I Z A Institute of Labor Economics

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DISCUSSION PAPER SERIES

IZA DP No. 16818

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Aurélie Dariel
New York University Abu Dhabi

John Ham
New York University Abu Dhabi, NYU Wagner and IZA

Nikos Nikiforakis
New York University Abu Dhabi

Jan Stoop
Erasmus University Rotterdam

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Disparities in Psychological Traits and Income: Race, Ethnicity, and Gender in the U.S.*

There are pronounced racial, ethnic, and gender gaps in income in the U.S. We investigate whether these correspond with differences in competitiveness, risk tolerance, and confidence relative to performance in a large, stratified sample of the U.S. prime-age population. We find substantial differences in all three traits across Black, Hispanic, and White males and females. These traits predict individual income. Competitiveness and risk tolerance help explain the White gender income gap. Competitiveness also affects the Black-White income gap between men. Confidence about one's performance helps explain a substantial and significant portion of all five race-gender income gaps with White men.

JEL Classification: C90, D03

Keywords: racial/gender income gaps, overconfidence, competitiveness, risk tolerance

Corresponding author:
John C. Ham
Department of Economics
NYU Abu Dhabi
PO Box 129188
Saadiyat Island
Abu Dhabi
United Arab Emirates
E-mail: jch18@nyu.edu

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1. Introduction

A growing body of research in economics has demonstrated that psychological traits play a role in explaining life outcomes such as income, educational attainment, employment, and health (Barsky et al. 1997, Borghans et al. 2008, Buser et al. 2014, Buser et al. 2017, Buser et al. 2021, Dohmen et al. 2011, Falk et al. 2018, Heckman et al. 2006, Reuben et al. 2017, Reuben et al. in press, Sutter et al. 2013). Understanding the degree of variability among individuals in traits that feature prominently in this literature such as risk tolerance, competitiveness and confidence relative to performance (hereafter confidence), therefore, is a topic of evident importance. This is particularly true when significant disparities are observed in life outcomes among different groups. A notable example is an influential research program in behavioral economics investigating the differences in psychological traits between men and women. Inspired by the persistent gender differences in earnings and employment (e.g., Blau & Kahn 2017, Goldin 2014), this research program has provided robust evidence showing that women tend to be less competitive, less risk tolerant, and less confident than men (Croson & Gneezy 2009, Niederle 2017, Santos-Pinto & Rosa 2020).

In this paper, we explore the disparities in psychological traits across race, ethnicity, and gender and assess the degree to which these disparities are linked to differences in income. Our research is motivated by the persistence of substantial income gaps across Blacks, Hispanics, and Whites in the U.S., as well as between men and women. The gap between Black men and White men in the U.S., for instance, is similar in magnitude to that between White women and White men (Bayer & Charles 2018, Chetty et al. 2019, Lang & Spitzer 2020, Lang & Lehmann 2012) and remains even after controlling for human capital variables. Little is known, however, about whether there exist corresponding differences in psychological traits that may help explain the income gaps across race, ethnicity, and gender. On the one hand, large data sets, such as the Census or the Current Population Survey, typically lack information regarding psychological traits. On the other hand, behavioral social scientists studying disparities in psychological traits tend to rely disproportionately on student samples, which are predominantly White (Henrich et al. 2010, Pollet & Saxton 2019).[1] The use of such samples implies that there will generally exist too few observations of minorities to conduct a

[1] The excessive reliance on predominantly White samples is not a feature of experimental research only in economics or the social sciences, but also in medical experiments. The 1993 NIH Revitalization Act Public Law 103-43 mandated that National Institute of Health funding for medical experiments should be available only if the researchers attempted to recruit a sufficiently large number of women and minorities. For a detailed description of the act, see: https://www.ncbi.nlm.nih.gov/books/NBK236531/. The rationale used to justify the act was that experimental findings may not generalize from one racial/ethnic/gender group to another. A similar concern applies to economic and social science research, given the different socio-economic realities experienced by people of different races, ethnicities, and genders.

meaningful analysis. This phenomenon could explain why behavioral studies rarely report information about individuals' race or ethnicity (Rad et al. 2018).[2]

We measure psychological traits in a stratified sample of 2,463 individuals drawn from the U.S. prime-age population. Drawing inspiration from the above-mentioned research program in behavioral economics on gender, we assess three traits characterized by significant disparities: competitiveness, risk tolerance, and confidence in one's relative performance. The sample is stratified over race/ethnicity (Black, Hispanic, and White) and gender; each of the six strata contains observations of approximately 400 individuals.[3] Hence, we can precisely estimate the effect of controlling for each trait on income gaps between White men and the other five racial/ethnic/gender (henceforth, REG) groups. Conditional on sample weights, each stratum is nationally representative with regard to age, years of education, region, and the 2016 presidential vote.

We use our dataset to address the following questions: (*i*) Are there racial/ethnic differences in competitiveness, risk tolerance, and confidence? (*ii*) Are the gender differences in competitiveness, risk tolerance, and confidence similar for Blacks, Hispanics, and Whites? (*iii*) Do these traits help predict income? (*iv*) If so, do the disparities in traits help explain income gaps between White men and the other five REG groups?

Regarding question (*i*), we find substantial differences in all three traits between Whites and Blacks, and between Whites and Hispanics, for both genders. Specifically, we find that Whites are, on average, less competitive, less risk tolerant, and less confident about their relative performance than both Blacks and Hispanics. These gaps are substantial and comparable in size to the overall gender gap in our data. Differences in competitiveness and risk tolerance are small and statistically insignificant between Blacks and Hispanics. Blacks, however, tend to be more confident in their relative performance than Hispanics. With regard to question (*ii*) concerning gender disparities, we find that the gender gaps in traits are similarly sized across Blacks, Hispanics, and Whites and not significantly different from one another. That is, women tend to be less competitive, less risk tolerant, and less overconfident than men, regardless of whether they are Black, Hispanic, or White.

[2] An alternative explanation is that economists care less than other social scientists about racial diversity and inclusion in research. In a recent research article, using a dataset of 500,000 academic publications from 1960 onwards, Advani et al. (2021) show that "economics lags far behind the other disciplines in the volume and share of race-related research", although they also note that "the share [of race-related publications] is higher in top-5 journals".

[3] According to the 2020 census, Blacks, Hispanics and Whites make up approximately 92% of the U.S. population (Blacks: ~13%; Hispanics: ~18%; Whites: ~61%).

Concerning question (*iii*), we first show that our measures of competitiveness, risk tolerance, and confidence predict income, both individually and jointly. The sizes of the effects are substantial: individuals above the median in terms of competitiveness and risk tolerance, for instance, have incomes that are 21.2% and 15.7% higher than those below the median, respectively, when jointly estimated. Confidence in relative performance is also associated with income: individuals in the upper and lower third of the distribution (the upper third being overconfident and the lower third being *under*confident) have incomes that are 23.5% and 16.7% lower than the middle third, who are better at evaluating their relative performance.

Finally, regarding question (*iv*) on whether the disparities in traits help explain income gaps across race/ethnicity and gender, the answer is nuanced. We find that controlling for confidence substantially and significantly reduces the unexplained income gaps between White men and all of our other five REG groups; the effects range from 7.2% of the differential (White women versus White men) to 18.7% (Hispanic men versus White men). Only controlling for competitiveness significantly reduces the unexplained income gap between White women and White men by 5.9%, but *increases* the unexplained income gap between Black men and White men by 5.1%. Only controlling for risk tolerance, on the other hand, does not significantly affect any of the income gaps, with the exception of a (marginally) significant reduction of 4.1% in the gap between White women and White men. Jointly controlling for the three traits significantly reduces the unexplained income gap between Black women and White men (by 15.2%), Hispanic women and White men (by 11.5%), and White women and White men (by 15.0%). However, these traits do not explain the gap between Black men and White men, as the overconfidence and competitiveness effects go in opposite directions.

Our paper contributes to three areas of existing literature. The first contribution is to the literature in behavioral economics comparing psychological traits across groups of individuals. Thus far, the focus has been on exploring gender differences among (predominantly) White samples. Here, we explore disparities in psychological traits across race, ethnicity, and gender. To the best of our knowledge, our study is the first to directly measure and compare competitiveness, risk attitudes, and confidence in one's relative performance across nationally-representative groups of Black, Hispanic, and White men and women in the U.S. prime-age population.[4]

[4] Barsky et al. (1997) compare the risk attitudes of U.S. Blacks, Hispanics, and Whites, among others, using a survey of older Americans. Specifically, approximately 90% of their sample is over 50 years old. They find that Whites are less risk tolerant than Blacks, who, in turn, are less risk tolerant than Hispanics. Benjamin et al. (2010) find that U.S. Black subjects recruited from a student population choose the safe lottery in similar proportions to White subjects. Finally, Nicholls (2022) shows that, in South Africa, Blacks are more competitive than Whites in a randomly drawn sample in which Blacks are ten times as numerous as Whites.

Our work also contributes to the literature in labor economics, identifying factors that predict income and account for gender or racial/ethnic income gaps (Bayer & Charles 2018, Blau & Kahn 2017, Chetty et al. 2019, Lang & Spitzer 2020, and Lang & Lehmann 2012). While some studies have shown that psychological traits can help explain differences in income across individuals (Borghans et al. 2008, Buser et al. 2021, Dohmen et al. 2011, Falk et al. 2018, Heckman et al. 2006, Reuben et al. 2017, Reuben et al. in press), to the best of our knowledge, our paper is the first to use a large, stratified sample of the U.S. prime-age population.[5]

Finally, our study contributes to a growing body of research in behavioral economics highlighting the importance of studying diverse samples. In the last five years, there has been an increasing number of studies recruiting nationally-representative samples to study cross-country differences in traits and behavior (Almås et al. 2020, Almås et al. 2022, Buser et al. 2021, Falk et al. 2018). Since our aim is to identify *within*-country differences among groups that include racial/ethnic minorities, we opted to recruit a large sample that is stratified over race/ethnicity and gender.

The paper proceeds as follows. In the next section, we discuss our sample and study design. In section 3, we present evidence of significant race/ethnicity and gender differences in competitiveness, risk tolerance, and confidence. In section 4, we use regression analysis to relate such differences in traits to REG income gaps. We conclude in Section 5 by discussing the implications of our findings and ideas for future research.

2. Data

We begin by providing information on the sample we collected for our study. We then discuss the main variables used to address our four research questions.

2.1 A stratified sample of the U.S. prime-age population

To obtain our data, we used the services of YouGov, an international research and analytics company with over 11 million panel members globally. Our online sample consists of 2,463 U.S. residents, age 25–54, who participated in our study between January 13 and February 8 of 2021. We consider six racial/ethnic and gender (REG) groups: Black men, Hispanic men,

[5] Buser et al. (2021) measure general competitiveness and risk tolerance (among other traits), and show that they help predict individual income in a large, representative sample of the Dutch population. These authors also study the impact of confidence as measured by the response to the question: "I have confidence in my capabilities." This concept of confidence is different to the one we consider here, which is confidence in one's relative performance. Our concept of confidence is similar to Reuben et al. (in press). Using a cohort of MBA students at the University of Chicago, they show that individuals who are more confident earn less seven years after graduation.

White men, Black women, Hispanic women, and White women. We use post-stratification weights to ensure that each REG group is nationally representative with regard to age, education, and political views.[6] Table 1 below summarizes the stratified sample by race/ethnicity and gender.

Table 1 - Sample distribution by race/ethnicity and gender

	Male	Female	Total
Black (non-Hispanic)	402	424	826
Hispanic	407	414	821
White (non-Hispanic)	412	409	821
Total	1,221	1,247	2,468

The online study took approximately 20 minutes to complete. Respondents earned, on average, \$8.80 from their participation, including a fee of \$1.50 for showing up.

2.2 Measures of competitiveness, risk tolerance, and overconfidence

We follow a growing literature in behavioral economics using experimentally-validated survey measures of competitiveness and risk tolerance (Bokern et al. 2023, Bönte et al. 2017, Buser et al. 2021, Dohmen et al. 2011, Falk et al. 2018, Fallucchi et al. 2020, Hauge et al., 2023, Klinowski & Niederle 2023). Since our aim is to compare individuals in groups that differ considerably in mean educational attainment, an attractive property for our purposes is that the questions are straightforward and easily comprehensible. Therefore, we have a priori no reason to expect that differences in education, which can be substantial across race/ethnicity in the U.S., will affect subjects' ability to report their competitiveness and risk tolerance.

Our measures of risk tolerance and competitiveness are adapted from Dohmen et al. (2011) and Buser et al. (2021), respectively. To measure risk tolerance, we ask respondents: "In general, how willing are you to take risks?" (on a scale from 1 to 5, where 1 means not willing at all, and 5 means very willing). To measure competitiveness, we ask: "In general, how competitive do you consider yourself to be?"[7] (on a scale from 1 to 5, where 1 means not competitive at all, and 5 means very competitive). We follow Buser et al. (2021) who refer to

[6] YouGov provides us with post-stratification weights based on the following variables: the 2016 presidential vote choice, and a four-way stratification of gender, age (four categories), race (three categories), and education (four categories).
[7] For comparability across questions, we made a minor modification to the question asked by Buser et al. (2021) ("How competitive do you consider yourself to be?") and added the words "in general" at the start.

these as measures of *general* risk tolerance and *general* competitiveness to distinguish them from measures obtained in narrower contexts (e.g., financial risk or competition for pay).[8, 9]

We follow previous studies by measuring confidence using an incentivized task. Confidence in one's relative performance has been described as among the most significant psychological traits (Kahneman 2011).[10] However, there are no experimentally-validated survey questions available to measure this trait. Furthermore, it seems difficult to construct a credible, self-reported measure of confidence relative to performance. Similar to previous studies (Niederle & Vesterlund 2007, Reuben et al. in press), we measure confidence by comparing individuals' beliefs about their relative performance in a real-effort task to their actual performance. The task involves counting the number of *1*'s in as many as possible 5x5 matrices consisting of only *0*'s and *1*'s within 75 seconds. Participants are then asked to guess the number of individuals *out of 100*, drawn randomly from a representative sample of the U.S. population, who would have performed better than them.[11] The more accurate a participant's belief, the greater the monetary reward (for details, see the Online Appendix). Importantly, like with our measures of competitiveness and risk tolerance, this question is straightforward to answer. To construct our measure of confidence, an individual's *actual* relative standing (1 being the best and 100 being the worst) in a randomly drawn representative sample of 100 Americans is subtracted from their stated *belief* about their relative standing. The variable, therefore, spans from –99 (they ranked the best but believed themselves to be the worst) to +99 (they ranked the worst but believed themselves to be the best), with negative values indicating

[8] Recent evidence suggests that the general measures may have another advantage for our purposes. Bokern et al. (2023) use a large sample of the Dutch population to study the impact of risk attitudes on financial decisions in daily life. They use both a battery of incentivized ("revealed") measures of risk preferences as well as "stated" risk preferences, i.e., the Dohmen et al. (2011) question of general risk tolerance that we adopt. They find that "[s]tated methods correlate well with most types of field behavior and correlations are of high economic significance . . . Revealed methods are at best weakly related to most types of field behavior, even when controlling for measurement error." Charness et al. (2020) also find that incentivized measures of risk preferences fail to predict life outcomes in a nationally-representative sample of the Dutch population, while Pedroni et al. (2017) find that different incentivized measures of risk do not reliably correlate at the individual level.

[9] As part of a larger research program on traits, we also collected differemt incentivized measures of competitiveness and risk attitudes. For the methodological reasons mentioned at the start of this section, in this paper, we focus our attention exclusively on the experimentally-validated, general measures of competitiveness and risk tolerance. The general and the incentivized measures we collected are significantly correlated (*p*-value<0.01, for both competitiveness and risk) and nearly always lead to the same conclusions regarding the REG disparities in psychological traits. Similar to Bokern et al. (2023), we find that the incentivized measures have little predictive power over income in our sample. Accordingly, adding the incentivized measures in the income regressions does not affect our full-sample estimates (see Appendix, Section B).

[10] Confidence in our paper is the same as what Moore and Healy (2008) refer to as "overplacement of one's performance". Here, we use the term confidence. When necessary, we distinguish between *high* and *low* confidence in one's relative performance. In our data, low confidence individuals underestimate their relative performance whereas high confidence people tend to overestimate it.

[11] Since our focus is on Blacks, Hispanics, and Whites, to obtain a representative sample of the U.S. prime-age population, prior to our main experiment we surveyed a small sample of Asians, native Americans, and other racial/ethnic groups.

underestimation of relative performance, and positive values indicating overestimation of relative performance.

2.3 Measures of personal income

To explore the relationship between income and competitiveness, risk tolerance, and confidence in relative performance, we asked each individual in our sample to report their personal monthly income. Specifically, we asked: "Give us your best estimate of your average personal monthly income in 2020, before taxes and including income from all sources."[12] Since the COVID-19 pandemic affected individual earnings in 2020, to reduce income fluctuations, we asked individuals to report their income *from all sources*, anticipating that government transfers would make up for some of the income lost due to COVID-19 in 2020. We also asked respondents for their personal income in 2019, using an analogous question. Using income information from 2019 and 2020 increases our statistical power as long as the income equations are stable across years.

Prior research has demonstrated the reliability of self-reported income in survey data, particularly data elicited by panel members, as is the case in our sample. Specifically, recent studies by Karadja et al. (2017) in Sweden and Hvidberg et al. (2023) in Denmark, which linked survey responses with register data, found low levels of income misreporting. Similar findings have been observed in the U.S., where surveys have been matched with administrative data to examine reported annual earnings (Bound et al. 1994, Duncan & Hill 1985, Pischke 1995). The reliability of self-reported financial information tends to be even higher when responses are obtained repeatedly (Bound & Krueger 1991, Bollinger 1998). This is the case with this study's YouGov opt-in panelists who repeatedly provide information about their income over time. As we will see, the estimated income gaps in our data are similar to those obtained using data from the U.S. Current Population Survey conducted by the Census Bureau (Paul et al. 2022).

3. Are there differences in psychological traits across race/ethnicity and gender?

3.1 Competitiveness

Figure 1 presents the mean score for competitiveness in our sample by race/ethnicity (Panel A), gender (Panel B), and race/ethnicity/gender (REG) (Panel C). As shown in Panel A, there is a substantial gap in competitiveness between Blacks and Whites ($p < 0.0001$) using a two-tailed Mann-Whitney U test or a weighted *t*-test, as well as between Hispanics and Whites ($p < 0.0001$) using the same tests. On the other hand, Blacks and Hispanics are similarly

[12] We provided respondents with the standard 18-item scale to indicate their income. This scale includes the options "Not applicable" and "Don't know/Refuse to say."

competitive (p = 0.5508, two-tailed, Mann-Whitney U test; p = 0.489, two-tailed, weighted t-test). On average, Blacks and Hispanics are 9.7% *more* competitive than Whites. Comparing Panel A to Panel B, the magnitude of the Black-White and Hispanic-White gap in competitiveness is comparable to the magnitude of the *gender* gap in competitiveness.[13] Specifically, across race/ethnicity, men are 11.8% more competitive than women (men: 3.70; women: 3.31; $p < 0.001$, two-tailed, Mann-Whitney U test and weighted t-test). Finally, Panel C shows that the widely-documented gender gap in competitiveness is similar in size across racial/ethnic groups. The differences in gender gaps across racial/ethnic groups are all statistically insignificant. One possible issue in the level differences described above is that the units are undefined. However, the percentage differences are unit free and readers may want to focus on them.

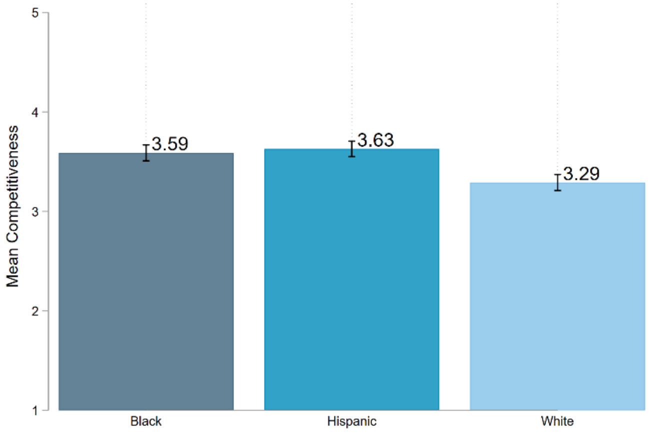
3.2 Risk tolerance

Figure 2 presents the mean score for risk tolerance in our sample by race/ethnicity (Panel A), gender (Panel B), and race/ethnicity/gender (REG) (Panel C). Panel A shows a substantial gap in general risk tolerance between Blacks and Whites ($p < 0.0001$; two-tailed, Mann-Whitney U test and weighted t-test) as well as between Hispanics and Whites ($p < 0.0001$; two-tailed, Mann-Whitney U test and weighted t-test). Blacks and Hispanics have similar levels of risk tolerance (p = 0.2184, two-tailed, Mann-Whitney U test; p = 0.331, two-tailed, weighted t-test). On average, Blacks and Hispanics are 11.0% *more* risk tolerant than Whites. Comparing Panel A to Panel B, the magnitude of the Black-White and Hispanic-White gap in risk tolerance is equivalent to the magnitude of the *gender* gap in risk tolerance. Specifically, we find that, across race/ethnicity, men are 11.0% more risk tolerant than women (men: 3.53; women: 3.19; $p < 0.0001$, two-tailed, Mann-Whitney U test and weighted t-test). Finally, Panel C reveals that although the widely-documented gender gap in risk tolerance is significant in each racial/ethnic group, the magnitude of the gender gap, in percentage terms, varies across racial/ethnic groups, with the gap being substantially *smaller* among Whites (Blacks: 14.3%, Hispanics: 11.2%, Whites: 6.9%, p = 0.0193, two-tailed, weighted t-test comparing Blacks to Whites; p = 0.1282, two-tailed, weighted t-test comparing Hispanics to Whites).

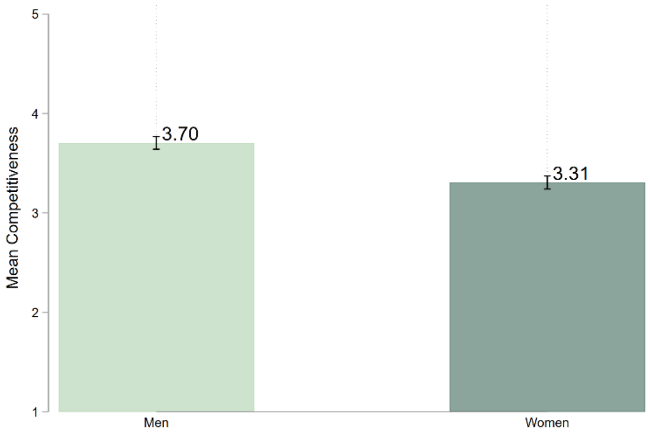
[13] In calculating the means in Panel B, we assign equal weight to each stratum in our sample to facilitate comparisons across panels. That is, the data has not been reweighted to reflect the general U.S. population with regard to race/ethnicity. We would argue that this is not an important issue here given that the similar gender gaps across race/ethnicity.

Figure 1: Differences in the mean score for competitiveness by race/ethnicity and gender

A: By race/ethnicity



B: By gender



C: By race/ethnicity/gender

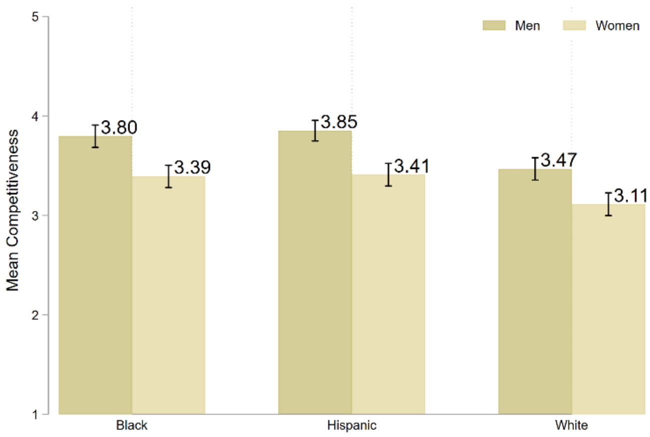
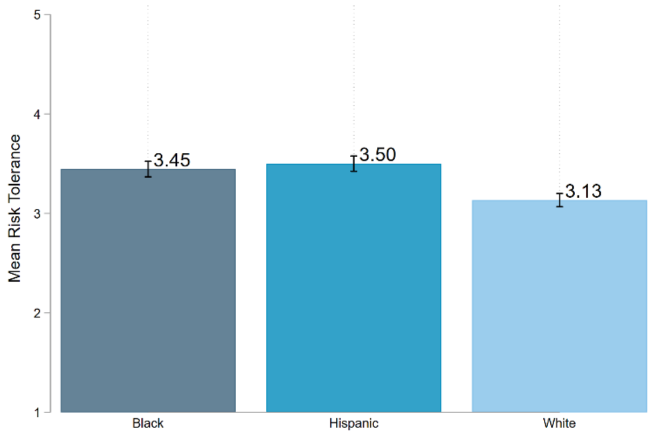
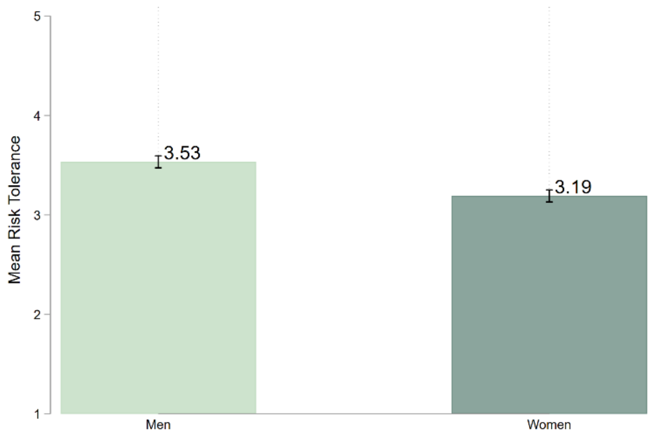


Figure 2: Differences in the mean score for risk tolerance by race/ethnicity and gender

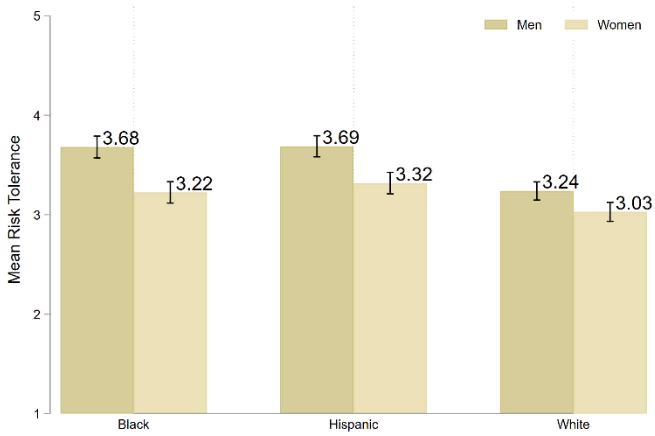
A: By race/ethnicity



B: By gender



C: By race/ethnicity and gender



3.3 Confidence relative to performance

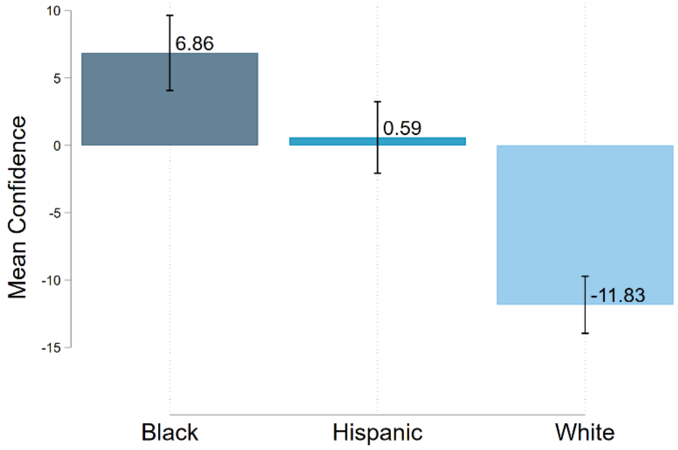
Figure 3 presents the mean score for confidence relative to performance by race/ethnicity (Panel A), gender (Panel B), and race/ethnicity/gender (REG) (Panel C). Recall that our measure of confidence can span from –99 (when an individual is the best performer in their group of 100, but believes they are the worst) to +99 (when an individual is the worst performer in their group of 100, but believes they are the best). In other words, negative values indicate an underestimation of relative performance while positive values indicate an overestimation of relative performance.

One complication when comparing confidence levels across groups is that one group may have a positive mean score while the other group has a negative mean score. To deal with this issue, we calculate the confidence *range*, which for two groups X and Y is defined as the X-value minus the Y-value. The Black-White range is 18.69 (6.86 – (–11.83)); the Black-Hispanic range is 6.27 (6.86 – 0.59), and the Hispanic-White range is 12.42 (0.59 – (–11.83)).[14] All racial/ethnic gaps are individually statistically significant ($p < 0.0001$; two-tailed Mann-Whitney U test and weighted t-tests). By comparison, as shown in Panel B, the male-female gap across race/ethnicity is 11.14 (4.22 – (–6.92)), with men significantly overestimating their relative performance and women significantly underestimating their relative performance ($p < 0.0001$; two-tailed, Mann-Whitney U test and weighted t-test). Finally, Panel C reveals that the widely-documented gender gap in confidence is similar in magnitude across racial/ethnic groups. The male-female range is 12.07 (13.05 – 0.98) for Blacks, 11.15 (6.22 – (–4.93)) for Hispanics, and 10.93 (–6.39 – (–17.32)) for Whites. The differences in the male-female range across race/ethnicity are all statistically insignificant.

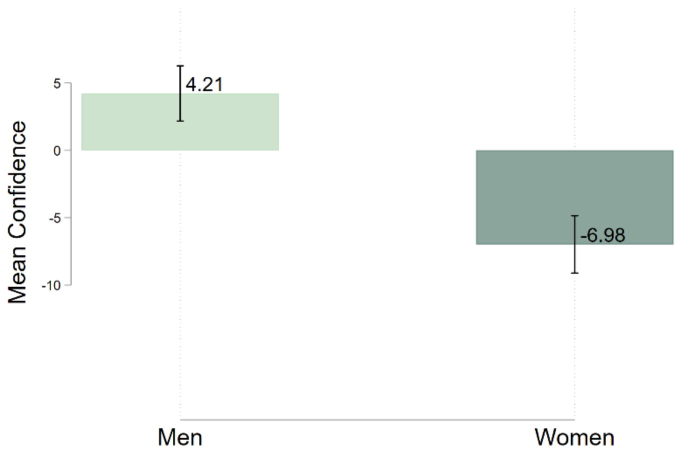
[14] An alternative measure would be to divide the Hispanic-White difference by the average of the absolute value of the Hispanic score and the absolute value of the White score. Doing so would not change the conclusions in this paragraph.

Figure 3: Differences in the mean score for overconfidence in relative performance by race/ethnicity and gender

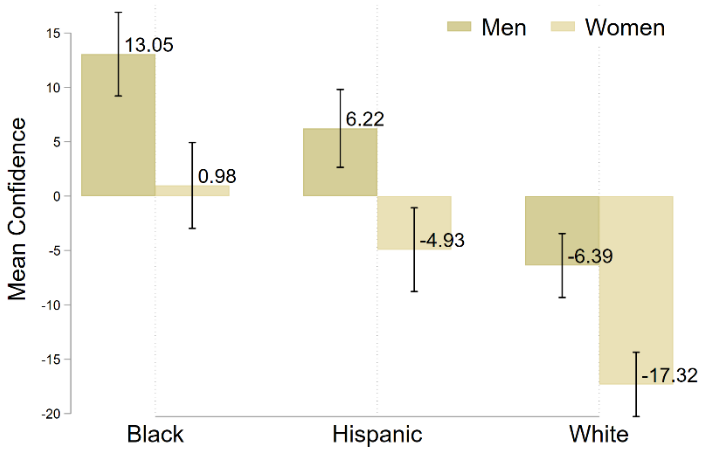
A: By race/ethnicity



B: By gender



C: By race/ethnicity/gender



4. Can our psychological traits help explain the income gaps across race/ethnicity and gender?

Having demonstrated the existence of pronounced racial/ethnic/gender (REG) differences in competitiveness, risk tolerance, and confidence in relative performance, we proceed to address our next two research questions: (*iii*) Do these traits help predict individual income? (*iv*) If so, do the disparities in traits help explain the racial/ethnic/gender income gaps in the U.S.? To answer these questions, we turn to an econometric analysis.

4.1 Empirical Framework

We follow the literature in labor economics (e.g., Mincer 1974) and use the natural logarithm of income as our dependent variable. In our specification, we allow for separate dummy variables for each of the five REG groups:

$$\ln(Y_{it}) = \alpha_0 + \beta_{BW_t}BW_i + \beta_{HW_t}HW_i + \beta_{WW_t}WW_i + \beta_{BM_t}BM_i + \beta_{HM_t}HM_i + \alpha_1 D2020_t + u_{it},\ t = 2019, 2020. \tag{1}$$

In equation (1), Y_{it} denotes income in year t for individual i from all sources, $D2020_t$ is a dummy variable taking the value 1 if the year is 2020 and 0 otherwise, and u_{it} is the error term.[15] Further, WW_i is a dummy variable taking the value 1 if the individual is a White woman and 0 otherwise, BW_i is a dummy variable taking the value 1 if the individual is a Black woman and 0 otherwise, HW_i is a dummy variable taking the value 1 if the individual is a Hispanic woman and 0 otherwise, BM_i is a dummy variable taking the value 1 if the individual is a Black man and 0 otherwise, and HM_i is a dummy variable taking the value 1 if the individual is a Hispanic man and 0 otherwise. The base case is White men.

We allowed the coefficients to vary by year. To investigate whether this is necessary, we test the null hypothesis that coefficients (except for the intercept) are the same in 2019 and 2020. We fail to reject the null hypothesis in all specifications presented in this paper. This result may be due to the fact that we asked for total personal income from all sources in each year, such that lower labor income in 2020 (due to the COVID-19 pandemic) could be offset by increased income from the government in that year. Given this result, we drop the time subscript of the coefficients except for the intercept and rewrite equation (1) as:[16]

[15] In calculating standard errors, we allow u_{it} to be heteroskedastic and correlated for the same person over time.

[16] In what follows, we make the t=2019,2020 implicit after the equations.

$$\ln(Y_{it}) = \alpha_{0t} + \beta_{BW}BW_i + \beta_{HW}HW_i + \beta_{WW}WW_i + \beta_{BM}BM_i + \beta_{HM}HM_i + \alpha_1 D2020_t + u_{it} \ . \tag{2}$$

Within this model, the approximate average percentage difference between the respective REG group's incomes and White men's incomes is 100 times the respective coefficient. For example, if we consider White women versus White men, the approximate percentage difference in income is $100 * \beta_{WW}$. Further, the approximate percentage difference in income between Hispanic men and Hispanic women is $(\beta_{HM} - \beta_{HW}) * 100$. We will refer to these as the unadjusted raw differentials since we do not control for any explanatory variables.[17]

These raw differentials do not control for productivity differences across groups. For example, if White women have more schooling than White men, the coefficient in (2) will be an underestimate of the true income differences. To control for human capital differences, we add a vector X_i representing a flexible function of age and education to (2):

$$\ln(Y_{it}) = \alpha_0 + \beta_{BW}BW_i + \beta_{HW}HW_i + \beta_{WW}WW_i + \beta_{BM}BM_i + \beta_{HM}HM_i + \delta X_i + \alpha_1 D2020_t + u_{it} \ . \tag{3}$$

The coefficients in (3) are typically referred to as the *unexplained* differences between the other REG groups and White men.[18] Our innovation here is to add measures of risk tolerance (RT_i), competitiveness (COM_i), and confidence in relative performance (CRP_i) to (3) and evaluate the resulting change in the unexplained differences between the REG groups and White men, i.e., the $\tilde{\beta}$ coefficients:

$$\ln(Y_{it}) = \tilde{\alpha}_0 + \tilde{\beta}_{BW}BW_i + \tilde{\beta}_{HW}HW_i + \tilde{\beta}_{WW}WW_i + \tilde{\beta}_{BM}BM_i + \tilde{\beta}_{HM}HM_i + \tilde{\delta}X_i + \tilde{\gamma}_{RT}RT_i + \tilde{\gamma}_{COM}COM_i + \tilde{\gamma}_{CRP}CRP_i + \tilde{\alpha}_1 D2020_t + \tilde{u}_{it} \tag{4}$$

To investigate whether there is a significant change in the unexplained differences between the REG groups and White males when we add the psychological traits, we test (individually) the following hypotheses:

$$H_0^1: \beta_{BW} = \tilde{\beta}_{BW},\ H_0^2: \beta_{HW} = \tilde{\beta}_{HW},\ H_0^3: \beta_{WW} = \tilde{\beta}_{WW},\ H_0^4: \beta_{BM} = \tilde{\beta}_{BM},\ H_0^5: \beta_{HM} = \tilde{\beta}_{HM}.$$

[17] When estimating equation (2), we use weights provided to us by YouGov such that our sample resembles the U.S. prime-age population for each REG group.

[18] One can also measure income differences using Oaxaca's (1967) seminal decomposition. However, this would involve estimating separate income equations for each of the six groups. To estimate these separate equations precisely would require a much larger sample that would more than double the cost of our dataset.

4.2 Full sample estimation results

Table 2 presents the regression results from the full sample.[19] The coefficients in Table 2A, column I present the unadjusted mean log income gaps between White men and the respective REG groups. The coefficients, therefore, denote the approximate mean percentage differences between White males and the respective REG groups without an adjustment for human capital differences. The estimates illustrate the large well-known differences in income between White men and the other REG groups. Importantly, these results are consistent, for example, with those reported by Paul et al. (2022; Table 1, top panel, column V) using data on annual wages for all workers from the 2017 Annual Social and Economic Supplement of the U.S. Current Population Survey conducted by the Census Bureau.

The estimates in Column II show the adjusted income gaps between White males and the other REG groups after controlling for age and education to account for differences in human capital across the groups. The age and education coefficients have the expected signs and significance. Note that the adjusted differences actually decrease in absolute value for all REG groups except White women. (White women have higher average schooling levels than White men, while the other groups have less education on average than White men.) Again, we find that these adjusted percentage differences are comparable to the results based on recent data in Paul et al. (2022; Tables 2 and 3, top panel, column V).[20]

Next, we examine how log income is affected by including measures of competitiveness, risk tolerance, and confidence relative to performance. We add these variables individually in columns III–V and jointly in column VI. Following Buser et al. (2021), we parametrize the risk tolerance measure into a dummy variable taking the value of 1 if the individual's risk tolerance is above the sample median and 0 otherwise. For similar reasons, we parametrize the competition measure into a dummy variable taking the value of 1 if the individual's competitiveness is above the sample median and 0 otherwise. Confidence relative to performance spans from –99 to +99; hence, we use a slightly more flexible parameterization by defining *Low Confidence* as a dummy variable equal to 1 if the individual was in the lowest third of the confidence relative to performance values and 0 otherwise. All individuals classified as having low confidence underestimated their relative performance. Similarly, we define *High Confidence* as a dummy variable equal to 1 if the individual was in the highest

[19] As each individual was asked to report their income in two years, the number of observations used in the analysis exceeds the total number of participants in each stratum. Some individuals did not report their income and are removed from the analysis. We also drop observations by individuals who reported monthy income in excess of $20,000. We relax this restriction in the Appendix (see Section A) and show that we obtain similar results.

[20] We believe that Paul et al. (2022) underestimate discrimination by controlling for industry and occupation. The debate on whether or not to include occupation and industries dates back to Sanborn (1967).

third of the confidence relative to performance values and 0 otherwise. All individuals classified as having high confidence overestimated their relative performance. Finally, for expositional ease, we will define someone as having medium confidence if they are in the middle third of the confidence relative to performance values (i.e., for whom the *Low Confidence* and *High Confidence* dummies are both equal to 0).

The estimates in Column III of Table 2A indicate that going from below the median in risk tolerance to above the median is associated with a statistically significant increase in income of 22.7%. Similarly, in Column IV we estimate that going from below the median in terms of competitiveness to above the median is associated with an increase in income of 25.8%. With regard to confidence relative to performance, in Column V we observe that having low confidence is associated with a statistically significant 16.7% reduction in income compared with someone with medium confidence, while having high confidence is associated with a statistically significant 22.1% reduction in income relative to someone with medium confidence. Further, the results in Column VI indicate that all the coefficients on the psychological traits remain sizable and statistically significant when jointly estimated.

We turn our attention to how including the psychological traits individually and jointly affects the difference between what White men and other REG groups earn; in what follows we will refer this as the *REG differential*. Table 2B indicates the percentage change in each REG differential from adding each personality trait. For example, Table 2B, column 1, row 1 indicates that adding the risk tolerance variable decreases the differential for Black women by 1.8%,[21] but column 2 indicates that this change only has a *p*-value of 0.39. From column 1 one sees that the biggest change in a differential is for White women at 4.1%. As shown in column 2, this is the only change in a differential that approaches significance at the 5% level.

Table 2B, column 3 shows the percentage change in the REG differentials when we include the competitiveness variable. Adding this trait significantly reduces the differential for White women by 5.9% and significantly increases it by about 5.0% for Black men.

[21] Specifically, when we add the risk tolerance measure the differential for Black women goes from -0.455 to -0.447.

Table 2A - Regression results: Full sample

	I	II	III	IV	V	VI
Black women	-0.543***	-0.455***	-0.447***	-0.444***	-0.403***	-0.386***
	(0.096)	(0.093)	(0.092)	(0.093)	(0.094)	(0.093)
Hispanic women	-0.493***	-0.366***	-0.363***	-0.353***	-0.337***	-0.324***
	(0.094)	(0.091)	(0.090)	(0.091)	(0.091)	(0.089)
White women	-0.408***	-0.461***	-0.442***	-0.434***	-0.428***	-0.392***
	(0.090)	(0.085)	(0.085)	(0.085)	(0.086)	(0.085)
Black men	-0.515***	-0.408***	-0.422***	-0.429***	-0.359***	-0.383***
	(0.098)	(0.088)	(0.087)	(0.088)	(0.088)	(0.087)
Hispanic men	-0.354***	-0.182*	-0.189*	-0.191*	-0.148	-0.157
	(0.104)	(0.099)	(0.099)	(0.099)	(0.097)	(0.097)
Age		0.041	0.040	0.048	0.044	0.050
		(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
Age^2/1000		-0.388	-0.373	-0.458	-0.429	-0.474
		(0.437)	(0.435)	(0.435)	(0.434)	(0.431)
High school		0.382***	0.387***	0.396***	0.351**	0.364**
		(0.147)	(0.148)	(0.146)	(0.147)	(0.147)
Some college		0.496***	0.504***	0.517***	0.460***	0.480***
		(0.154)	(0.155)	(0.153)	(0.155)	(0.154)
Two-year college		0.476***	0.481***	0.497***	0.434***	0.453***
		(0.146)	(0.147)	(0.145)	(0.147)	(0.147)
Four-year college		0.778***	0.787***	0.788***	0.739***	0.750***
		(0.144)	(0.145)	(0.144)	(0.145)	(0.145)
Postgraduate		1.107***	1.116***	1.125***	1.057***	1.075***
		(0.145)	(0.146)	(0.144)	(0.147)	(0.146)
Risk tolerance			0.228***			0.158**
			(0.072)			(0.076)
Competitiveness				0.258***		0.212***
				(0.070)		(0.073)
Low Confidence					-0.167**	-0.166**
					(0.067)	(0.066)
High Confidence					-0.221***	-0.234***
					(0.073)	(0.073)
Year 2019	8.253***	6.671***	6.480***	6.274***	6.733***	6.282***
	(0.061)	(0.764)	(0.765)	(0.761)	(0.760)	(0.759)
Year 2020	8.143***	6.561***	6.370***	6.164***	6.623***	6.172***
	(0.061)	(0.764)	(0.765)	(0.761)	(0.760)	(0.759)
Observations	3296	3296	3296	3296	3296	3296

Notes: Robust standard errors, with respect to correlation across the observations for the same individuals and heteroskedasticity are in parentheses. Statistical significance is denoted by * 0.10, ** 0.05, *** 0.01. Dependent variable: Ln Income 2019 & 2020 (monthly income of $20,000 or lower).

Table 2B - Percentage changes in the REG differentials across models

	Model II vs. III (including Risk Tolerance)		Model II vs. IV (including Competitiveness)		Model II vs. V (including Relative Confidence)		Model II vs. VI (including all three traits)	
	% change (1)	*p*-value (2)	% change (3)	*p*-value (4)	% change (5)	*p*-value (6)	% change (7)	*p*-value (8)
Black women	-1.76	0.3904	-2.42	0.2626	-11.43	0.0047	-15.16	0.0014
Hispanic women	-0.82	0.8136	-3.55	0.2367	-7.92	0.0355	-11.48	0.0167
White women	-4.12	0.0763	-5.86	0.0287	-7.16	0.0404	-14.97	0.0015
Black men	3.43	0.1353	5.15	0.0269	-12.01	0.017	-6.13	0.3024
Hispanic men	3.85	0.4926	4.95	0.3858	-18.68	0.0407	-13.74	0.2207

Notes: Robust standard errors are in parentheses; *p*-values refer to the null hypothesis that the change in the coefficient is zero.

Table 2B, column 5 presents the REG differentials when we add confidence relative to performance. Doing this significantly decreases the differential for each of the REG groups. Moreover, these changes are large compared to those in columns 1 and 3. Specifically, adding the confidence variable significantly reduces by 7.2%, 7.9%, and 11.4% the differential for White, Hispanic and Black women, respectively. Moreover, adding this variable significantly reduces the differential by 12.0% and 18.7% for Black and Hispanic men, respectively.

In Table 2B, column 7, we show the changes in the REG differential when we include all of the psychological variables. Column 8 shows that this significantly lowers the differential for Black women, Hispanic women, and White women by more than 10%. Interestingly, controlling for risk tolerance, competitiveness and confidence all reduce the differential for White women. For Black men, however, controlling for competitiveness increases the differential, whereas controlling for confidence decreases it. Hence, when we include all three traits simultaneously, this results in an insignificant change in the differential for Black men. Similarly, the change in the differential for Hispanic men is also insignificant, even though it is quite large.

4.3 *Estimation results for specific subsamples*

In this section, we focus on the racial/ethnicity differentials for men and women separately. Table 3A shows the results for the male sample. Importantly, the coefficients for risk tolerance, competitiveness, and confidence relative to performance are large and statistically significant. The Black (Hispanic) coefficients in Table 3A again show the percentage differences in income between White men and Black (Hispanic) men given various conditioning variables. Thus, these coefficients are comparable to those for Black and Hispanic men in Table 2A. As in that table, the Black coefficient is always sizeable and statistically significant in Table 3A. Also, as in Table 2A, once we control for human capital in column 2, the Hispanic coefficient in

Table 3A is always insignificant.

Consistent with Table 2B, columns 3–4 of Table 3B indicate that the Black differential in the male sample increases (at the 7% significance level) when we control for competitiveness, while columns 5–6 indicate that the Black coefficient differential decreases when we control for confidence by 18.8%. Controlling for confidence relative to performance significantly reduces the coefficient change for Hispanic men by 39.2%. Columns 7–8 indicate that the effect of competitiveness and confidence counteract each other such that the change in the overall differential is not statistically significant for either Black men or Hispanic men.

Table 4A displays the results for the female sample. Neither of the race/ethnicity coefficients are close to statistical significance. The coefficients for competitiveness and risk tolerance are similar to those in Table 2A, showing that the influence of these traits on income is similar in the female-only sample and the full sample. However, the same is not true for the confidence variables, as neither the *Low Confidence* nor *High Confidence* variables are statistically significant.[22] Table 4B formally examines the changes in the Black and Hispanic differentials we include the psychological traits. Consistent with the above, Table 4B shows that none of the changes in the differentials are statistically significant for females. In the Appendix, we explore the impact of the psychological traits in samples of Blacks only, Hispanics only and Whites only. Note that these are relatively small samples and we would expect to have fewer significant variables.

[22] We cannot reject the null hypothesis that both confidence variables jointly equal zero.

Table 3A - Regression results: Male sample

	I	II	III	IV	V	VI
Black	-0.515***	-0.368***	-0.381***	-0.388***	-0.299***	-0.322***
	(0.098)	(0.087)	(0.086)	(0.087)	(0.088)	(0.088)
Hispanic	-0.355***	-0.120	-0.127	-0.130	-0.073	-0.084
	(0.104)	(0.096)	(0.095)	(0.096)	(0.093)	(0.093)
Age		0.071	0.072	0.079*	0.070	0.078*
		(0.047)	(0.047)	(0.047)	(0.046)	(0.046)
Age^2/1000		-0.710	-0.718	-0.812	-0.704	-0.792
		(0.566)	(0.566)	(0.566)	(0.554)	(0.553)
High school		0.334	0.332	0.352	0.284	0.298
		(0.224)	(0.225)	(0.223)	(0.224)	(0.224)
Some college		0.649***	0.651***	0.677***	0.574**	0.597***
		(0.229)	(0.230)	(0.227)	(0.230)	(0.229)
Two-year college		0.584***	0.579***	0.606***	0.512**	0.527**
		(0.222)	(0.223)	(0.220)	(0.223)	(0.223)
Four-year college		1.002***	1.006***	1.029***	0.924***	0.948***
		(0.218)	(0.219)	(0.217)	(0.220)	(0.220)
Postgraduate		1.245***	1.245***	1.258***	1.175***	1.185***
		(0.224)	(0.225)	(0.223)	(0.226)	(0.225)
Risk tolerance			0.205*			0.127
			(0.111)			(0.115)
Competitiveness				0.255**		0.212*
				(0.109)		(0.108)
Low Confidence					-0.161*	-0.157*
					(0.089)	(0.088)
High Confidence					-0.306***	-0.309***
					(0.094)	(0.095)
Year 2019	8.254***	5.916***	5.723***	5.517***	6.090***	5.642***
	(0.061)	(1.018)	(1.017)	(1.015)	(1.006)	(1.005)
Year 2020	8.141***	5.803***	5.610***	5.404***	5.977***	5.529***
	(0.063)	(1.018)	(1.017)	(1.014)	(1.005)	(1.004)
Observations	1,706	1,706	1,706	1,706	1,706	1,706

Notes: See notes to Table 2A.

Table 3B - Test for equality of Black/Hispanic differential across models in the male sample

	Model II vs. III (including Risk Tolerance)		Model II vs. IV (including Competitiveness)		Model II vs. V (including Relative Performance)		Model II vs. VI (including all three traits)	
	% change (1)	*p*-value (2)	% change (3)	*p*-value (4)	% change (5)	*p*-value (6)	% change (7)	*p*-value (8)
Black	3.53	0.2161	5.43	0.0678	-18.75	0.0101	-12.50	0.1457
Hispanic	5.83	0.4615	8.33	0.3391	-39.17	0.0291	-30.00	0.1593

Notes: See notes to Table 2B.

Table 4A - Regression results: Female sample

	I	II	III	IV	V	VI
Black	-0.135	-0.045	-0.057	-0.063	-0.045	-0.063
	(0.100)	(0.098)	(0.098)	(0.097)	(0.099)	(0.099)
Hispanic	-0.084	0.028	0.010	0.012	0.022	-0.002
	(0.099)	(0.101)	(0.100)	(0.101)	(0.101)	(0.100)
Age		0.003	0.000	0.009	0.007	0.010
		(0.055)	(0.055)	(0.055)	(0.055)	(0.054)
Age^2/1000		0.036	0.080	0.006	-0.017	-0.011
		(0.668)	(0.661)	(0.662)	(0.665)	(0.657)
High school		0.464**	0.478**	0.475***	0.461**	0.474**
		(0.186)	(0.187)	(0.182)	(0.187)	(0.185)
Some college		0.336	0.351*	0.347*	0.340	0.355*
		(0.207)	(0.209)	(0.205)	(0.209)	(0.208)
Two-year college		0.385**	0.402**	0.405**	0.382**	0.404**
		(0.188)	(0.189)	(0.185)	(0.191)	(0.189)
Four-year college		0.567***	0.583***	0.560***	0.571***	0.570***
		(0.186)	(0.187)	(0.183)	(0.188)	(0.187)
Postgraduate		0.985***	1.005***	1.005***	0.973***	0.996***
		(0.184)	(0.186)	(0.180)	(0.188)	(0.187)
Risk tolerance			0.246***			0.172*
			(0.094)			(0.100)
Competitiveness				0.273***		0.223**
				(0.092)		(0.098)
Low confidence					-0.133	-0.134
					(0.099)	(0.098)
High confidence					-0.094	-0.121
					(0.111)	(0.110)
Year 2019	7.843***	7.114***	6.956***	6.740***	7.123***	6.714***
	(0.068)	(1.115)	(1.114)	(1.109)	(1.110)	(1.104)
Year 2020	7.736***	7.007***	6.849***	6.633***	7.016***	6.607***
	(0.068)	(1.116)	(1.114)	(1.109)	(1.110)	(1.104)
Observations	1,590	1,590	1,590	1,590	1,590	1,590

Notes: See notes to Table 2A.

Table 4B - Test for equality of Black/Hispanic differentials across models in the female sample

	Model II vs. III (including Risk Tolerance)		Model II vs. IV (including Competitiveness)		Model II vs. V (including Relative Performance)		Model II vs. VI (including all three traits)	
	% change (1)	*p*-value (2)	% change (3)	*p*-value (4)	% change (5)	*p*-value (6)	% change (7)	*p*-value (8)
Black	26.67	0.2638	40.00	0.1585	0.00	0.9733	40.00	0.4320
Hispanic	64.29	0.1452	57.14	0.198	21.43	0.5138	107.14	0.0799

Notes: See notes to Table 2B.

5. Conclusion

We measure competitiveness, risk tolerance, and confidence in relative performance among a stratified sample of Black men, Black women, Hispanic men, Hispanic women, White men, and White women in the US. Conditional on sample weights, each stratum is nationally representative in terms of age, years of education, region, and the 2016 presidential vote. The data reveal substantial differences across race/ethnicity and gender in the three traits. Further, the traits are shown to predict individual income, and help explain income gaps. Specifically, competitiveness and risk tolerance help explain the gender income gap among Whites. Confidence in relative performance helps explain a significant share of all five REG income gaps relative to White men.

Our findings have implications for behavioral/experimental research in economics and, more broadly, the social sciences. On the one hand, our study contributes to a growing literature showing the importance of studying psychological traits – a topic of special interest for many behavioral and experimental social scientists – as these traits help predict important real-world outcomes (e.g., Dohmen et al. 2011, Buser et al. 2014, Buser et al. 2017, Buser et al. 2021, Reuben et al. 2017, Falk et al. 2018, Sutter et al. 2013). Also, we show that gender differences in competitiveness, risk tolerance, and confidence in relative performance observed in (predominantly) White samples, extend without a single exception to U.S. Blacks and Hispanics. On the other hand, the substantial variation in traits observed across race/ethnicity indicates the importance of sampling diverse populations for behavioral/experimental studies. Our data also indicate that, in the absence of such diversity, we should avoid generalizations across races/ethnicities. Although scholars have previously identified the need to avoid generalizations across different countries (Henrich et al. 2010, Rad et al. 2018), our findings show that similar caution should be exercised when drawing inferences from distinct subgroups within a country.

Our results will also be of interest to researchers exploring the source of disparities in life outcomes across Blacks, Hispanics, and Whites in the U.S. The finding that competitiveness, risk tolerance, and confidence in relative performance all predict income and help explain a substantial part of the unexplained income gaps across race/ethnicity and gender highlights the importance of collecting measures of psychological traits. Traits such as those studied here can help understand other disparities in life outcomes across race/ethnicity (Barsky et al. 1997, Borghans et al. 2008, Dohmen et al. 2011, Heckman et al. 2006, Buser et al. 2014, Buser et al. 2017, Buser et al. 2021, Reuben et al. 2017, Falk et al. 2018, Sutter et al. 2013). For instance, Blacks and Whites in the U.S. differ not only in terms of income, but also in terms of education, employment, health outcomes, risky behavior, home ownership, and entrepreneurship (Black et al. 2006, Bound & Freeman 1992, Boustan & Margo 2016, Collins & Margo 2011, LaFree et al. 2010, Mora & Davila 2014, Neal & Johnson 1996, Ritter & Taylor 2011). Future research should explore the extent to which disparities in psychological traits can account for these differences. Finally, our study is silent about the origins of these disparities. This would be a topic for future work.

References

Advani, A., Ash, E., Cai, D., & Rasul, I. (2021). Race-related research in economics and other social sciences. CEPR Discussion Paper No. DP16115. SSRN. https://ssrn.com/abstract=3846227

Almås, I., Cappelen, A. W., & Tungodden, B. (2020). Cutthroat capitalism versus cuddly socialism: Are Americans more meritocratic and efficiency-seeking than Scandinavians? *Journal of Political Economy, 128*(5), 1753–1788. https://doi.org/10.1086/705551

Almås, I., Cappelen, A. W., Sørensen, E. Ø., & Tungodden, B. (2022). Global evidence on the selfish rich inequality hypothesis. *Proceedings of the National Academy of Sciences, 119*(3), Article e2109690119.

Barsky, R. B., Juster, F. T., Kimball, M. S., & Shapiro, M. D. (1997). Preference parameters and behavioral heterogeneity: An experimental approach in the Health and Retirement Study. *The Quarterly Journal of Economics, 112*(2), 537–579. https://doi.org/10.1162/003355397555280

Bayer, P., & Charles, K. K. (2018). Divergent paths: A new perspective on earnings differences between Black and White men since 1940. *The Quarterly Journal of Economics, 133*(3), 1459–1501. https://doi.org/10.1093/qje/qjy003

Benjamin, D. J., Choi, J. J., & Strickland, A. J. (2010). Social identity and preferences. *American Economic Review, 100*(4), 1913–1928. https://doi.org/10.1257/aer.100.4.1913

Black, D., Haviland, A., Sanders, S., & Taylor, L. (2006). Why do minority men earn less? A study of wage differentials among the highly educated. *Review of Economics and Statistics, 88*(2), 300–313. https://doi.org/10.1162/rest.88.2.300

Blau, F. D., & Kahn, L. M. (2017). The gender wage gap: Extent, trends, and explanations. *Journal of Economic Literature, 55*(3), 789–865. https://doi.org/10.1257/jel.20160995

Bokern, P., Linde, J., Riedl, A., Schmeets, H., & Werner, P. (2023). The convergent and external validity of risk preference elicitation methods: Controlling for Measurement Error in a Large Population Sample. Netspar Discussion Paper # 08/2023-038.

Bollinger, C. R. (1998). Measurement error in the Current Population Survey: a nonparametric look. *Journal of Labor Economics, 16*(3), 576–594. https://doi.org/10.1086/209899

Bönte, W., Lombardo, S., & Urbig, D. (2017). Economics meets psychology: Experimental and self-reported measures of individual competitiveness. *Personality and Individual Differences, 116*, 179–185. https://doi.org/10.1016/j.paid.2017.04.036

Borghans, L., Duckworth, A. L., Heckman, J., & Weel, B. (2008). The economics and psychology of personality traits. *Journal of Human Resources, 43*(4), 972–1059. https://doi.org/10.3368/jhr.43.4.972

Bound, J., & Freeman, R. B. (1992). What went wrong? The erosion of relative earnings and employment among young black men in the 1980s. *The Quarterly Journal of Economics, 107*(1), 201–232. https://doi.org/10.2307/2118327

Bound, J., & Krueger, A. B. (1991). The extent of measurement error in longitudinal earnings data: Do two wrongs make a right? *Journal of Labor Economics, 9*(1), 1-24. https://doi.org/10.1086/298256

Bound, J., Brown, C., Duncan, G. J., & Rodgers, W. L. (1994). Evidence on the validity of cross-sectional and longitudinal labor market data. *Journal of Labor Economics, 12*(3), 345–368. https://doi.org/10.1086/298348

Boustan, L. P., & Margo, R. A. (2016). Racial differences in health in the United States: A long-run perspective. In J. Komlos & I. R. Kelly (Eds.), *The Oxford Handbook of Economics and Human Biology* (pp. 730–750). New York: Oxford University Press.

Buser, T., Niederle, M., & Oosterbeek, H. (2014). Gender, competitiveness, and career choices. *The Quarterly Journal of Economics, 129*(3), 1409–1447. https://doi.org/10.1093/qje/qju009

Buser, T., Niederle, M., & Oosterbeek, H. (2021). Can competitiveness predict education and labor market outcomes? Evidence from incentivized choice and survey measures (Working Paper No. 28916). National Bureau of Economic Research. http://www.nber.org/papers/w28916

Buser, T., Peter, N., & Wolter, S. C. (2017). Gender, competitiveness, and study choices in high school: Evidence from Switzerland. *American Economic Review, 107*(5), 125–130. https://doi.org/10.1257/aer.p20171017

Charness, G., Garcia, T., Offerman, T., & Villeval, M. C. (2020). Do measures of risk attitude in the laboratory predict behavior under risk in and outside of the laboratory? *Journal of Risk and Uncertainty, 60*, 99–123. https://doi.org/10.1007/s11166-020-09325-6

Chetty, R., Hendren, N., Jones, M. R., & Porter, S. R. (2019). Race and economic opportunity in the United States: An intergenerational perspective. *The Quarterly Journal of Economics, 135*(2), 711–783. https://doi.org/10.1093/qje/qjz042

Collins, W. J., & Margo, R. A. (2011). Race and home ownership from the end of the Civil War to the present. *American Economic Review, 101*(3), 355–359. https://doi.org/10.1257/aer.101.3.355

Croson, R., & Gneezy, U. (2009). Gender differences in preferences. *Journal of Economic Literature, 47*(2), 448–474. https://doi.org/10.1257/jel.47.2.448

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., & Wagner, G. G. (2011). Individual risk attitudes: Measurement, determinants, and behavioral consequences. *Journal of the European Economic Association, 9*(3), 522–550. https://doi.org/10.1111/j.1542-4774.2011.01015.x

Duncan, G. J., & Hill, D. H. (1985). An investigation of the extent and consequences of measurement error in labor-economic survey data. *Journal of Labor Economics, 3*(4), 508–532. https://doi.org/10.1086/298067

Eckel, C. C., & Grossman, P. J. (2008). Men, women and risk aversion: Experimental evidence. In *Handbook of Experimental Economics Results* (pp. 1061–1073). https://doi.org/10.1016/s1574-0722(07)00113-8

Falk, A., Becker, A., Dohmen, T., Enke, B., Huffman, D., & Sunde, U. (2018). Global evidence on economic preferences. *The Quarterly Journal of Economics, 133*(4), 1645–1692. https://doi.org/10.1093/qje/qjy013

Fallucchi, F., Nosenzo, D., & Reuben, E. (2020). Measuring preferences for competition with experimentally validated survey questions. *Journal of Economic Behavior and Organization, 178*, 402–423. https://doi.org/10.1016/j.jebo.2020.07.028

Goldin, Claudia. 2014. A grand gender convergence: Its last chapter." *American Economic Review*, 104 (4): 1091-1119. https://doi.org/10.1257/aer.104.4.1091

Hauge, K. E., Kotsadam, A., & Riege, A. (2023). Culture and gender differences in willingness to compete. *The Economic Journal, 133*(654), 2403–2426. https://doi.org/10.1093/ej/uead033

Heckman, J. J., Stixrud, J., & Urzua, S. (2006). The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. *Journal of Labor Economics, 24*(3), 411–482. https://doi.org/10.1086/504455

Henrich, J., Heine, S. J., & Norenzayan, A. (2010). The weirdest people in the world? *Behavioral and Brain Sciences, 33*(2–3), 61–83. https://doi.org/10.1017/s0140525x0999152x

Hvidberg, K. B., Kreiner, C., & Stantcheva, S. (2023). Social positions and fairness views on inequality. *Review of Economic Studies*. https://doi.org/10.1093/restud/rdad019

Kahneman, D. (2011). *Thinking, fast and slow*. Macmillan.

Karadja, M., Mollerstrom, J., & Seim, D. (2017). Richer (and holier) than thou? The effect of relative income improvements on demand for redistribution. *Review of Economics and Statistics, 99*(2), 201–212. https://doi.org/10.1162/rest_a_00623

Klinowski, D., & Niederle, M. (2023). Female empowerment and female competitiveness. Work in progress.

LaFree, G., Baumer, E. P., & O'Brien, R. (2010). Still separate and unequal? A city-level analysis of the black-white gap in homicide arrests since 1960. *American Sociological Review, 75*(1), 75–100. https://doi.org/10.1177/0003122409357045

Lang, K., & Lehmann, J.-Y. K. (2012). Racial discrimination in the labor market: Theory and empirics. *Journal of Economic Literature, 50*(4), 959–1006. https://doi.org/10.1257/jel.50.4.959

Lang, K., & Spitzer, A. K. (2020). Race discrimination: An economic perspective. *Journal of Economic Perspectives, 34*(2), 68–89. https://doi.org/10.1257/jep.34.2.68

Mincer, J. A. (1974). *Schooling, experience, and earnings*. National Bureau of Economic Research, New York, N.Y.

Moore, D.A., & Healy, P.J., (2008). The trouble with overconfidence. *Psychological Science, 115*(2), 502–517.

Mora, M. T., & Dávila, A. (2014). Gender and business outcomes of Black and Hispanic new entrepreneurs in the United States. *American Economic Review, 104*(5), 245–249. https://doi.org/10.1257/aer.104.5.245

Oaxaca, Ronald 1973. Male-Female Wage Differentials in Urban Labor Markets. *International Economic Review,* 14(3), 693-709. https://doi.org/10.2307/2525981

Neal, D. A., & Johnson, W. R. (1996). The role of premarket factors in black-white wage differences. *Journal of Political Economy, 104*(5), 869–895. https://doi.org/10.1086/262045

Nicholls, N. (2022). Race, gender and willingness to compete. *Economics Letters, 213*, 110382. https://doi.org/10.1016/j.econlet.2022.110382

Niederle, M. (2017). Gender. In *The Handbook of Experimental Economics, Volume 2* (pp. 481-562). Princeton, NJ: Princeton University Press. https://doi.org/10.1515/9781400883172-009

Niederle, M., & Vesterlund, L. (2007). Do women shy away from competition? Do men compete too much? *The Quarterly Journal of Economics, 122*(3), 1067–1101. https://doi.org/10.1162/qjec.122.3.1067

Paul, M., Zaw, K., & Darity, W. (2022). Returns in the labor market: A nuanced view of penalties at the intersection of race and gender. *Feminist Economics, 28*(2), 1–31. https://doi.org/10.1080/13545701.2022.2042472

Pedroni, A., Frey, R., Bruhin, A., Dutilh, G., Hertwig, R., & Rieskamp, J. (2017). The risk elicitation puzzle. *Nature Human Behaviour, 1*(11), 803–809. https://doi.org/10.1038/s41562-017-0219-x

Pischke, J. S. (1995). Measurement error and earnings dynamics: Some estimates from the PSID Validation Study. *Journal of Business & Economic Statistics, 13*(3), 305–314. https://doi.org/10.1080/07350015.1995.10524604

Pollet, T. V., & Saxton, T. K. (2019). How diverse are the samples used in the journals 'Evolution & Human Behavior' and 'Evolutionary Psychology'? *Evolutionary Psychological Science, 5*(3), 357–368. https://doi.org/10.1007/s40806-019-00192-2

Rad, M. S., Martingano, A. J., & Ginges, J. (2018). Toward a psychology of Homo sapiens: Making psychological science more representative of the human population. *Proceedings of the National Academy of Sciences, 115*(45), 11401–11405. https://doi.org/10.1073/pnas.1721165115

Reuben, E., Sapienza, P., & Zingales, L. (In press). Taste for competition and the gender gap among young business professionals. *Journal of Finance*.

Reuben, E., Wiswall, M., & Zafar, B. (2017). Preferences and biases in educational choices and labour market expectations: Shrinking the black box of gender. *The Economic Journal, 127*(604), 2153–2186. https://doi.org/10.1111/ecoj.12350

Ritter, J. A., & Taylor, L. J. (2011). Racial disparity in unemployment. *The Review of Economics and Statistics, 93*(1), 30–42. https://doi.org/10.1162/REST_a_00063

Sanborn, H. (1964). Pay differences between men and women. *Industrial and Labor Relations Review*, *17*(4), 534–550. https://doi.org/10.1177/001979396401700402

Santos-Pinto, L., & de la Rosa, L. E. (2020). Overconfidence in labor markets. In *Handbook of Labor, Human Resources and Population Economics* (pp. 1–42). Springer. https://doi.org/10.1007/978-3-319-57365-6_117-1

Sutter, M., Kocher, M. G., Glätzle-Rützler, D., & Trautmann, S. T. (2013). Impatience and uncertainty: Experimental decisions predict adolescents' field behavior. *American Economic Review, 103*(1), 510–531. https://doi.org/10.1257/aer.103.1.510

APPENDIX

A. Income regressions for full sample when monthly income is up to $25,000

	I	II	III	IV	V	VI
Black women	-0.439***	-0.359***	-0.354***	-0.350***	-0.309***	-0.296***
	(0.097)	(0.095)	(0.094)	(0.095)	(0.096)	(0.095)
Hispanic women	-0.352***	-0.231**	-0.225**	-0.217**	-0.200**	-0.184*
	(0.097)	(0.095)	(0.095)	(0.095)	(0.096)	(0.095)
White women	-0.320***	-0.362***	-0.346***	-0.334***	-0.327***	-0.293***
	(0.092)	(0.088)	(0.088)	(0.088)	(0.089)	(0.088)
Black men	-0.372***	-0.270***	-0.282***	-0.291***	-0.223**	-0.246**
	(0.106)	(0.099)	(0.098)	(0.099)	(0.101)	(0.100)
Hispanic men	-0.252**	-0.091	-0.099	-0.101	-0.058	-0.069
	(0.112)	(0.107)	(0.106)	(0.107)	(0.105)	(0.104)
Age		0.166	0.169	0.237	0.206	0.268
		(0.396)	(0.394)	(0.394)	(0.393)	(0.390)
Age^2/1000		-0.105	-0.102	-0.175	-0.153	-0.208
		(0.477)	(0.475)	(0.475)	(0.473)	(0.470)
High school		0.330*	0.335*	0.343**	0.294*	0.306*
		(0.172)	(0.173)	(0.172)	(0.172)	(0.172)
Some college		0.514***	0.519***	0.534***	0.471***	0.488***
		(0.182)	(0.182)	(0.181)	(0.181)	(0.180)
Two-year college		0.400**	0.406**	0.418**	0.355**	0.371**
		(0.170)	(0.170)	(0.169)	(0.171)	(0.170)
Four-year college		0.646***	0.654***	0.653***	0.604***	0.612***
		(0.168)	(0.168)	(0.167)	(0.169)	(0.168)
Postgraduate		1.010***	1.019***	1.027***	0.958***	0.974***
		(0.170)	(0.170)	(0.169)	(0.171)	(0.170)
Risk tolerance			0.205***			0.131
			(0.076)			(0.080)
Competitiveness				0.251***		0.213***
				(0.075)		(0.077)
Low Confidence					-0.184**	-0.185**
					(0.073)	(0.072)
High Confidence					-0.225***	-0.235***
					(0.078)	(0.078)
Year 2019	8.287***	7.271***	7.080***	6.882***	7.328***	6.882***
	(0.061)	(0.826)	(0.824)	(0.824)	(0.821)	(0.818)
Year 2020	8.165***	7.149***	6.959***	6.761***	7.207***	6.761***
	-0.439***	-0.359***	-0.354***	-0.350***	-0.309***	-0.296***
Observations	3550	3550	3550	3550	3550	3550

Notes: See notes to Table 2A. Dependent variable: Ln Income 2019 & 2020 (monthly income of $25,000 or lower).

Test for equality of REG differentials after adding psychological variables

	Model II vs. III (including Risk Tolerance)		Model II vs. IV (including Competitiveness)		Model II vs. V (including Relative Confidence)		Model II vs. VI (including all three traits)	
	% change (1)	*p*-value (2)	% change (3)	*p*-value (4)	% change (5)	*p*-value (6)	% change (7)	*p*-value (8)
Black women	-1.39	0.5107	-2.51	0.2988	-13.93	0.0068	-17.55	0.0026
Hispanic women	-2.60	0.4985	-6.06	0.1740	-13.42	0.0270	-20.35	0.0057
White women	-4.42	0.0763	-7.73	0.0287	-9.67	0.0404	-19.06	0.0015
Black men	4.44	0.1353	7.78	0.0269	-17.41	0.0170	-8.89	0.3024
Hispanic men	8.79	0.4926	10.99	0.3858	-36.26	0.0407	-24.18	0.2207

Notes: See notes to Table 2B. Dependent variable: Ln Income 2019 & 2020 (monthly income of $25,000 or lower).

B. Income regressions for full sample adding incentivized measures of competitiveness/risk

	I	II	III	IV	V	VI
Black women	-0.543***	-0.455***	-0.443***	-0.443***	-0.403***	-0.380***
	(0.096)	(0.093)	(0.093)	(0.093)	(0.094)	(0.094)
Hispanic women	-0.493***	-0.366***	-0.356***	-0.354***	-0.337***	-0.320***
	(0.094)	(0.091)	(0.090)	(0.090)	(0.091)	(0.089)
White women	-0.408***	-0.461***	-0.435***	-0.436***	-0.428***	-0.390***
	(0.090)	(0.085)	(0.086)	(0.085)	(0.086)	(0.086)
Black men	-0.515***	-0.408***	-0.418***	-0.428***	-0.359***	-0.380***
	(0.098)	(0.088)	(0.087)	(0.088)	(0.088)	(0.087)
Hispanic men	-0.354***	-0.182*	-0.184*	-0.190*	-0.148	-0.150
	(0.104)	(0.099)	(0.098)	(0.099)	(0.097)	(0.097)
Age		0.409	0.416	0.481	0.443	0.510
		(0.364)	(0.363)	(0.362)	(0.362)	(0.359)
Age^2/1000		-0.388	-0.390	-0.458	-0.429	-0.492
		(0.437)	(0.435)	(0.435)	(0.434)	(0.431)
High school		0.382***	0.389***	0.395***	0.351**	0.361**
		(0.147)	(0.147)	(0.146)	(0.147)	(0.146)
Some college		0.496***	0.504***	0.516***	0.460***	0.477***
		(0.154)	(0.155)	(0.153)	(0.155)	(0.154)
Two-year college		0.476***	0.482***	0.496***	0.434***	0.451***
		(0.146)	(0.146)	(0.145)	(0.147)	(0.146)
Four-year college		0.778***	0.790***	0.787***	0.739***	0.751***
		(0.144)	(0.145)	(0.143)	(0.145)	(0.144)
Postgraduate		1.107***	1.108***	1.124***	1.057***	1.065***
		(0.145)	(0.147)	(0.144)	(0.147)	(0.147)
Risk tolerance†			0.225***			0.157**
			(0.073)			(0.077)
Competitiveness†				0.260***		0.221***
				(0.070)		(0.073)
Incentivized risk†			0.069			0.062
			(0.058)			(0.057)
Incentivized competitiveness†				-0.019		-0.050
				(0.057)		(0.057)
Low Confidence					-0.167**	-0.167**
					(0.067)	(0.066)
High Confidence					-0.221***	-0.232***
					(0.073)	(0.072)
Year 2019	8.253***	6.671***	6.412***	6.282***	6.733***	6.239***
	(0.061)	(0.764)	(0.762)	(0.759)	(0.760)	(0.754)
Year 2020	8.143***	6.561***	6.302***	6.172***	6.623***	6.129***
	(0.061)	(0.764)	(0.762)	(0.759)	(0.760)	(0.754)
Observations	3296	3296	3296	3296	3296	3296

Notes: See notes to Table 2A. † Indicates (median-split) dummy variables for risk tolerance and competitiveness.

Test for equality of REG differentials after adding psychological variables

	Model II vs. III (including Risk Tolerance)		Model II vs. IV (including Competitiveness)		Model II vs. V (including Relative Confidence)		Model II vs. VI (including all three traits)	
	% change (1)	*p*-value (2)	% change (3)	*p*-value (4)	% change (5)	*p*-value (6)	% change (7)	*p*-value (8)
Black women	-2.64	0.2534	-2.64	0.2490	-11.43	0.0047	-16.48	0.0010
Hispanic women	-2.73	0.4227	-3.28	0.2867	-7.92	0.0355	-12.57	0.0169
White women	-5.64	0.0763	-5.42	0.0287	-7.16	0.0404	-15.40	0.0015
Black men	2.45	0.1353	4.90	0.0269	-12.01	0.0170	-6.86	0.3024
Hispanic men	1.10	0.4926	4.40	0.3858	-18.68	0.0407	-17.58	0.2207

Notes: See notes to Table 2B. Results show effect of adding both incentivized and survey measure.

C. Income regressions for the Black sample

	I	II	III	IV	V	VI
Female	-0.029	-0.054	-0.034	-0.033	-0.045	-0.017
	(0.107)	(0.100)	(0.099)	(0.101)	(0.100)	(0.100)
Age		-0.017	-0.017	-0.010	-0.012	-0.008
		(0.065)	(0.065)	(0.064)	(0.064)	(0.064)
Age^2/1000		0.360	0.368	0.285	0.294	0.260
		(0.777)	(0.772)	(0.769)	(0.770)	(0.757)
High school		0.736***	0.757***	0.743***	0.710***	0.731***
		(0.200)	(0.200)	(0.199)	(0.198)	(0.198)
Some college		0.759***	0.774***	0.772***	0.734***	0.751***
		(0.214)	(0.215)	(0.214)	(0.211)	(0.212)
Two-year college		0.920***	0.940***	0.929***	0.875***	0.897***
		(0.198)	(0.198)	(0.197)	(0.196)	(0.195)
Four-year college		1.205***	1.212***	1.209***	1.155***	1.162***
		(0.199)	(0.199)	(0.199)	(0.199)	(0.199)
Postgraduate		1.358***	1.379***	1.367***	1.313***	1.335***
		(0.197)	(0.198)	(0.196)	(0.199)	(0.201)
Risk tolerance			0.210			0.174
			(0.133)			(0.150)
Competitiveness				0.168		0.094
				(0.129)		(0.143)
Underconfidence					-0.254*	-0.254*
					(0.132)	(0.131)
Overconfidence					-0.292**	-0.298**
					(0.123)	(0.122)
Year 2019	7.730***	6.992***	6.764***	6.672***	7.138***	6.777***
	(0.077)	(1.313)	(1.327)	(1.304)	(1.324)	(1.323)
Year 2020	7.637***	6.899***	6.671***	6.579***	7.045***	6.684***
	(0.080)	(1.316)	(1.330)	(1.307)	(1.327)	(1.326)
Observations	543	543	543	543	543	543

Notes: Notes: See notes to Table 2A.

Test for equality of female differential after adding psychological variables.

	Model II vs. III (including Risk Tolerance)		Model II vs. IV (including Competitiveness)		Model II vs. V (including Relative Performance)		Model II vs. VI (including all three traits)	
	% change (1)	*p*-value (2)	% change (3)	*p*-value (4)	% change (5)	*p*-value (6)	% change (7)	*p*-value (8)
Female	-37.04	0.1704	-38.89	0.2180	16.67	0.5935	-68.52	0.1195

Notes: See notes to Table 2B.

D. Income regressions for the Hispanic sample

	I	II	III	IV	V	VI
Female	-0.140	-0.154	-0.147	-0.129	-0.169	-0.142
	(0.111)	(0.105)	(0.105)	(0.105)	(0.104)	(0.104)
Age		-0.027	-0.027	-0.027	-0.027	-0.026
		(0.072)	(0.072)	(0.072)	(0.072)	(0.072)
Age^2/1000		0.323	0.333	0.340	0.328	0.350
		(0.884)	(0.886)	(0.889)	(0.879)	(0.884)
High school		0.091	0.089	0.116	0.046	0.063
		(0.230)	(0.231)	(0.229)	(0.230)	(0.230)
Some college		0.260	0.272	0.306	0.215	0.261
		(0.270)	(0.268)	(0.265)	(0.271)	(0.265)
Two-year college		0.165	0.168	0.181	0.115	0.124
		(0.235)	(0.236)	(0.234)	(0.237)	(0.236)
Four-year college		0.576**	0.565**	0.573**	0.535**	0.519**
		(0.232)	(0.233)	(0.232)	(0.233)	(0.232)
Postgraduate		0.993***	1.014***	1.040***	0.933***	0.982***
		(0.230)	(0.229)	(0.234)	(0.236)	(0.239)
Risk tolerance			0.156			0.077
			(0.143)			(0.141)
Competitiveness				0.283*		0.297**
				(0.148)		(0.147)
Underconfidence					-0.100	-0.124
					(0.123)	(0.121)
Overconfidence					-0.210	-0.251*
					(0.136)	(0.135)
Year 2019	7.921***	8.247***	8.118***	7.942***	8.377***	8.016***
	(0.088)	(1.495)	(1.491)	(1.499)	(1.478)	(1.480)
Year 2020	7.761***	8.088***	7.959***	7.782***	8.217***	7.856***
	(0.085)	(1.495)	(1.490)	(1.499)	(1.477)	(1.480)
Observations	516	516	516	516	516	516

Notes: See notes to Table 2A.

Test for equality of female differential after adding psychological variables.

	Model II vs. III (including Risk Tolerance)		Model II vs. IV (including Competitiveness)		Model II vs. V (including Relative Performance)		Model II vs. VI (including all three traits)	
	% change (1)	*p*-value (2)	% change (3)	*p*-value (4)	% change (5)	*p*-value (6)	% change (7)	*p*-value (8)
Female	-4.55	0.4763	-16.23	0.1627	9.74	0.5199	-7.79	0.6733

Notes: See notes to Table 2B.

E. Income regressions for the White sample

	I	II	III	IV	V	VI
Female	-0.409***	-0.464***	-0.439***	-0.433***	-0.437***	-0.398***
	(0.090)	(0.084)	(0.085)	(0.084)	(0.086)	(0.086)
Age		0.177***	0.176***	0.187***	0.180***	0.187***
		(0.055)	(0.055)	(0.055)	(0.055)	(0.054)
Age^2/1000		-1.977***	-1.963***	-2.090***	-2.022***	-2.089***
		(0.660)	(0.651)	(0.659)	(0.651)	(0.646)
High school		0.365	0.350	0.375	0.327	0.322
		(0.281)	(0.282)	(0.273)	(0.280)	(0.276)
Some college		0.444	0.435	0.456*	0.401	0.403
		(0.282)	(0.283)	(0.273)	(0.281)	(0.277)
Two-year college		0.301	0.275	0.343	0.258	0.270
		(0.284)	(0.284)	(0.276)	(0.283)	(0.278)
Four-year college		0.637**	0.654**	0.657**	0.594**	0.620**
		(0.274)	(0.278)	(0.266)	(0.275)	(0.273)
Postgraduate		1.019***	1.004***	1.033***	0.963***	0.962***
		(0.277)	(0.278)	(0.267)	(0.278)	(0.273)
Risk tolerance			0.308***			0.240**
			(0.103)			(0.109)
Competitiveness				0.296***		0.221**
				(0.097)		(0.101)
Underconfidence					-0.136	-0.117
					(0.096)	(0.094)
Overconfidence					-0.174	-0.172
					(0.119)	(0.118)
Year 2019	8.241***	3.978***	3.745***	3.475***	4.023***	3.464***
	(0.061)	(1.140)	(1.132)	(1.142)	(1.133)	(1.130)
Year 2020	8.158***	3.896***	3.663***	3.392***	3.941***	3.382***
	(0.063)	(1.137)	(1.128)	(1.139)	(1.130)	(1.126)
Observations	589	589	589	589	589	589

Notes: See notes to Table 2A.

Test for equality of female differential after adding psychological variables.

	Model II vs. III (including Risk Tolerance)		Model II vs. IV (including Competitiveness)		Model II vs. V (including Relative Performance)		Model II vs. VI (including all three traits)	
	% change (1)	*p*-value (2)	% change (3)	*p*-value (4)	% change (5)	*p*-value (6)	% change (7)	*p*-value (8)
Female	-5.39	0.0901	-6.68	0.0517	-5.82	0.1979	-14.22	0.0186

Notes: See notes to Table 2B.