that contains a rich set of career outcomes and psychological traits. Our results show that both measures are strong predictors of the same education and labor market outcomes. Conditional on performance in the task, gender, age, education level, risk preferences, confidence, and the Big Five personality traits, individuals who compete in the experiment earn significantly more and are much more likely to hold a high-level managerial or professional position. Individuals who compete are also more likely to have gone to college and, conditional on having gone to college, chose more prestigious study majors that lead to higher salaries.[6] We find the same effects for people who score themselves higher on competitiveness in our new survey question. Comparing the predictive power of different traits, competitiveness is consistently among the strongest predictors. The fact that the incentivized and unincentivized measures predict the same outcomes justifies the use of the unincentivized survey question as a valid measure of competitiveness in future research.

With both our incentivized and our unincentivized measure, we replicate the finding of a gender gap in competitiveness. We analyze to what extent the gender difference in competitiveness can account for gender differences in education and labor market outcomes. Controlling for our survey measure reduces the estimated gender gap in earnings by about 5% (10% for college-educated individuals) and the gender differences in occupation and chosen college major by about 10%. These effects are higher than those obtained for most of the other traits. These results contribute

[3]Defined as the extent to which the "job requires the worker to compete or to be aware of competitive pressure." O*NET stands for Occupational Information Network.

[4]The extent to which a respondent agrees with the statement "I like situations in which I compete with others." Bönte (2015) uses the same data to study cross-country differences in the competitiveness gender gap.

[5]They further find that a group of athletes agreed more with this statement than a group of nonathletes of the same age.

[6]Another paper that collects an incentivized measure of competitiveness in a representative sample is Boschini et al. (2019). They collected incentivized measures of competitiveness and risk preferences using telephone interviews with a random sample of 926 people from the Swedish population. Their paper focuses on gender differences in competitiveness and risk preferences, finding no gender difference in competitiveness when participants perform a language task and replicating the lab finding that men are more likely to compete in a math task. Regressions of competitiveness on gender, age, age squared, income, education, and gender of the interviewer show positive conditional associations between competitiveness and income and between competitiveness and education. The results do not show how strong a predictor competitiveness is for education and income, nor can the authors condition on other personality traits or compare the predictive power of competitiveness with that of other traits (other than risk preferences).

to a recent discussion on whether differences in personality and preferences can partially explain gender differences in labor market outcomes (Bertrand, 2011; Cortes & Pan, 2018; Shurchkov & Eckel, 2018; Lozano et al., 2022).

The remainder of this paper is organized as follows. The next section introduces the survey and incentivized measures of competitiveness and the other variables from the LISS panel that we use in the analysis. Section III presents the empirical findings. We first report results for the relation between the incentivized competitiveness measure and education and labor market outcomes. We next present similar results for the survey measure of competitiveness and compare the predictive power of the survey measure to those of other relevant trait measures (risk attitudes, confidence, and the the Big Five personality traits). Finally, we examine to which extent gender differences in competitiveness can explain gender differences in education and labor market outcomes. Section IV summarizes and concludes.

II. Data

We collected our data on the Dutch LISS panel (Longitudinal Internet Studies for the Social sciences), an ongoing online survey panel. The panel has been in operation since October 2007. It is based on a true probability sample of households drawn from the population register by Statistics Netherlands (www.lissdata.nl). Panel members answer yearly repeated "core" questionnaires that cover a large range of topics including work, education, wealth, family, and, importantly for our purposes, personality. On top of this, researchers can pay to run questionnaires on the panel, including incentivized experiments, which can then be linked to all other data available on the respondents. All LISS data, including researcher-run questionnaires, are publicly available to all researchers.

The time line of our data collection is as follows. In March 2017, we collected two survey measures of competitiveness, as well as measures of risk preferences and of confidence. This questionnaire was aimed at all panel members. A year later, in April 2018, we ran the incentivized choice experiment on a subsample that represents a random selection of working-age panel members. In this section, we explain the measures we collected, the trait measures already present in the LISS questionnaires, and the education and labor market variables.

A. *Survey Measure of Competitiveness*

In March 2017, we included two survey questions in the LISS panel aimed at eliciting respondents' competitiveness. The first question, which is the one we use for our main analyses, asks respondents about their general competitiveness through the question "How competitive do you consider yourself to be? Please choose a value on the scale below, where the value 0 means 'not competitive at all' and the value 10 means 'very competitive'." This question is a variation on the general risk preference question validated in Dohmen et al. (2011).[7,8,9]

From our analysis of the data, we conclude that the general question results in a better measure of competitiveness than the hypothetical choice question. Both are correlated significantly with the incentivized measure, but the general measure shows stronger associations with education and labor market variables.[10] For readability, we will therefore in the main text report only results based on the general competitiveness question. Results for the hypothetical competitiveness question are very similar and are reported in online appendix B. There we also show that although the first, simpler measure predicts outcomes better, predictive power can still be meaningfully increased by including both measures jointly.

B. *Incentivized Choice Experiment*

In the original Niederle-Vesterlund choice experiment (Niederle & Vesterlund, 2007), subjects are seated behind computer screens in a laboratory to perform the same task during three subsequent rounds. In the first round they are paid for their performance through a piece rate. In the second round they are paid in the form of a winner-takes-all tournament. For the third round, subjects have to choose whether they want to be compensated in the form of a piece rate or

[7]Their question reads "How do you see yourself: Are you a person who is generally willing to take risks, or do you try to avoid taking risks?" The answering scale runs from 0 (completely unwilling) to 10 (completely willing). The second question describes the experimental design of Niederle and Vesterlund (2007) and asks respondents whether they would choose piece-rate or tournament compensation in the hypothetical case that they would participate in this choice experiment.

[8]The exact phrasing reads as follows: "Imagine the following hypothetical scenario. You participate in an experiment where you are paid for your performance in a simple task. This task consists in adding up sets of five two-digit numbers without the help of a calculator (so, for example, $43 + 82 + 11 + 94 + 68 =$?). You have five minutes to solve as many problems of this type as you can. You have to choose how you want to be paid for your performance in this task: Option 1: Piece rate: you receive 1 Euro for each correctly solved problem; Option 2: Competition: you compete against 3 other people. If you perform better than all three, you receive 4 euros per correctly solved problem, otherwise you receive nothing. Your three opponents will be randomly selected among the other participants of the LISS panel. Which option would you choose?" To measure confidence on the task, we asked how well the respondents think they would perform in the Niederle-Vesterlund numbers task compared to other panel members.

[9]This question was phrased as follows: "In the described task (adding up sets of five two-digit numbers) how well do you think you would perform compared to other participants? In particular, compared to 10 randomly selected LISS panel members, do you think you would come 1st, 2nd, 3rd, . . ., 10th?" We also elicited the general risk preference question of Dohmen et al. (2011). The four questions were asked in the order they are described here for all participants. The survey was answered by 5,255 individuals, 3,082 of whom are between 25 and 65 years old. This corresponds to a response rate of 86%.

[10]Moreover, in regressions of both survey measures on outcomes, the coefficient of general competitiveness is typically unaffected by the inclusion of hypothetical competitiveness whereas the coefficient of hypothetical competitiveness often becomes smaller and sometimes insignificant after the inclusion of general competitiveness.

Figure 1.—Example Matrix Task (Choice Experiment)

◯ 54	◯ 64	◯ 59
◯ 52	◯ 44	◯ 23
◯ 88	◯ 40	◯ 41

a tournament. The task that subjects perform in this original experiment is to add up sets of five two-digit numbers. The instructions tell the participants that the use of a calculator is not allowed.

The advantage that the use of a calculator gives on this particular task makes it unattractive for an online version of the experiment. The alternative task that we use here is to find the two numbers that add up to 100 in a 3×3 matrix of nine two-digit numbers (see figure 1). There were three rounds of two minutes, during which participants could solve as many matrices as possible. One of the three rounds was randomly chosen for payment ex post. Before the start of the three rounds, participants had to correctly solve three practice matrices. At the start of each round, they were informed how they would be paid if that round were to be randomly chosen for payment:

1. Participants receive 40 cents per correctly solved matrix (piece rate).
2. Participants receive 80 cents per correctly solved matrix if their score is higher than the score of a randomly chosen other participant and zero if their score is lower[11] (tournament).
3. Participants have to choose between the piece-rate and tournament schemes. If they choose the tournament, their score is compared to the score of a randomly selected other participant. That other participant is chosen among all participants regardless of the payment scheme they chose.

The third-round choice is our incentivized measure of competitiveness. To measure confidence on the task, we asked how well, on a scale from 0 (the worst) to 10 (the best), participants thought they performed compared to other participants. We also asked what they thought their chance was of beating a randomly selected opponent.[12] The two confidence measures are very highly correlated. To measure risk attitudes, we again included the validated risk question of Dohmen et al. (2011).

In April 2018, we ran this incentivized choice experiment on a subsample of the LISS population. The sample frame was a random selection of participants below 65 years of age who filled in the previous questionnaire.[13]

C. *Measures of Career Outcomes and Other Individual Traits*

The LISS data sets contain thousands of variables. We concentrate on four education and labor market outcomes: how much people earn, the level of their occupation, their education level, and, in cases where they went to college, which major they chose. Participants are asked about their gross monthly income every time they answer a questionnaire. We use the measure that was collected in the same wave as our questionnaire measures.[14]

Occupation level is based on the answer to the question "What is your current profession?"[15] LISS gives respondents the following answer options:[16]

1. Higher academic or independent profession (e.g., architect, physician, scholar, academic instructor, engineer)
2. Higher supervisory profession (e.g., manager, director, owner of large company, supervisory civil servant)
3. Intermediate academic or independent profession (e.g., teacher, artist, nurse, social worker, policy assistant)
4. Intermediate supervisory or commercial profession (e.g., head representative, department manager, shopkeeper)
5. Other mental work (e.g., administrative assistant, accountant, sales assistant, family carer)
6. Skilled manual (e.g., car mechanic, foreman, electrician) or semiskilled manual (e.g., driver, factory worker)
7. Unskilled (e.g., cleaner, packer) or agrarian (e.g., farm worker)

For some analyses, we groups 1 and 2 into a single "high-level" category that we use as a binary outcome measure. The question is asked on a yearly basis as part of the "Work and Schooling" core questionnaire. If available, we use the measure from 2017. If a participant did not answer the questionnaire in 2017, we use the information from 2016. Highest completed level of education is elicited every time

[11] And 40 cents per correct answer in case of a tie.

[12] On a scale from zero (the lowest) to ten (the highest).

[13] We excluded 312 individuals who participated in a small-scale competition experiment run in 2014 (Buser et al., 2018). The panel members completed the experiment online at a time of their choosing, and, for those who chose competition, the outcome was determined ex post once the data collection was complete. We had 2,098 individuals participating in the choice experiment. Because of a programming error on the part of LISS, the program crashed halfway through the choice experiment for 418 participants. Another six participants quit the experiment before choosing a payment scheme. This leaves us with 1,674 observations. Among these, 1,437 are between 25 and 65 years old. In section IID, we will show that these individuals do not differ significantly from the other members of the panel in the same age range who participated in the survey one year earlier. They are also not different from the participants who experienced the error.

[14] If a panel member does not enter their gross income but reports their net income, then gross income is imputed based on net income and other variables. See https://www.dataarchive.lissdata.nl/study_units/view/322.

[15] Or, in case a participant was currently not working, "What profession did you exercise in your last job?"

[16] We combine the answer options "Skilled and supervisory manual work (e.g., car mechanic, foreman, electrician)" and "Semi-skilled manual work (e.g., driver, factory worker)" into category 6. We also combine the answer options "Unskilled and trained manual work (e.g., cleaner, packer)" and "Agrarian profession (e.g., farm worker, independent agriculturalist)" into category 7.

somebody answers a questionnaire and is measured in the following categories:[17]

1. Primary schooling
2. Prevocational education
3. Vocational education
4. Upper (precollege) tracks of secondary school
5. University of applied sciences
6. University

For some analyses, we groups 5 and 6 into a single "college" category that we use as a binary measure. For those who completed college, we divide their field of study into the following categories based on the question "In what field did you complete your highest level of education?"

1. Nursing
2. Humanities and art
3. Social and behavioral sciences
4. Economics and business
5. Law
6. STEM
7. Medicine

The fields are ordered based on the average income of individuals above age 45 in our sample who have completed college in that field. We use this ordering in some of our analyses to see whether competitive individuals choose study majors with better career prospects. The question is asked on a yearly basis as part of the "Work and Schooling" core questionnaire. If available, we use the measure from 2017. If a participant did not answer the questionnaire in 2017, we use information from 2016.[18]

The "Personality" core module contains a 50-question elicitation of the Big Five personality traits: extraversion, agreeableness, conscientiousness, stability, and openness (Goldberg et al., 2006). From the same module, we use the answer to the question "I have confidence in my capabilities" (1 = totally disagree to 7 = totally agree) as a measure of general confidence. We also use the results from the ten-item Rosenberg self-esteem scale (Rosenberg, 1965), where each item is scored on a seven point scale (1 = totally disagree to 7 = totally agree). We do not have access to a test-based measure of cognitive skills, but we can use the "need for cognition" scale (Cacioppo & Petty, 1982) as a proxy. This eighteen-item scale elicits agreement with statements such as "I would prefer complex to simple problems" or "The notion of thinking abstractly is appealing to me" and has been shown to predict fluid intelligence (Fleischhauer et al., 2010; Hill et al., 2013).[19] If available, we use information from the 2017 personality questionnaire. If a participant did not answer that questionnaire, we use personality traits measured in 2014.[20]

D. *Descriptive Statistics*

Table A1 in the online appendix shows the means and standard deviations of the competitiveness measures as well as of the LISS panel variables we use as controls and as education and labor market outcomes. The first column reports this for the panel members who participated in the choice experiment, and the second column for respondents of the unincentivized survey questions. The samples are restricted to individuals between 25 and 65 years old, which is the sample we use for our analyses of the relationship between competitiveness and career outcomes. Around 40% of this group has a college degree, around 17% holds a high-level occupation, and their average gross monthly income amounts to 2,480 euros.

The subsample who participated in the incentivized choice experiment was randomly selected from those who had answered the questionnaire a year earlier. Because not everybody who was selected participated, we check whether the participants in the experiment differ in any way from the rest of the sample. The third column of the table shows that these differences are small and not significantly different from zero, with the exception of the proportion who completed a college degree, which is slightly (and marginally significantly) higher in the full sample compared to the experimental sample. In column 4, we check whether the participants who were affected by the software error differ from the majority of participants who were able to complete the experiment. The differences are small and insignificant in all cases, indicating that the occurrence of the error is essentially random and should not influence any of our conclusions.

Slightly over 27% of the participants in the choice experiment opted for the tournament payment instead of the piece rate. This share is lower than the shares typically reported in lab experiments using student populations, but very similar

[17] In Dutch, these correspond to 1 basisonderwijs, 2 VMBO, 3 MBO, 4 HAVO/VWO, 5 HBO, and 6 WO.

[18] When answering the question, respondents can pick one or several out of the following: 1. General or no specific field, 2. Teacher training or education, 3. Art, 4. Humanities, 5. Social and behavioral studies, 6. Economics, management, business administration, accountancy, 7. Law, public administration, 8. Mathematics, physics, IT, 9. Technology, 10. Agriculture, forestry, environment, 11. Medical, health services, nursing, etc., 12. Personal care services, 13. Catering, recreation, 14. Transport, logistics, 15. Telecommunication, 16. Public order and safety. We drop respondents who choose 1, and we ignore categories 10, 12, 13, 14, 15, and 16, which do not correspond clearly to any college major, meaning that we drop people who exclusively fit one of these categories. We also drop participants who fit more than one category from our major-related analyses. We group 2, 3, and 4 into Humanities and Art and 8 and 9 into STEM. We split individuals who answer 11 into two groups that we label as "Medicine" and "Nursing," depending on whether they attend a university (which offer only medical studies, leading to a career as a medical doctor or dentist) or university of applied sciences (which offer other health-related studies, leading mainly to nursing careers but also related careers such as midwife; other care-related careers such as assistant nurse or doctor's assistant do not require college-level studies in the Netherlands).

[19] The Big Five trait openness has also been shown to correlate with cognitive skills (Anglim et al., 2022). We are therefore confident that our personality controls capture individual differences in cognitive skills.

[20] The Personality module was not collected in 2016. In 2015, only participants who did not answer the Big Five questions in 2014 received the full Big Five questionnaire.

to the 28% found for the math task by Boschini et al. (2019) in their telephone interviews. The mean response to the general competitiveness question equals 6.2. Figure A1 in the online appendix shows the entire distribution of this variable. We see 46% of the respondents score themselves below a 7, which is the median value.

Table A2 in the online appendix shows the correlations between the various trait measures for the experimental sample as well as the sample as a whole. Competitiveness is positively correlated with the confidence measures, risk seeking, extraversion, conscientiousness, stability, and openness. The correlations between competitiveness and the Big Five personality traits are stronger for our questionnaire measure than for our binary incentivized measure. The strongest correlation we find is between competitiveness and extraversion. We will take a closer look at the correlation between our incentivized and unincentivized competitiveness measures in section IIIB.

III. Results

We present the results in three parts. The first part shows that the incentivized competitiveness measure is a significant and relevant predictor of education and labor market outcomes in a representative sample of the Dutch working-age population. In the second part, we show that our unincentivized questionnaire measure predicts the same outcomes with similar predictive power and is often a stronger predictor of these outcomes compared to the other nonincentivized trait measures (risk seeking, confidence, and the Big Five personality traits). In the third part, we look at the gender difference in competitiveness and show that it can statistically explain a moderate but meaningful part of gender differences in education and labor market outcomes.

A. *Incentivized Measure of Competitiveness*

Figure 2 shows how respondents who chose the tournament option and respondents who chose the piece-rate option are distributed across different levels of each of the four education and labor market variables. In the two upper-most panels, we divide the sample into income quintiles. Because the income distributions of men and women are very different, we do this separately by gender. For each gender, the income distributions of individuals who chose to compete and individuals who chose not to compete differ strongly. Individuals who compete are more than twice as likely to be in the highest quintile and much less likely to be in lowest two quintiles.

In the center panel, we graph the distribution of occupational level by competitiveness. Individuals who compete are around three times as likely to work in a high academic or independent position and more than two times as likely to work in a high supervisory position compared to individuals who do not compete. Individuals who do not compete are more likely to work in nonacademic and nonsupervisory occupations.

In the two lower panels, we look at educational outcomes. In the lower-left panel, we split the sample by education level. Individuals who compete are more highly educated on average than noncompeting individuals, being three times as likely to have graduated from university and 36% more likely to have graduated from a university of applied sciences. In the lower-right panel, we look at the choice of college major for individuals with a college (university or university of applied sciences) degree. In the graph, majors are ordered according to the average income of individuals over 45 years of age in our sample who graduated from that major. College graduates who chose competition are more than twice as likely to have graduated from one of the two highest paying majors (medicine or STEM) and about 40% less likely to have graduated from one of the two lowest paying majors (nursing or humanities and art).

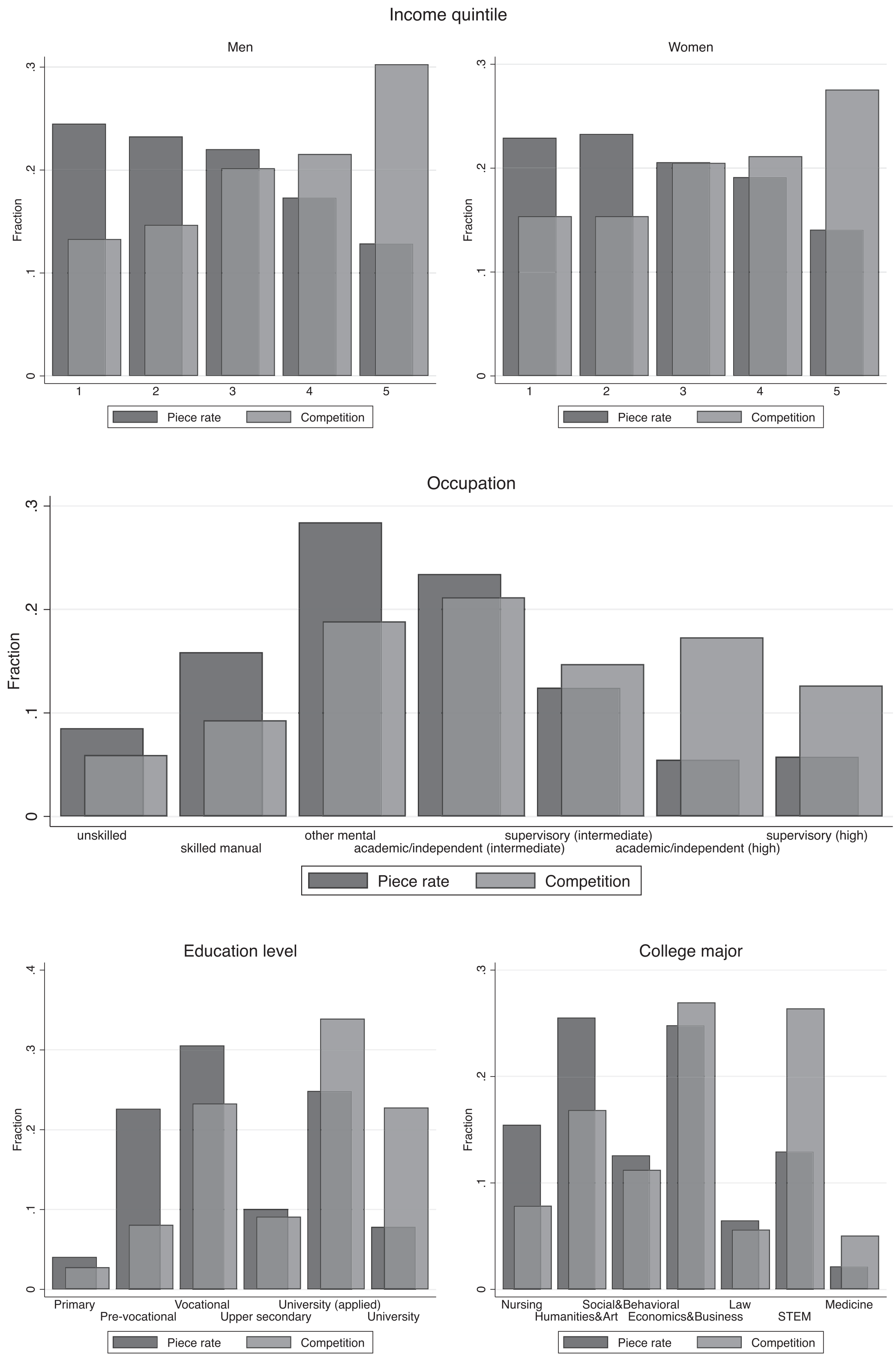
In table 1, we examine the robustness of the predictive power of the incentivized competition choice for these career outcomes to the inclusion of controls for performance in the experimental task, gender, age, risk seeking, confidence, the Big Five personality traits, and need for cognition. In each regression, we limit the sample to individuals for whom we have both the outcome variable as well as all the control variables. The number of observations fluctuates slightly across outcomes because not all outcome variables are available for all participants. The sample is much smaller for the regressions using college major as the outcome variable because they include only participants with a college degree.

Panels A to D report results from regressions of monthly gross income on incentivized competitiveness. In panel A, we use a simple OLS regression.[21] Conditional on performance in the task, gender, and age, individuals who compete in the experiment earn 550 euros more per month (relative to an average monthly income of 2,205 euros for individuals who do not compete). Additionally controlling for the Big Five personality traits, need for cognition, risk attitudes, and confidence only slightly changes the estimate: competitive individuals still earn 434 euros more. Additionally controlling for education level dummies, the difference is 283 euros. This indicates that part of the relationship between competitiveness and income is due to the relationship between competitiveness and level of education.

In order to deal with outliers and to investigate the predictive power of competitiveness at different parts of the income distribution, we use quantile regressions in panels B, C, and D (20th percentile, median, and 80th percentile, respectively). Conditional on the other traits, the competition coefficient is equal to 541 euros at the 80th percentile, 396

[21] We do not think that the common strategy of using log income is appropriate here because it eliminates zero earners from the sample, who, in our case, are disproportionally women. It also puts disproportionate weight on differences occurring at the lower end of the income distribution, rather than the upper end where we would expect the strongest effects of competitiveness.

FIGURE 2.—EXPERIMENTALLY MEASURED COMPETITIVENESS AND CAREER OUTCOMES



The figures show the distribution of participants across different values of our outcome variables separately for participants who chose competition in the online experiment and participants who chose the piece rate payment in the online experiment. The classifications of occupational levels, education levels, and college majors are explained in section IIC.

TABLE 1.—CAREER OUTCOMES AND INCENTIVIZED COMPETITIVENESS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Monthly gross income (OLS)							
Compete	717.3***	550.1***	424.9***	433.9***	302.6***	259.5***	283.1***
	(116.3)	(106.8)	(99.7)	(102.1)	(95.7)	(93.3)	(96.1)
N	1,325	1,325	1,325	1,325	1,325	1,325	1,325
Adj. R^2	0.074	0.240	0.300	0.306	0.350	0.371	0.377
Panel B: Monthly gross income (quantile regression: 20th decile)							
Compete	570.0***	397.7***	483.4***	421.7***	312.1***	230.7**	316.1***
	(148.8)	(107.5)	(123.4)	(107.3)	(116.5)	(108.8)	(110.0)
	1,325	1,325	1,325	1,325	1,325	1,325	1,325
Panel C: Monthly gross income (quantile regression: median)							
Compete	524.7***	503.2***	338.4***	396.2***	239.3***	272.4***	264.4***
	(120.3)	(99.9)	(103.4)	(104.3)	(85.7)	(85.7)	(86.2)
	1,325	1,325	1,325	1,325	1,325	1,325	1,325
Panel D: Monthly gross income (quantile regression: 80th decile)							
Compete	897.9***	772.9***	531.2***	541.0***	330.0**	244.6*	275.4**
	(158.4)	(139.5)	(111.9)	(125.0)	(128.8)	(126.5)	(130.3)
	1,325	1,325	1,325	1,325	1,325	1,325	1,325
Panel E: High-level professional or managerial position (OLS)							
Compete	0.158***	0.145***	0.113***	0.111***	0.066***	0.058**	0.061***
	(0.026)	(0.026)	(0.025)	(0.025)	(0.023)	(0.023)	(0.023)
N	1,385	1,385	1,385	1,385	1,385	1,385	1,385
Adj. R^2	0.062	0.075	0.150	0.152	0.288	0.303	0.302
Panel F: Occupation (ordered probit)							
Compete	0.378***	0.366***	0.282***	0.282***	0.167**	0.141**	0.153**
	(0.067)	(0.069)	(0.069)	(0.070)	(0.068)	(0.069)	(0.070)
N	1,385	1,385	1,385	1,385	1,385	1,385	1,385
Panel G: College (OLS)							
Compete	0.185***	0.172***	0.126***	0.119***			
	(0.030)	(0.030)	(0.028)	(0.029)			
N	1,408	1,408	1,408	1,408			
Adj. R^2	0.079	0.109	0.214	0.223			
Panel H: Education level (ordered probit)							
Compete	0.466***	0.438***	0.353***	0.324***			
	(0.068)	(0.068)	(0.068)	(0.069)			
N	1,408	1,408	1,408	1,408			
Panel I: College major (ordered probit)							
Compete	0.372***	0.235**	0.243**	0.165			
	(0.103)	(0.104)	(0.106)	(0.108)			
N	449	449	449	449			
Score	√	√	√	√	√	√	√
Gender, age		√	√	√	√	√	√
Education level					√	√	√
Big 5, cognition			√	√		√	√
Confidence and risk				√			√

Each estimate comes from a separate regression of a career outcome on the binary incentivized competition choice and the control variables indicated in the bottom rows. Score is individuals' performance in the first and second round of the choice experiment. Education level is measured by dummy variables indicating different levels. Big 5 are obtained from the fifty questions elicitation of the Big Five personality traits: extraversion, agreeableness, conscientiousness, stability, and openness. Cognition refers to the need for cognition scale. Risk attitudes are measured by the Dohmen et al. (2011) survey measure, which we elicited at the same time as our unincentivized measures of competitiveness. We use three separate measures for confidence: an individual's confidence in their own relative performance in the experimental task, their Rosenberg's self-esteem scale, and their confidence in their own capabilities judged on a seven-point scale. Standard errors in parentheses. *Significant at 10%, **significant at 5%, and ***significant at 1%.

euros at the median, and 422 euros at the 20th percentile. Conditional on education level, the competition coefficient is significant and similar at all three levels, fluctuating between 264 and 316 euros, indicating that for those who compete, the entire income distribution is shifted to the right.

We use two methods to analyze the predictive power of incentivized competitiveness for occupational position. First, we use OLS to regress a dummy indicating that an individual holds a high-level academic, independent or supervisory position on the competition choice plus controls. Second, we rank positions according to the ranking laid out in section IIC and use ordered probit regressions. Conditional on performance in the task, gender, and age, individuals who compete in the experiment are 14 percentage points more likely to hold a high-level position (a large difference relative to 11% for those who choose the piece rate). Again, the estimate does not change much when controlling for risk seeking, confidence, the Big Five personality traits, and need for cognition (11 percentage points). The coefficient is reduced by roughly half when we control for education level, indicating that the relationship between competitiveness and occupation is partially due to a relationship between competitiveness and education level. The coefficient on incentivized competitiveness is also consistently significant in the ordered probit regressions.

Moving to education level in panels G and H, we use OLS regressions of a dummy indicating that an individual completed college on incentivized competitiveness and controls, as well as ordered probit regressions using the ordering of educational levels laid out in section IIC. Conditional on performance in the task, gender, and age, individuals who compete are seventeen percentage points more likely to have attended college (relative to 33% of individuals who do not compete). The coefficient decreases to eleven percentage points when controlling for the Big Five traits, risk attitudes, confidence, and need for cognition. The ordered probit regressions confirm that competitiveness consistently predicts a higher education level. Finally, for the subsample who have attended college, in panel I we regress college major (ranked according to the average income of individuals over 45 years of age in our sample who graduated from each major) on incentivized competitiveness using ordered probit. Conditional on performance in the task, gender, and age, competing is associated with graduating from a major that is ranked significantly higher. The coefficient is robust to controlling for the Big Five personality traits and need for cognition, but reduces in size and loses statistical significance when we additionally control for confidence and risk attitudes.

B. *Survey Measure of Competitiveness*

Having shown that the incentivized measure of competitiveness is a strong predictor of outcomes, in this section we will focus on our unincentivized survey measure. We will validate this measure, which was collected approximately one year prior to the incentivized measure, in two ways. First, we will show that the unincentivized measure predicts the incentivized competition choice that was elicited a year later, a method previously applied by Dohmen et al. (2011) and Falk et al. (2016). Second, we assess whether the unincentivized measure predicts the same outcomes we analyzed in the previous section for the incentivized measure.[22]

We find that for individuals of working age who participated in our experiment, their incentivized choice and their answer to our unincentivized eleven-point measure are highly significantly correlated. The correlation coefficient is equal to 0.153 ($p < 0.001$). To properly judge the strength of this correlation, we have to take into account that the experimental measure and the survey measure were elicited one year apart. This is a strength because it rules out spurious correlation due to a desire to be consistent (Falk & Zimmermann, 2013) or other direct effects between the two elicitations, but it also introduces noise due to the passing of time. One approach to correct for this is to use the test-retest correlation of a related measure across the same time span as benchmark. We elicited the exact same survey measure of risk preferences taken from Dohmen et al. (2011) in both surveys. We can use the correlation between the two answers as a benchmark for the correlation between our incentivized and nonincentivized competitiveness measures. The correlation between the two risk preference answers elicited one year apart is 0.404.[23] Using this as a benchmark to scale the correlation between the two competitiveness measures leads to a correlation of $0.154/0.404 = 0.380$. This is similar to the correlation between the eleven-point survey measure and the simultaneously elicited hypothetical choice measure, which is equal to 0.300.[24] Falk et al. (2016) estimate correlations between qualitative and experimental measures of several economic preferences including risk taking, time discounting, trust, and negative reciprocity. The correlations range between 0.161 for negative reciprocity and 0.404 for time discounting. The qualitative and incentivized measures were collected one week apart compared to one year in our case. It is also interesting to know how stable our nonincentivized competitiveness measure is across time. To answer this question, we elicited it again in 2021 as part of a different LISS panel survey. The test-retest correlation across this four-year period for working-age participants is 0.578.[25] This is similar to test-retest correlations reported in the literature for risk preferences over shorter time intervals (Beauchamp et al., 2017).

In figure 3, we show the relationship between our survey measure of competitiveness and outcomes, repeating the analysis in figure 2. To make the graphs comparable, we dichotomize our eleven-point measure by splitting the sample

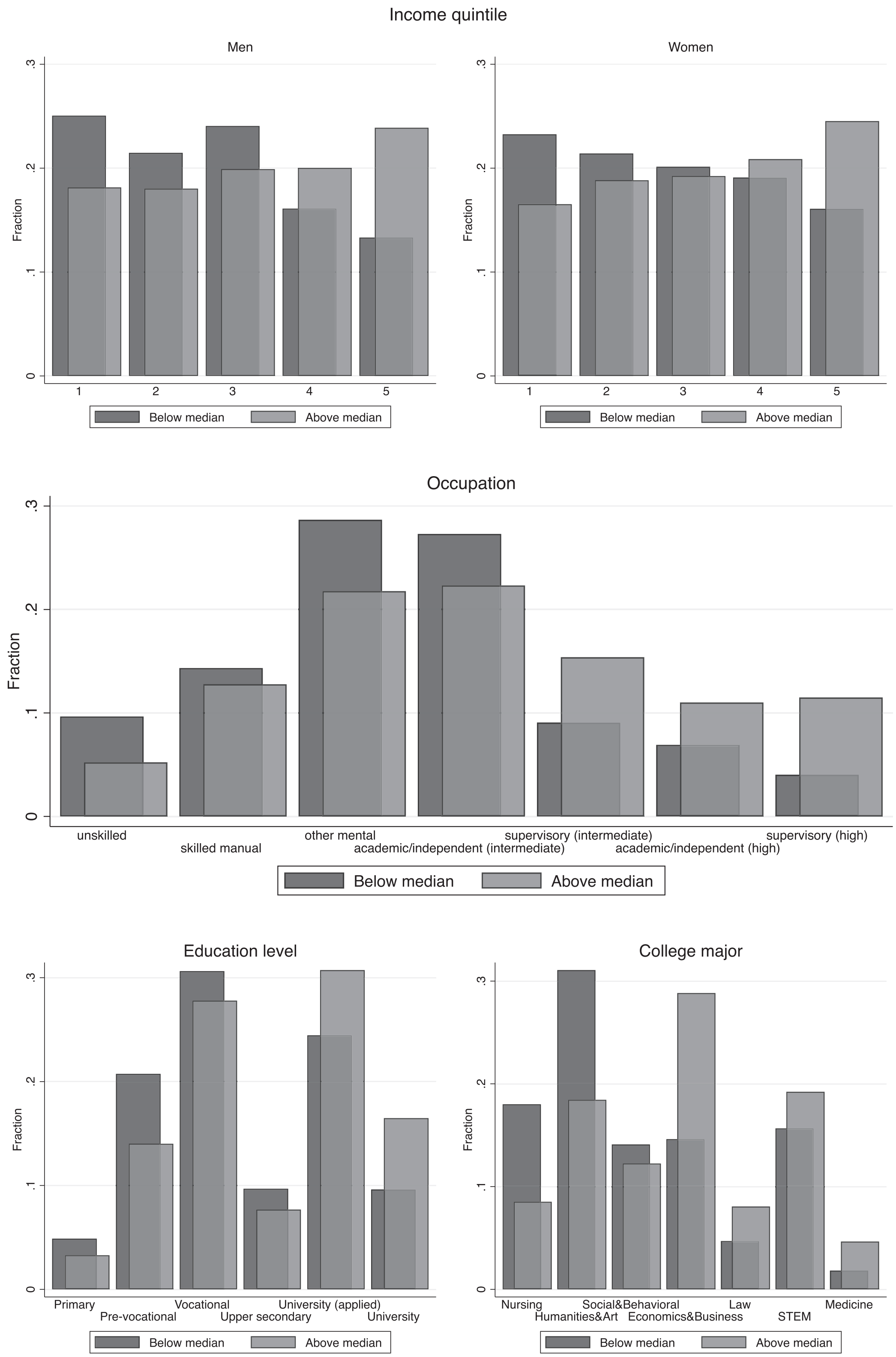
[22]See online appendix B for results for the second unincentivized measure—respondents' answers to a hypothetical Niederle-Vesterlund tournament entry decision.

[23]This is within the range of test-retest correlations in the meta-analysis by Mata et al. (2018).

[24]The correlation between our second, hypothetical choice measure and the incentivized choice is 0.200 ($p < 0.001$). A composite measure created by standardizing and adding up the two survey measures has a correlation of 0.216 ($p < 0.001$). If we scale these correlations up using the test-retest correlation of the risk preference measure as a benchmark, we get a correlation of 0.495 for the hypothetical choice measure and a correlation of 0.536 for the composite measure. An alternative way to correct for the passing of time is to compare how choosing the tournament option in the experiment is correlated to the contemporaneous risk measure and the risk measure elicited one year before. The contemporaneous correlation is 3.11 times stronger (0.364 versus 0.117). If we use this factor to scale up the correlations between our survey measures and the incentivized competition choice, we get correlations of 0.478 for the eleven-point measure, 0.622 for the hypothetical choice measure, and 0.673 for the composite measure.

[25]There is some turnover of panel participants across the years resulting in 1,755 repeat observations for participants who were of working age in 2021.

FIGURE 3.—QUESTIONNAIRE MEASURE OF COMPETITIVENESS AND CAREER OUTCOMES



The figures show the distribution of participants across different values of our outcome variables separately for survey respondents who judged themselves to be above-median (7–10) and below-median (0–6) competitive on an eleven-point scale. The classifications of occupational levels, education levels, and college majors are explained in section IIC.

into people whose competitiveness is below or above the median.[26] The unincentivized survey measure is strongly related to income. For both men and women, individuals who are above-median competitive are substantially more likely to be in the highest quintile (86% more likely for men and 49% for women) and less likely to be in the lowest quintile (28% for men and 28% for women) than individuals who are below-median competitive. Looking at occupation level, we again find that the results from the incentivized measure replicate quite closely. Individuals who are above-median competitive are around three times as likely to work in a high supervisory position and 60% more likely to work in a high academic or independent position. They are also 70% more likely to work in an intermediary supervisory position.

Looking at education, above-median competitive individuals are 70% more likely to have graduated from a university and 26% more likely to have graduated from a university of applied sciences. The unincentivized measure is also related to the choice of college major. As with the incentivized measure, more competitive individuals tend to have graduated from more lucrative majors. Nevertheless, the picture looks slightly different compared to the incentivized choice. When using the incentivized measure, competitive people were much more likely to have chosen medicine or STEM (and less likely to have chosen nursing or humanities and art). Using the unincentivized measure, we again find a much higher likelihood of having a degree in medicine and a much lower likelihood of having a degree in nursing or humanities and art, but we now also find that individuals who judge themselves to be more competitive are about twice as likely to have a degree in economics and business or law (on the other hand, they are only slightly more likely to have a STEM degree). Overall, the graphs indicate that the unincentivized survey measure is related to education and labor market outcomes in ways that are very similar to the patterns observed for the incentivized measure.

In table 2, we repeat the analysis in table 1 for the unincentivized survey measure using data from the full working-age sample. Using regressions, we examine whether the predictive power of the survey measure for education and labor market variables is robust to the inclusion of controls for gender, age, risk attitudes, confidence, the Big Five personality traits, and need for cognition.

The unincentivized survey measure of competitiveness significantly predicts all four outcomes conditional on all mentioned controls. The coefficients are substantial. For instance, panel A, column 2 shows that individuals who judge themselves one point more competitive (on an eleven-point scale) earn 109 euros more per month. Conditional on gender, age, confidence, risk preference, the Big Five personality traits, and need for cognition, the most competitive people (those who score themselves highest on the eleven-point scale) earn 824 euros more per month, are eleven percentage points more likely to hold a high-level occupation, and are thirteen percentage points more likely to have gone to college relative to the least competitive people.

How do the coefficients compare to the ones for the incentivized measure in table 1? We answer this question focusing on the regressions in column 2, which control for gender and age. For monthly salary, the coefficient on choosing competition in the incentivized choice experiment is roughly equivalent to moving up five (out of eleven) steps on the survey scale. Comparing coefficients in the ordered probit regressions, the coefficient on choosing competition in the incentivized choice experiment is roughly equivalent to moving up five steps for occupation, ten steps for education level, and three steps for college major. This means that compared to the incentivized measure, the survey measure is a relatively strong predictor of college major choice and occupation and a relatively weaker predictor of education level.

Having established that our survey measure of competitiveness is a strong and robust predictor of education and labor market outcomes, we now want to compare the predictive power of our survey measure to that of the other traits, namely, the Big Five personality traits, confidence, risk attitudes, and need for cognition. These traits are measured on varying scales. To make the effects comparable, we use a method inspired by Heckman et al. (2006).[27] We use OLS regressions to estimate the effect on the outcome variables of moving from the bottom 30% to the top 30% on each of the trait variables.

Results are presented in figure 4. Here we graph the regression coefficients for each trait controlling for age, gender, education (in the case of income and occupational position), as well as all other traits; that is, the coefficients tell us how predictive a trait is on top of all the other traits.[28] In figure A2 in the online appendix, we show the effects of moving from the bottom 30% to the top 30% on each trait not controlling for the other traits (that is, controlling only for age, gender, and, in the case of income and occupation, education).

We start with gross monthly income. Competitiveness is one of the the strongest predictors, together with need for cognition (our indicator of cognitive skills), stability, confidence, and self-esteem. Agreeableness also significantly predicts income, albeit in a negative direction. The effects of the Big Five traits are in line with the literature. For example, Mueller and Plug (2006) equally find that stability predicts income positively, whereas agreeableness is a negative predictor. Competitiveness is also one of the strongest predictors for holding a high-level occupation, and the only one apart from openness that significantly predicts the outcome

[26] This splits the sample into individuals with a competitiveness of 0–6 and individuals with a competitiveness of 7–10.

[27] In their analysis of the importance of cognitive and noncognitive abilities on labor market outcomes and social behavior, Heckman et al. (2006) calculate what would happen to an outcome if a person's (non)cognitive ability increases from the lowest to the highest decile.

[28] The exception are the two measures of confidence which are supposed to elicit the same underlying trait and where we therefore control for all other traits except the other confidence measure.

TABLE 2.—CAREER OUTCOMES AND QUESTIONNAIRE MEASURE OF COMPETITIVENESS

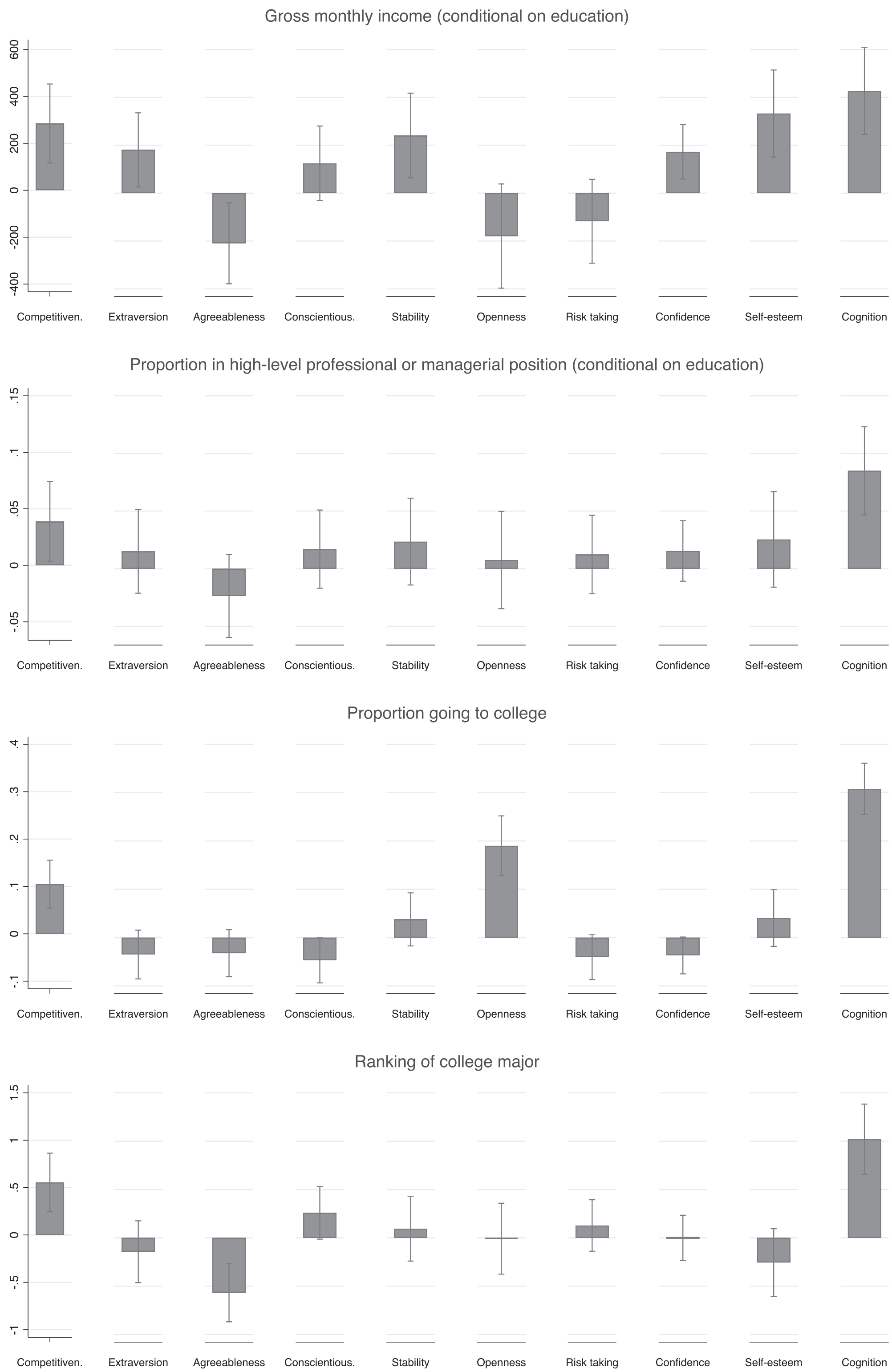
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Monthly gross income (OLS)							
Competitiveness	168.8***	109.2***	63.8***	69.3***	79.6***	54.5***	55.5***
	(15.6)	(14.7)	(14.4)	(15.8)	(13.5)	(13.5)	(14.7)
N	2,878	2,878	2,878	2,878	2,878	2,878	2,878
Adj. R^2	0.038	0.202	0.268	0.272	0.347	0.367	0.370
Panel B. Monthly gross income (quantile regression: 20th decile)							
Competitiveness	141.8***	65.0***	27.9	47.5**	53.7***	27.4	31.7*
	(18.8)	(19.2)	(21.0)	(20.0)	(18.9)	(18.5)	(18.3)
	2,878	2,878	2,878	2,878	2,878	2,878	2,878
Panel C. Monthly gross income (quantile regression: median)							
Competitiveness	157.4***	93.5***	64.7***	66.8***	60.5***	43.2***	38.6***
	(16.4)	(16.1)	(16.8)	(17.0)	(12.6)	(13.1)	(13.9)
	2,878	2,878	2,878	2,878	2,878	2,878	2,878
Panel D. Monthly gross income (quantile regression: 80th decile)							
Competitiveness	168.6***	128.5***	79.2***	64.2***	86.4***	63.8***	63.2***
	(25.1)	(20.7)	(20.6)	(19.6)	(17.8)	(17.1)	(17.9)
	2,878	2,878	2,878	2,878	2,878	2,878	2,878
Panel E. High-level professional or managerial position (OLS)							
Competitiveness	0.027***	0.020***	0.010***	0.011***	0.013***	0.009***	0.008***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
N	2,967	2,967	2,967	2,967	2,967	2,967	2,967
Adj. R^2	0.020	0.044	0.126	0.126	0.287	0.297	0.297
Panel F. Occupation (ordered probit)							
Competitiveness	0.080***	0.070***	0.035***	0.034***	0.056***	0.031***	0.025**
	(0.009)	(0.009)	(0.010)	(0.010)	(0.009)	(0.010)	(0.010)
N	2,967	2,967	2,967	2,967	2,967	2,967	2,967
Panel G. College (OLS)							
Competitiveness	0.029***	0.023***	0.010**	0.013***			
	(0.004)	(0.004)	(0.004)	(0.005)			
N	3,074	3,074	3,074	3,074			
Adj. R^2	0.014	0.041	0.161	0.165			
Panel H: Education level (ordered probit)							
Competitiveness	0.064***	0.045***	0.017*	0.027**			
	(0.009)	(0.009)	(0.010)	(0.011)			
N	3,074	3,074	3,074	3,074			
Panel I: College major (ordered probit)							
Competitiveness	0.116***	0.072***	0.065***	0.066***			
	(0.018)	(0.019)	(0.020)	(0.021)			
N	1,002	1,002	1,002	1,002			
Gender, age		√	√	√	√	√	√
Education level					√	√	√
Big 5, cognition			√	√		√	√
Confidence and risk				√			√

Each estimate comes from a separate regression of a career outcome on the unincentivized competitiveness variable and the control variables indicated in the bottom rows. Education level is measured by dummy variables indicating different levels. Big 5 are obtained from the fifty questions elicitation of the Big Five personality traits: extraversion, agreeableness, conscientiousness, stability, and openness. Cognition refers to the need for cognition scale. Risk attitudes are measured by the Dohmen et al. (2011) survey measure, which we elicited at the same time as our unincentivized measures of competitiveness. We use two separate measures for confidence: their Rosenberg's self-esteem scale, and their confidence in their own capabilities judged on a seven-point scale. Standard errors in parentheses. * Significant at 10%, ** significant at 5%, and *** significant at 1%.

above all other traits. The strongest predictors for holding a college degree are need for cognition and openness, followed by competitiveness. Finally, need for cognition, competitiveness, and agreeableness (negatively) are the strongest predictors of having chosen a higher-ranked college major.

The question of which trait predicts best can also be answered in a complementary way by estimating the additional proportion of the variance in each outcome that is explained by each trait. In figure A3 in the online appendix, we show the increase in R^2 that is caused by adding each trait measure to regressions of our career outcomes on age, gender, and all the other traits (plus, in the case of income and occupation, education level). In figure A4 in the online appendix, we show the increase in R^2 caused by each trait not controlling for the other traits. The results largely confirm those presented in figure 4. Competitiveness is the strongest

FIGURE 4.—PREDICTIVE POWER OF INDIVIDUAL TRAITS COMPARED: EFFECT OF MOVING FROM BOTTOM 30% TO TOP 30% CONDITIONAL ON ALL OTHER TRAITS



Each figure shows the coefficient from a separate OLS regression of a dummy indicating that a respondent is in the top 30% (vs. bottom 30%) on a given trait on an outcome variable. Each coefficient is from a separate regression controlling for gender, age, education level (in the case of the first two graphs), and all other traits (with the exception of confidence and self-esteem where we control for all other traits except the other confidence measure). The sample in each regression consists of respondents aged between 25 and 65 who are either in the bottom or top 30% on the given trait. Error bars represent 95% confidence intervals.

predictor—apart from need for cognition—of income, holding a high-level occupation, and rank of college major.

Taken together, these results confirm that competitiveness significantly predicts education and labor market outcomes conditional on a range of other traits that are commonly studied in the literature on noncognitive skills (Borghans et al., 2008; Dohmen et al., 2011), indicating that competitiveness is a new trait that is not well captured by existing measures of personality and economic preferences. The results in figure A2 in the online appendix, where we show the predictive power of each trait when not controlling for the other traits, confirm this picture. Competitiveness is consistently one of the strongest predictors, meaning that if one has to choose a single trait to predict the education and labor market outcomes of an individual, competitiveness is more often than not one of the top choices.

In the online appendix B, we also present results for our second unincentivized measure of competitiveness, the hypothetical choice in the Niederle-Vesterlund experiment. The results in table B1 and figure B1 show that this binary measure predicts the same outcomes as our incentivized measure and our eleven-point survey question. Conditional on gender and age, individuals who say they would compete in an incentivized experiment earn 314 euros more per month (177 conditional on education) are eight percentage points more likely to hold a high-level position (five conditional on education), eight percentage points more likely the hold a college degree, and, conditional on having gone to college, have picked a more lucrative major. However, these effects are consistently lower than those obtained with the incentivized choice measure and are less robust to controlling for other traits. When we add both of our unincentivized measures to our regressions, the coefficients on our eleven-point measure hardly change while the coefficients on the hypothetical measure tend to become insignificant. We conclude that our eleven-point questionnaire item is a better measure of competitiveness, on top of being quicker (and therefore cheaper) to elicit.[29] However, in situations where it is not too costly to elicit both measures, the hypothetical measure still adds additional explanatory power. In figure B2 in the online appendix, we show that using both measures simultaneously leads to meaningful increases in the variance explained by competitiveness relative to using the eleven-point measure alone.

Our results so far demonstrate that competitiveness is a strong predictor of labor market and education outcomes. The estimated associations do, however, not necessarily represent causal relationships. A particular concern is reverse causality, whereby the ambitiousness of the chosen career path influences an individual's perception of their own competitiveness. To partially address this concern, we can take advantage of the fact that a few years have passed since we elicited our survey measure in early 2017. In particular, we can check whether competitiveness can predict an individual's future income conditional on their income at the time competitiveness was elicited. To this end, we construct a panel data set that contains the average monthly income in every year from 2016 to 2022. The sample consists of individuals who were between twenty and sixty years old in 2017 (and therefore still of working age in 2022) and for whom we have income data for all subsequent years.

In figure A5 in the online appendix, we graph the results from a panel regression with individual fixed effects where average monthly income during each year is the outcome variable. We divide the sample into people with low (0–5), medium (6–7), and high (8–10) competitiveness, which splits the sample into three groups of roughly 30%-40%-30%. We include binary indicators for each year. We set 2016 as the base year, and the coefficients for each of the other year dummies therefore represent salary increases (in euros) for each of the three competitiveness groups compared to the base year. We interact year dummies with dummies representing the three competitiveness groups to see whether individuals who judged themselves to be more competitive were professionally more successful—experienced faster income growth—over the subsequent years. We control for individual fixed effects to capture any baseline differences between survey participants, including differences in baseline income, gender, and age. Additionally, we interact the year dummies with age, gender, and baseline income to control for differential time trends. In the year 2022, conditional on all baseline differences and the dynamic controls, the monthly income of people who are highly competitive increased by roughly 360 euros more compared to people in the low competitiveness group. People in the middle group still had nearly 150 euros extra growth of their monthly income relative to the low group.[30]

Two recent papers argue that a large part of the gender difference in competitiveness, as measured by the Niederle and Vesterlund (2007) design, can be explained by gender differences in risk preferences and confidence (Gillen et al., 2019; van Veldhuizen, 2022). Although these papers concentrate on the gender difference in competitiveness, their results raise the question whether competitiveness—rather than being a new, separate trait—is well captured by

[29]The hypothetical measure requires an explanation of the experimental design of Niederle and Vesterlund (2007).

[30]An interesting question is whether this difference occurs mainly within or across education majors. We can check this by additionally controlling for major dummies interacted with the year dummies. For college-educated individuals, the difference in salary increase between people in the high and low competitiveness groups is 462 euros without and 368 euros with these controls added (for medium vs low competitiveness these numbers are 291 and 215, respectively). This means that most of the difference in salary growth occurs within groups of people with a similar educational background and is therefore due to differences in occupation choice or job performance. It is also interesting to check whether the differences are larger for young people—who are at a steeper part of their salary profile—than for older people—whose salaries tend to be more stable. This is indeed the case. For people aged 20–40 in 2017, the difference in salary increase between people in the high and low competitiveness groups is 632 euros whereas for people aged 40–60, it is 217 euros (for medium vs. low competitiveness these numbers are 307 and 98, respectively).

risk preferences and confidence. Our results so far already show that competitiveness predicts outcomes independently of risk preferences and confidence and should therefore be considered as a separate trait. Most of the regression coefficients reported in table 2 do not change much when risk preferences and confidence are added as controls. Figure 4 shows that our survey measure of competitiveness significantly predicts education and labor market outcomes even when controlling for survey measures of risk preferences, confidence, self-esteem, and personality.

The effects of risk preferences on the other hand are not consistently robust to controlling for the other traits. This, however, does not mean that risk preferences are not predictive of important life outcomes. The four outcomes we consider—income, professional position, education level, and major choice—are not necessarily directly linked to risk taking (for instance, being willing to compete against others is arguably more important for moving up the corporate hierarchy than being willing to take risk). We can go a step further in establishing that competitiveness and risk attitudes are separate traits that predict different outcomes by considering choices that are risky but not necessarily competitive. We can use the same method as in figure 4 to estimate the predictive power of our trait measures for risky outcomes. To obtain a nonarbitrary selection of such outcomes, we pick the four outcomes that were studied in the seminal study of Dohmen et al. (2011): the propensities to invest in stocks, practice sport, be self-employed, and smoke. Arguably only one of the four, practicing sports, is obviously related to enjoying competition (self-employed people have competitors but so do employees).[31] Figure A6 in the online appendix shows the difference in the risky outcomes between individuals in the top 30% and individuals in the bottom 30% on each trait, controlling for age and gender. We replicate the Dohmen et al. (2011) result that risk seeking is a significant predictor of all four outcomes. Competitiveness does not predict investing in stocks, being self-employed or smoking. On the other hand, competitiveness is the strongest predictor of practicing sports. This analysis further underlines that competitiveness and risk attitudes are both relevant individual traits which predict different economically important outcomes and should therefore be accounted for separately.

C. *Gender Differences in Competitiveness*

A large experimental literature documents gender differences in competitiveness (Gneezy et al., 2003; Niederle & Vesterlund, 2007; Niederle, 2016). Figure A7 in the online appendix shows that this is also true for the competitiveness measures used in this paper. Although 34% of working-age men choose to compete in the experiment, only 22% of working-age women do so ($p < 0.001$; chi-squared test).[32] 65% of men and 47% of women rate their competitiveness as at or above the median ($p < 0.001$).[33] In the rightmost panel, we show a histogram of competitiveness levels by gender that reveals large gender differences in the tails. Men are more than twice as likely as women to rate themselves as very competitive (9 or 10 on a 0–10 scale). On the other hand, women are nearly twice as likely as men to rate their competitiveness as very low (0–2). We also observe gender differences in most of the other traits we consider. Figure A8 in the online appendix shows that apart from being less competitive, women are more agreeable and more conscientious while men rate themselves higher on stability, openness, risk seeking, both confidence measures, and need for cognition. We find no gender difference in extraversion. These differences are in line with findings in the literature on gender differences in risk seeking (Croson & Gneezy, 2009) and confidence (Niederle, 2016). The gender differences in agreeableness, conscientiousness, and mental stability also go in the expected direction, whereas many other studies find no difference in openness (Mueller & Plug, 2006; Schmitt et al., 2008).

Three of the four education and labor market variables exhibit significant gender differences. Conditional on age and education level, working age women in our sample earn 1,414 euros less per month ($p < 0.001$; OLS) and are eleven percentage points less likely to hold a high-level occupation ($p < 0.001$). Their likelihood of having gone to college is similar to that of men, but conditional on having gone to college, they pick a major that is ranked 1.3 positions lower in the ranking by income prospects ($p < 0.001$). In the analyses reported in figure 5, we ask whether our unincentivized measure of competitiveness, as well as the other trait measures, can explain a significant part of these gender gaps. To do so, we estimate the percent reduction in the gender gap upon controlling for each of the traits separately and jointly.[34]

Controlling for the unincentivized competitiveness measure reduces the gender gap in income conditional on education level by 4.3%. Competitiveness is among the traits which explain most of the gender gap in income, together with stability and need for cognition. In the rightmost graph in each panel, we show the proportion of the gender

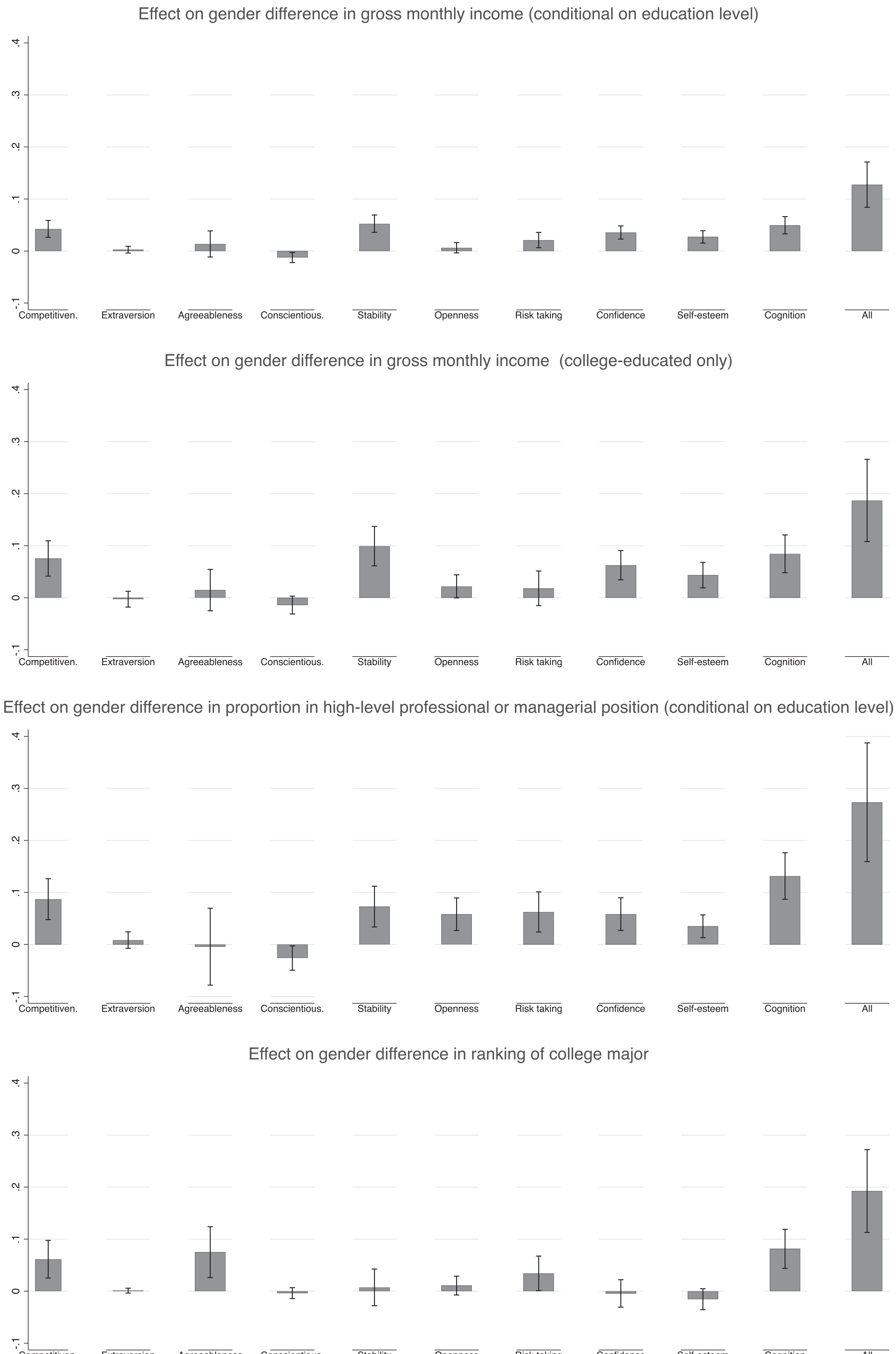
[31] Some past studies have found correlations between willingness to compete and entrepreneurship. Bönte and Piegeler (2013) find a significant correlation using the Eurobarometer 283 survey on entrepreneurship, which contains an unincentivized survey measure of competitiveness. Urbig et al. (2020), in a lab-in-the-field study conducted in a shopping mall, find that individuals who compete in an incentivized task are more likely to have ever been self-employed or to plan to become self-employed in the future.

[32] This difference is smaller than in some lab studies with university students but in line with, for example, the results of Boschini et al. (2019), who use a representative sample of the Swedish population and Buser et al. (2022) who use a sample of secondary students that covers all ability levels. See Dariel et al. (2017) for a survey of estimates of the gender difference in willingness to compete across different subject pools.

[33] Because of the discrete nature of the competitiveness measure, slightly more than 50% of individuals are at or above the median of 7 (54%).

[34] These coefficients are from OLS regressions of the education and labor market variables on a gender dummy, a second-degree polynomial in age, and (in the case of income and occupation) education level dummies. The sample consists of 25-to-65-year-olds who answered our questionnaire.

FIGURE 5.—PERCENTAGE REDUCTION IN GENDER DIFFERENCES WHEN ADDING EACH INDIVIDUAL TRAIT SEPARATELY AND JOINTLY (WHOLE SAMPLE)



The figures show the part (in percent) of the gender gap in an outcome variable that can be explained by each trait separately and jointly. The estimates are from separate OLS regressions of gender, age, and age squared on an outcome variable with and without a trait variable added to the regression. The sample consists of respondents aged between 25 and 65. Error bars represent 95% confidence intervals.

gap that is explained by all traits together. We estimate that around 13% of the gender gap in income in our sample can statistically be explained by the psychological traits we consider. Following previous results that the potential of competitiveness for explaining differences in educational career choices is highest at the top of the ability distribution (Buser et al., 2022), we repeat this exercise for college-educated individuals. Here competitiveness explains 7.5% of the gender gap. Other strong predictors are stability, confidence, and need for cognition. All traits jointly explain roughly 19% of the gender difference in income for college-educated individuals.

Competitiveness also has significant explanatory power for the gender gap in holding a high-level occupation conditional on education level (8.7%). All psychological traits jointly explain around 27% of this gender gap. For those who graduated from college, competitiveness explains 6.1% of the gender gap in major choice. Agreeableness, risk seeking, and need for cognition are the only other significant explanatory traits. All traits jointly explain 19% of the gender gap.

In figure B3 in the online appendix, we repeat this exercise using both of our unincentivized competitiveness measures separately and jointly. Although our eleven-point survey question consistently does a better job explaining the gender gap, adding both measures jointly still leads to an increase in the part of the gender gap in outcomes that can be explained by competitiveness. The two measures can jointly explain 4.9% of the gender difference in income conditional on education, 9.6% of the gender difference in income for college graduates, 9.9% of the gender gap in holding a high-level position conditional on education, and 8.4% of the gender difference in major choice for college graduates.

A small number of studies have investigated how the gender difference in competitiveness varies with age (Mayr et al., 2012; Bönte, 2015; Flory et al., 2018). Figure A9 in the online appendix shows the fraction of men and women competing in the experiment as well as the average competitiveness score for ten-year age bins. The experimental sample was limited to individuals below the age of 65, but the survey measure is also available for older individuals. For both measures, men are more competitive than women at any age, consistent with the results of Mayr et al. (2012) and Bönte (2015), but not Flory et al. (2018) who find that the gender gap in competitiveness disappears above age 50 due to a large increase in the competitiveness of women. Both measures show a general decline with age, meaning that in in our representative sample, we do not observe a midlife peak in competitiveness as in Mayr et al. (2012).[35]

[35]Our results are most consistent with Bönte (2015) who also uses European data and a large representative sample. His paper is based on an unincentivized survey measure of competitiveness. Flory et al. (2018) conduct an incentivized experiment in a sample of more than 700 participants from villages in Malawi and a much smaller U.S. sample ($N = 84$). Mayr et al. (2012) conduct an incentivized experiment in a sample of more than 500 adults recruited in a U.S. shopping mall.

IV. Conclusion

A large literature documents individual and gender differences in competitiveness in the lab. Following up on this literature, a number of studies link competitiveness, typically measured through an incentivized choice experiment in a classroom setting, to educational decisions and early career choices. Many important questions remain unanswered, including whether competitiveness predicts choices and outcomes along the whole career cycle, where individual and gender differences in competitiveness originate, and how average competitiveness differs across other demographic groups and across countries. Answering these questions requires new ways of measuring preferences for competition that do not necessitate gathering respondents in the same physical location. Many applications will require a measure that can be added to large-scale surveys without significant increase in survey time (and therefore cost).

In this paper, we introduce such measures of competitiveness. The first is incentivized and is an online adaptation of the original Niederle-Vesterlund measure. The second is a single unincentivized survey question that can be quickly elicited in any setting. The two measures are strongly correlated at the individual level, and both measures are strong and consistent predictors of completed level of education, field of study in college, occupation, and income. The predictive power of the unincentivized measure for these outcomes is robust to controlling for other traits, including risk seeking, confidence, and the Big Five personality traits. For most outcomes, the predictive power of competitiveness exceeds that of the other traits.

We also contribute to the literature on gender differences in the labor market. We find that gender differences in competitiveness can explain 5%–10% of the observed gender differences in education and labor market outcomes and that gender differences in competitiveness, risk seeking, confidence, and the Big Five personality traits combined can explain up to 25% of gender differences. We also show that competitiveness and risk attitudes predict a separate set of outcomes. While risk attitudes are only weakly related to career outcomes they predict choices that are intrinsically risky but not competitive.

Our estimates are (conditional) associations and cannot necessarily be interpreted causally. In particular, reverse causality—whereby a successful career leads to people seeing themselves as more competitive—is a potential alternative explanation for the documented correlations between competitiveness and career outcomes. We take an initial step toward addressing this issue by showing that answers to our survey measure in 2017 predict labor market success—as measured by salary growth—over the following five years conditional on baseline salary and individual fixed effects.

To the extent that there is a causal effect of competitiveness on success in education and the labor market, this raises the question of policy implications. One could jump to the conclusion that we should train or encourage people—in particular women—to be more competitive. Although some evidence suggests that interventions at a young age can influence willingness to compete (Alan & Ertac, 2019; Boneva et al., 2022), it is debatable whether it would be socially beneficial—or even feasible—to increase competitiveness across whole populations.[36] An alternative—and in our view more promising—approach is to reevaluate the design of educational institutions and the way companies select and incentivize their employees (see also Niederle, 2017). Is competitiveness correlated with certain majors and occupations because it is a productive trait in these careers or because of the way people are selected into the careers and interact with each other?

In the future, the introduction of our unincentivized survey measure of competitiveness will also make it possible to measure competitiveness repeatedly and in much larger and more diverse samples than has been the case so far. This in turn paves the way for research that can uncover which factors influence competitiveness. See Boneva et al. (2022)—who estimate the impact of an exogenous change to children's social environment on competitiveness as measured by our survey questions—for a first example of the possibilities.

[36]See, for example, Harbring and Irlenbusch (2008); Bartling et al. (2009); Charness et al. (2014); Buser and Dreber (2016), or Buser et al. (2021) for potentially socially problematic aspects of competition and competitiveness.

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