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Economic Preferences and Personality Traits Among Finance Professionals and the General Population

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Abstract

Since the financial crisis, the behavior and personality traits of finance professionals have come under scrutiny. As comprehensive scientific findings are lacking, we run artefactual field experiments with finance professionals and a sample of the working population to investigate differences across industry-relevant economic preferences and personality traits. We report that finance professionals are more risk tolerant, more selfish, less trustworthy, and show higher levels of narcissism, psychopathy, and Machiavellianism. However, we find that many of these differences disappear after adjusting for socio-economic characteristics, indicating that finance professionals are similar to employees in other industries with a comparable socio-economic background.

JEL: C93, G11, G41.
Keywords: Experimental finance, economic preferences, personality traits, finance professionals, general working population.

1. Introduction

The finance industry is one of the biggest industries worldwide[1] and bears systemic relevance and risk for the economy in general (Acharya et al., 2016). Its main protagonists—finance professionals—shape the finance industry with their personality traits, economic preferences, and behavioral biases. In recent years, finance professionals have come under close scrutiny. Especially after the financial crisis of 2008 and subsequent scandals, such as the *Libor* manipulation, the public reputation of finance professionals took a nose dive. Many times the resulting public debate and negative press coverage have drawn an undifferentiated picture of finance professionals as being a greedy and dishonest cohort, substantially different from other occupational groups.[2] This debate about the "banking culture" has also gained scientific attention. For instance, Cohn et al. (2014) report that finance professionals are more likely to behave dishonestly in their professional identity than in their private identity. Moreover, some studies show that finance professionals care more about social comparison and competition than other subject pools (Kirchler et al., 2018, 2020).

Most studies on finance professionals' behavior only focus on one particular behavioral bias or a single economic preference dimension (see, e.g., Glaser et al., 2005; Haigh and List, 2005; Alevy et al., 2007; Gilad and Kliger, 2008; Kaustia et al., 2008; Cohn et al., 2014; Pikulina et al., 2017; Kirchler et al., 2018; Huber et al., 2019; Holzmeister et al., 2020b). These studies usually do not account for socio-economic background characteristics of finance professionals that could potentially drive much of the variation between finance professionals and other subject pools like students or the general population. Thus, although several studies investigate certain behavioral and personality-related aspects characterizing finance professionals, an answer to the question whether and in which regards finance professionals differ from people employed in other sectors is missing in the literature.

With our study, we try to narrow this research gap and shed light on the economic preferences and personal characteristics of a sample of finance professionals by comparing a selection of industry-relevant economic preferences and personality traits of finance professionals with those of a randomly selected sample of the general working population (henceforth also referred to as "general population sample"). We contribute to the literature by providing a comprehensive picture of a multitude of characteristics to gain insights along which dimensions finance professionals differ from people employed in other industries.

In particular, we conducted artefactual field experiments, eliciting participants' risk preferences, distributional preferences, trustworthiness, dishonesty, and various personality traits. In total, 298 financial analysts, investment advisors, traders, fund-managers, and financial brokers, and 395 participants from a randomly selected sample of the Swedish working population, excluding finance professionals, participated in our study. Comparing preferences and personality traits

[1] For instance, the share of the financial services industry of the gross domestic product in the United States was approximately 20% in 2019 (Bureau of Economic Analysis, https://bit.ly/39c9rHW; retrieved November 25, 2020).

[2] See, for instance, the self-critique of the chief executive officer of *JP Morgan*, Jamie Dimon, on the critical role of the finance industry before and during the financial crisis (https://cbsn.ws/3okzG3j; retrieved December 1, 2020).

between the two subject pools allows inferring whether finance professionals differ from a sample of the general working population, and whether the negative picture frequently sketched by the media is actually justifiable. Importantly, we additionally adjust the differences between subject pools for the variation in socio-economic background characteristics like gender, age, income, and education from the Swedish registry provided by *Statistiska centralbyrån* (SCB; Statistics Sweden).[3]

A multifaceted line of research has demonstrated that preference relations and personal traits tend to be systematically correlated with various demographic and socio-economic characteristics (see, e.g., Croson and Gneezy, 2009; Algan and Cahuc, 2010; Niederle and Vesterlund, 2011; Falk et al., 2018). Considering that the groups of finance professionals and the general working population are likely to differ systematically in the socio-economic variables (e.g., due to self-selection into the industry), not adjusting for this potential source of heterogeneity may induce an omitted variable bias in estimating effects between subject pools: Differences in preferences and traits may be spuriously attributed to the variation in a subject pool indicator, although (part of) the variation may actually be due to the systematic heterogeneity in socio-economic characteristics. By adjusting the differences between subject pools for the variability in potentially relevant socio-economic drivers, we can infer whether differences between the subject pools actually persist over and beyond the variation explained by participants' socio-economic background.

In order to examine preferences and personality traits that are particularly relevant for financial decision-making, our experiment involved four incentivized tasks. In particular, we set up single choice lists (Eckel and Grossman, 2002) to assess participants' attitudes toward risk, losses, and skewness, and elicited distributional preferences (Kerschbamer, 2015), trustworthiness (Berg et al., 1995), and cheating behavior (Fischbacher and Föllmi-Heusi, 2013). In addition, we analyze individuals' personality traits, measured by means of the *Big-5* personality test by Rammstedt and Oliver (2007), the *Dark Triad* inventory by Jonason and Webster (2010), and the sub-module of the *Work and Family Orientation questionnaire* focusing on competitiveness (Helmreich and Spence, 1978).

We find that the sample of finance professionals, as compared to participants from the general population, is significantly more risk tolerant, more selfish, less trustworthy, more competitive, and shows higher levels of narcissism, psychopathy, and Machiavellianism. These results suggest that finance professionals effectively differ from people employed in other industries—particularly in those characteristics that the general public is keen to pick up to sketch the dark side of the finance industry. This finding is in line with the assumption that the finance industry—in our case proxied by financial analysts, investment advisors, traders, fund-managers, and financial brokers—is indeed different to other industries. However, this argument leaves aside

[3] Sweden has also not been without scandals in the financial sector. For example, in 2020, one of the biggest banks, Swedbank, was found guilty and had to pay 4 billion SEK for money laundering in their Baltic subsidiaries. It was argued that the bank most likely suspected it but did not take appropriate actions (https://www.reuters.com/article/us-europe-moneylaundering-swedbank-idUSKBN2163LU; retrieved April 09, 2021). In 2010, one of the largest Swedish bank crashes ever happened when HQ Bank was liquidated after it was found out that they were severely manipulating the values in the trading book in order to hide losses. (https://en.wikipedia.org/wiki/HQ_Bank; retrieved April 09, 2021).

that finance professionals also differ from the general working population along several socio-economic dimensions.

A substantial part of the differences between finance professionals and the general population can be explained by the variation in participants' socio-economic characteristics. In particular, we observe that after adjusting the differences between subject pools for gender, age, income, and educational background, finance professionals tend to be only slightly more risk tolerant, remain less trustworthy, show a slightly increased level of psychopathy, and are still more competitive than comparable participants from other industries. While several differences entirely disappear when adjusting for socio-demographic characteristics, the effect sizes of those characteristics that remain statistically significant tend to be deflated. Thus, given the number of preferences and traits examined in our study, our results indicate that finance professionals and people employed in other industries with comparable socio-economic background are not that different after all. The behavioral differences between the general working population and finance professionals rest to a certain degree on the fact that finance professionals are predominantly male and more educated than workers in many other industries. These results on the effects of gender and education suggest that selection effects—both on behalf of the finance industry (i.e., in terms of recruitment strategies) and in terms of individuals self-selecting into the sector—can be of potential importance.

With our study, we add to the emerging literature addressing finance professionals' behavior and personal characteristics and how they potentially differ from those of other subject pools.[4] We also add to the related strand of literature investigating the "banking culture" that, for instance, focuses on cheating behavior (Cohn et al., 2014; Rahwan et al., 2019; Huber and Huber, 2020), social comparison and competition (Kirchler et al., 2018, 2020), and trustworthiness of people entering the finance industry (Gill et al., 2020). We contribute to these strands of research with a battery of economic preferences and personality traits, which results in a broader picture of finance professionals' behavior. Moreover, we shed light on the importance of adjusting for socio-economic background variables when comparing professionals' behavior to that of other subject pools: Apparently, the general implications of our paper would be different, if we would not have taken into account the variation in participants' socio-economic characteristics. It is noteworthy that a limited set of standard socio-economic characteristics substantially diminishes differences between subject pools.

2. Experimental Procedure

We conducted an online experiment in Sweden in cooperation with Statistics Sweden (*SCB*), who invited participants and provided a set of predefined variables from the registry for those participants who completed the experiment. The hard-copy invitations were distributed to a subset of highly skilled finance professionals and a random sample of Sweden's general working population (excluding finance professionals). In particular, invitations were sent out to all

[4] See, among others, Glaser et al. (2005) Haigh and List (2005), Alevy et al. (2007), Gilad and Kliger (2008), Kaustia et al. (2008), Pikulina et al. (2017), Holzmeister et al. (2020b), Weitzel et al. (2020).

(and only) finance professionals with *SCB*'s job code classifications "2413" (financial analysts and advisers), "2414" (traders and fund managers), and "3311" (financial brokers). While the average age of both subject pools is almost identical (FP = 41.0, GP = 41.2), the fraction of females (FP = 24.5%, GP = 41.0%), the annual gross income (in Swedish Krona, SEK) (FP = 711,268, GP = 396,878), and the fraction of participants without a university degree (FP = 8.1%, GP = 28.1%) differ significantly ($p < 0.001$ for all three comparisons) between the two samples and reveal first industry-specific peculiarities of the finance sector. Further details and additional information on the recruitment, data collection, and experimental implementation are provided in Appendix A.

Once participants logged in to the software (programmed in *oTree*; Chen et al., 2016) using a personal identifier, they were presented with a detailed outline of the experiment and could continue once they provided informed consent. The experiment consisted of four parts which were presented to each participant in random order. At the end of the experiment, one of the parts was randomly selected for payout. Details of the experimental tasks, treatment variations, and payments are described in Section 3. For completing the online experiment, participants received a participation fee of 100 Swedish Krona (SEK).[5] The experimental data was collected between January 7 and February 24, 2019. In total, 298 finance professionals and 395 people from the general population, working in other sectors, completed the experiment. The experiment was conducted in Swedish and took on average 15 minutes to complete. The average payment to participants was 211.13 SEK (sd= 51.92), which was approximately $23.50 by the time the experiment ended. To ensure full privacy of the data collected during the experiment, payouts were handled by the third party survey firm *Enkätfabriken*.

In addition to the data collected in the online experiment, we obtained register data from *SCB* for each participant who completed the experiment. In the analysis of the experimental results, we use part of the registry data as adjustment variables, in particular, participants' gender (binary indicator for female), age (in years), net income from major employment in 2017 (in thousand SEK's), and maximum education level (dichotomous indicators for high school education or less, university education smaller or equal to three years, and university education larger than three years).[6] See Appendix A for further details on the register data.

3. Experiments and Results

We address each of the five parts in our experiment separately. In particular, each subsection briefly motivates our research agenda, provides a concise description of the experimental implementation, relates our contribution to the previous literature, and discusses the main findings related to the particular part of our study. Each of the subsections is accompanied by a separate annex (see Appendices B–E), providing additional details on the experimental design and the definition of measures, descriptive results, as well as supporting and ancillary analyses.

[5] At the time of the experiment, the exchange rate between USD and SEK was about 1:9; the exchange rate between EUR and SEK was about 1:10.5.

[6] Please note that we use only part of the available registry data. The main reasons is that for some of the registry data provided by *SCB* we face substantial restrictions that are discussed in Appendix A.

The figures in the main text show the coefficient estimates of the dummy variable indicating the finance professionals subject pool in the corresponding regression models (which are presented in the accompanying tables). The combination of figures and tables provides an readily accessible overview paired with detailed analyses.

For the sake of interpretability, we report standardized effect sizes whenever suitable. We follow the Open Science Collaboration (2015) and Camerer et al. (2018) and determine standardized correlation coefficients (r_s) and 95% confidence intervals (CIs) for key effects relevant to our research questions—in particular, the effects attributable to differences between the two subject pools.[7] Standardized correlation coefficients allow us to provide a unified measure of the magnitude of an effect, which is independent of the scaling of the dependent variable and the statistical method used to determine the effect. As a rule of thumb, we follow the guidelines proposed by Cohen (1992) and refer to correlation coefficients with thresholds of 0.1, 0.3, and 0.5 as being indicative of small, medium, and large effects, respectively.

In an exploratory analysis, we present correlations between the different preferences and personality traits for the two subject pools in Table F1 in Appendix F. In general, we find qualitatively homogeneous correlation patterns in both subject pools.

3.1. Attitudes towards Risk, Loss, and Skewness

Since risk taking is at the core of financial decision-making (Nosić and Weber, 2010; Weber et al., 2013), the question whether finance professionals differ in their risk preferences from other populations arises naturally. The qualification for the finance profession might require a certain attitude towards risk, and the individual risk appetite might change with specific training and day-to-day experience in making risky decisions. For instance, Ert and Haruvy, 2017 find that with experience in an experimental risk elicitation method, students' choices tend to be closer to risk neutrality, i.e., payoff maximization. Despite the regular exposure to risky decision environments, there is some evidence of higher myopic loss aversion (Haigh and List, 2005) and a more intuitive risky decision-making process (Gilad and Kliger, 2008) among finance professionals as compared to student participants. Moreover, existing evidence indicates that professionals' behavior can be explained by prospect theory (Gurevich et al., 2009; Abdellaoui et al., 2013), and that professionals—similar to laypeople—perceive risk as the likelihood of incurring losses rather than symmetric deviations from the expected return (Holzmeister et al., 2020b). Since a mere focus on "risk-as-variance" might fall short of contributing to a better understanding of finance professionals' behavior in "risky" decision environments, we address attitudes towards a broad spectrum of characteristics that are intimately related to the concept of risk. We ask the following research question: Is there a the difference in tolerance towards volatility, skewness, and losses between finance professionals and people from the general working population?

[7] We calculate standardized correlation coefficients per degree of freedom. For z-statistics, the standardized correlation coefficient r_s is given by $r_s = \tanh(z \cdot (n-3)^{-0.5})$; for $t(df)$-statistics, $r_s = (t^2 \cdot (t^2 + df)^{-1})^{0.5}$ is applied. The 95% confidence intervals around r_s are determined by $r_s \pm \tan(\arctan^{-1}(r_s) - \Phi^{-1}(0.975) \cdot (n-3)^{-0.5})$, where $\Phi^{-1}(\cdot)$ denotes the inverse cumulative standard normal distribution function.

Method. To answer this research question, we implemented a series of four single choice lists, based on Eckel and Grossman (2002). In particular, we varied the lotteries' prospective payoffs in such a way, that a single characteristic of the gambles was systematically varied while holding the other characteristics constant. In each of these four tasks, participants were presented with a menu of six lotteries, and were asked to indicate which of the prospects they prefer. In all four tasks, the lotteries were decreasing in the risk-adjusted expected return. To assess participants' attitudes towards risk, skewness, and losses, we varied two characteristics of the gambles—the skewness of lottery outcomes and the possibility to incur losses—using a factorial design.

Table 1: Parametrization of the four tasks used to elicit participants' attitudes towards risk, losses, and skewness. S_i and L_i are indicator functions for skewness and losses, respectively; e.g., S_1L_0 indicates the task with skewed lottery outcomes in the gain domain. x_1, x_2, and x_3 indicate the potential lottery outcomes in SEK. EV, SD, and SK denote the lotteries' expected value, standard deviation, and skewness, respectively.

Task S_0L_0

x_1	x_2			
50%	50%	EV	SD	SK
96.0	96.0	96.0	0.0	
80.0	128.0	104.0	24.0	0.0
64.0	160.0	112.0	48.0	0.0
48.0	192.0	120.0	72.0	0.0
32.0	224.0	128.0	96.0	0.0
16.0	240.0	128.0	112.0	0.0

Task S_1L_0

x_1	x_2	x_3			
50%	49%	1%	EV	SD	SK
96.0	96.0	96.0	96.0	0.0	
82.1	123.9	223.0	104.0	24.0	1.1
68.2	151.8	350.1	112.0	48.0	1.1
54.2	179.8	477.1	120.0	72.0	1.1
40.3	207.7	604.2	128.0	96.0	1.1
26.4	220.4	684.0	128.0	111.5	1.1

Task S_0L_1

x_1	x_2			
50%	50%	EV	SD	SK
16.0	16.0	16.0	0.0	
0.0	48.0	24.0	24.0	0.0
−16.0	80.0	32.0	48.0	0.0
−32.0	112.0	40.0	72.0	0.0
−48.0	144.0	48.0	96.0	0.0
−64.0	160.0	48.0	112.0	0.0

Task S_1L_1

x_1	x_2	x_3			
50%	49%	1%	EV	SD	SK
16.0	16.0	16.0	16.0	0.0	
2.1	43.9	143.0	24.0	24.0	1.1
−11.8	71.8	270.1	32.0	48.0	1.1
−25.8	99.8	397.1	40.0	72.0	1.1
−39.7	127.7	524.2	48.0	96.0	1.1
−53.6	140.4	604.0	48.0	111.5	1.1

For the sake of denotation, we introduce the indicator functions S_i and L_i for skewness and losses, respectively. The parametrization of the four tasks is shown in Table 1. While the lottery outcomes in the tasks S_0L_* were symmetric, the outcomes were positively skewed in the tasks S_1L_* (without altering their standard deviation). In the tasks S_*L_0, the minimum outcome was strictly positive, whereas a constant was subtracted from all payoffs in the tasks S_*L_1 (i.e., the prospects' standard deviation and skewness were unaffected). While a participant's lottery choice in S_0L_0, which only involves symmetric gambles in the non-negative domain, serves as a proxy of the decision-maker's risk tolerance, the other preference types are characterized by the difference in the lottery choices between tasks. For instance, $S_0L_1 - S_0L_0$ captures the difference in choice behavior between the tasks S_0L_1 and S_0L_0 which is attributable to loss tolerance; likewise, $S_1L_0 - S0_L0$ accounts for the difference in choice behavior attributable to attitudes towards skewness.[8] Further details regarding the implementation, as well as descriptive and supplementary results are provided in Appendix B.

Results. Panel (a) of Figure 1 depicts the cumulative distributions of choices attributed to risk, skewness, and loss tolerance, separated for finance professionals (FP) and the general population (GP), respectively. While we report that finance professionals, on average, are significantly more risk tolerant than participants from the general population, we do not find evidence of systematic differences between the two samples in terms of attitudes towards skewness or losses (see the test statistics of Kolmogorov-Smirnov (KS) tests in panel (a) of Figure 1).

Turning to panels (b) and (c) of Figure 1, these effects can be examined in more detail: Panel (b) shows the differences in the average lottery choices between finance professionals and the general population sample for each of the four tasks eliciting attitudes towards risk, skewness, and losses. The coefficients represent the dichotomous variable indicating differences between the finance professionals subject pool and the general population estimated using ordinary least squares regressions summarized in Table 2.

We find that the coefficient estimates of the dummy variable indicating the finance professionals sample turns out being significantly positive in each of the four tasks, in both models not including and models including adjustment variables. While the significant coefficient for task S_0L_0 immediately points towards a systematic difference in risk preferences (in the absence of skewness and losses), the coefficients for the tasks S_0L_1, S_1L_0, and S_1L_1 only indicate that finance professionals, on average, are also systematically more willing to take risk in decision environments that involve skewed payouts and/or potential losses.

To isolate differences in choice behavior attributable to skewness and loss tolerance between the subject pools, we illustrate the effect of the subject pool indicator variable on the differences in risky choices between tasks in panel (c) (see also the full regression results in panel (b) in Table 2). In contrast to contributions by Haigh and List (2005) and Abdellaoui et al. (2013), we do not find evidence for systematic differences in participants' loss tolerance between subject pools, neither in decision environments without skewed outcomes ($S_0L_1 - S_0L_0$) nor in decision environments with skewed outcomes ($S_1L_1 - S_1L_0$). Likewise, we do not find evidence for differences in skewness tolerance between subject pools if the lottery payoffs are non-negative ($S_1L_0 - S_0L_0$). If the decision situation involves the possibility to incur losses, however, our data suggests that finance professionals are more skewness tolerant than laypeople, but the effect size is small ($r_s = 0.079$, 95% CI = $[0.005, 0.155]$).

As indicated, Table 2 also reports the main results including adjustments for participants' socio-economic characteristics, showing a significant difference in risk tolerance (S_0L_0) between males and females. Comparable but smaller effects are also found in the tasks S_0L_1 and S_1L0; for the task S_1L_1, the gender effect is not significantly different from zero. Notably, we do not find any evidence for a gender effect in attitudes towards losses or skewness (see panel (b) of

[8] While our focus is on attitudes towards risk, skewness, and losses, the symmetric 2×2 variation across tasks also allows to assess attitudes towards skewness in a mixed domain (including losses) or towards losses given skewed gambles, respectively. However, we will only discuss these two types of attitudes parenthetically.

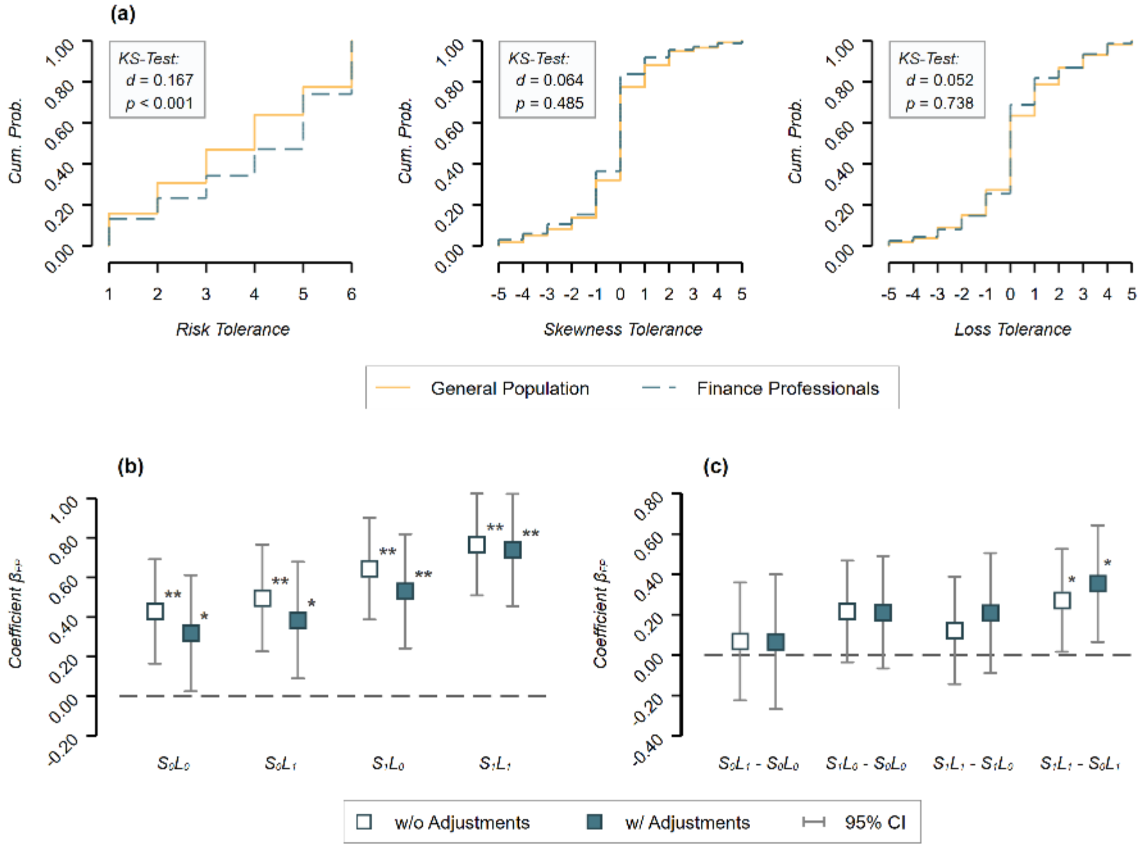

Figure 1: **(a)** Cumulative distributions of risk tolerance (S_0L_0), skewness tolerance ($S_1L_0 - S_0L_0$), and loss tolerance ($S_0L_1 - S_0L_0$), separated for the general population and the finance professionals sample. Kolmogorov-Smirnov (KS) tests are reported in boxes. $n_{GP} = 395$, $n_{FP} = 298$. **(b)** Coefficient plots for the dichotomous variable indicating the finance professionals subject pool in ordinary least squares regressions for each of the four tasks eliciting attitudes towards risk, skewness, and losses. S_i and L_i are indicator functions for skewness and losses, respectively; e.g., S_1L_0 indicates the task with skewed lottery outcomes in the gain domain. **(c)** Differences between coefficient estimates per task, i.e., estimates isolating the effects of attitudes towards losses and towards skewness, respectively. $S_0L_1 - S_0L_0$, for instance, denotes the difference in choice behavior attributable to loss tolerance (in lotteries without skewed outcomes). Hollow markers in panels (b) and (c) show estimates from models without adjustments ($n = 693$); solid markers show estimates from models with adjustment variables ($n = 688$). Error bars indicate 95% confidence intervals based on robust standard errors. The regression estimates are summarized in Table 2. * $p < 0.05$, ** $p < 0.005$.

Table 2). The effects of the other adjustment variables—age, income, and education—turn out to be statistically insignificant for attitudes towards risk, losses, and skewness alike.

Based on the analyses outlined above, we conclude that finance professionals, on average, tend to be systematically less risk averse. While the difference in risk-taking behavior between finance professionals and laypeople is in line with results reported in the literature (see, e.g., Kirchler et al., 2018; Holzmeister et al., 2020a; Kirchler et al., 2020), it should be noted that the magnitude of the effect is rather small in our sample ($r_s = 0.120$, 95% CI $= [0.046, 0.198]$). Adjusting the difference in choice behavior between the subject pools for participants' socio-economic characteristics decreases the effect size further ($r_s = 0.081$, 95% CI $= [0.007, 0.157]$). This reduction in magnitude can be partly attributed to a systematic gender effect in risk-taking

Table 2: Regression analyses of participants' attitudes towards risk, losses, and skewness. **(a)** Ordinary least squares regressions (organized in rows) of participants' lottery choices in each of the four tasks on an indicator variable for the finance professionals subject pool and socio-economic adjustment variables (gender, age, income, and education). S_i and L_i are indicator functions for skewness and losses, respectively; e.g., S_1L_0 indicates the task with skewed lottery outcomes in the gain domain. **(b)** Estimates of the differences in coefficient estimates between tasks on the same covariates based on seemingly unrelated regressions, i.e., estimates isolating the effects of attitudes towards losses and skewness, respectively. $S_0L_1 - S_0L_0$, for instance, captures the difference in choice behavior attributable to loss tolerance (in lotteries without skewed outcomes). Robust standard errors are provided in parentheses. $n = 693$ in models without adjustments; $n = 688$ in models with adjustments. * $p < 0.05$, ** $p < 0.005$.

(a) Tasks

	Fin. Prof.	*Female*	*Age*	*Income*	*Edu. = 2*	*Edu. = 3*	*Constant*
S_0L_0	0.428**						3.646**
	(0.134)						(0.089)
S_0L_0	0.318*	−0.481**	−0.004	0.071	−0.089	−0.020	3.958**
	(0.149)	(0.147)	(0.006)	(0.092)	(0.184)	(0.194)	(0.789)
S_0L_1	0.496**						3.430**
	(0.137)						(0.091)
S_0L_1	0.384*	−0.403*	−0.004	0.020	−0.039	0.206	3.960**
	(0.150)	(0.150)	(0.006)	(0.091)	(0.193)	(0.199)	(0.777)
S_1L_0	0.644**						3.825**
	(0.131)						(0.087)
S_1L_0	0.530**	−0.310*	−0.010	0.084	−0.136	0.119	4.001**
	(0.147)	(0.140)	(0.006)	(0.086)	(0.172)	(0.180)	(0.746)
S_1L_1	0.767**						3.592**
	(0.131)						(0.087)
S_1L_1	0.738**	−0.211	−0.009	−0.031	−0.079	0.099	4.510**
	(0.144)	(0.143)	(0.006)	(0.086)	(0.182)	(0.194)	(0.754)

(b) Differences

	Fin. Prof.	*Female*	*Age*	*Income*	*Edu. = 2*	*Edu. = 3*	*Constant*
$S_0L_1 - S_0L_0$	0.068						−0.215*
	(0.149)						(0.099)
$S_0L_1 - S_0L_0$	0.066	0.078	0.000	−0.051	0.050	0.226	0.002
	(0.170)	(0.173)	(0.007)	(0.111)	(0.222)	(0.225)	(0.947)
$S_1L_0 - S_0L_0$	0.216						0.180*
	(0.128)						(0.084)
$S_1L_0 - S_0L_0$	0.212	0.171	−0.006	0.013	−0.047	0.139	0.043
	(0.142)	(0.143)	(0.006)	(0.081)	(0.172)	(0.187)	(0.722)
$S_1L_1 - S_1L_0$	0.122						−0.233*
	(0.136)						(0.091)
$S_1L_1 - S_1L_0$	0.208	0.099	0.001	−0.115	0.057	−0.020	0.509
	(0.152)	(0.152)	(0.006)	(0.078)	(0.197)	(0.201)	(0.700)
$S_1L_1 - S_0L_1$	0.271*						0.162
	(0.130)						(0.088)
$S_1L_1 - S_0L_1$	0.354*	0.192	−0.005	−0.051	−0.040	−0.107	0.550
	(0.147)	(0.147)	(0.006)	(0.097)	(0.178)	(0.182)	(0.825)

Notes: Estimates of the regressions are organized in rows, i.e., the row headings indicate the dependent variable and the column headings indicate the covariates in the model. *Fin. Prof.* is a dummy variable taking value 0 for the general population sample, and 1 for finance professionals. *Female* is a dummy variable indicating participants' gender; *Age* is measured in years. *Income* is measured in logs of 1,000 SEK (gross) per year. *Edu. = 2* denotes a dummy variable for university education smaller or equal to three years; *Edu. = 3* indicates a dummy for university education larger than three years.

(see Table 2), which is consistent with existing findings in the literature (see, e.g., Croson and Gneezy, 2009; Charness and Gneezy, 2012). Interestingly, we do not find evidence for gender effects in skewness or loss tolerance (see, e.g., Schmidt and Traub, 2002; Rau, 2014, for findings on the latter). However, when comparing our findings, differences in the definition of loss and skewness tolerance can result in contradictory findings with regards to gender effects (see, e.g., Bouchouicha et al., 2019).

3.2. Distributional Preferences

For a long time, economic theory has assumed that economic decisions are only determined by the decision-maker's self-interest. The study of "social preferences" has become a focal point for a modified view on economic decision-making (see, e.g., Becker, 1974; Rabin, 1993). With regards to the finance industry, there seems to be a common perception of finance professionals being closer to the conceptualization of fully rational and selfish decision-makers. Yet, this view is not always supported by existing evidence on behavioral biases, for instance with regards to overconfidence (Deaves et al., 2010; Pikulina et al., 2017), anchoring (Kaustia et al., 2008), or framing (Roszkowski and Snelbecker, 1990). Moreover, existing experimental evidence suggests that distributional preferences are heterogeneous for various groups within a society (see, e.g., Fisman et al., 2015, 2017), and that economics students value efficiency more than equality compared to students in other fields and non-academics (Fehr et al., 2006). Moreover, there is evidence that studying in economics leads to more selfish (Bauman and Rose, 2011) and more corrupt (Frank and Schulze, 2000) behavior, although Frey and Meier (2003) report a lack of such evidence in their data. Since finance professionals have been trained in economic thinking, these findings might suggest that they are likely to differ from the rest of society in terms of distributional preferences. Furthermore, since finance professionals frequently act as "money doctors" (Gennaioli et al., 2015)—involving decisions about other people's money—distributional preferences can be of utmost importance. For instance, conflicts of interest in financial advise might be mediated by benevolent preferences towards the client, or rather be aggravated by purely selfish preferences (see, e.g., Angelova and Regner, 2013). Thus, we address the following yet unexplored research question: Is there a difference in distributional preferences between finance professionals and people from the general population?

Method. We elicit distributional preferences using the Equality Equivalence Test (EET) introduced by Kerschbamer (2015). The EET consists of two lists with five binary choices each—one in the domain of disadvantageous inequality (x-list) and one in the domain of advantageous inequality (y-list). In both lists, each outcome of the five binary choices specifies a payoff for both the decision-maker and a randomly matched counterpart, and participants are asked to indicate whether they prefer option "Left" or option "Right." For all items in both lists, option "Right" implies an equal payoff distribution, yielding 100 SEK for both participants. Outcomes associated with the option "Left" in the x-list increase from 60 SEK to 140 SEK (in steps of 20 SEK) for the decision-maker, whereas the matched counterpart receives a payment of 160 SEK (disadvantageous inequality). The five prospectus outcomes for the decision-maker in the y-list increase from 60 SEK to 140 SEK, but the counterpart receives a payment of 40 SEK instead (advantageous inequality). Based on a participant's switching points in the menu of binary choices in the two lists, the EET assigns one of nine archetypes of distributional preferences and a two-dimensional index of preference intensity, measured as the decision-makers' willingness-to-pay in case the second player is ahead or behind, respectively. The parametrization used in the experiment is summarized in Table 3. Details about the implementation of the task, the derivation of measures to characterize participants' distributional concerns, as well as descriptive and supplementary results are provided in Appendix C.

Table 3: Parametrization of the Equality Equivalence Test (EET). The table shows the monetary payoffs (in SEK) for the "active" player (m, for "me") and the "inactive" player (o, for "other") for the two choices "Left" and "Right," for both the x-list (disadvantageous inequality) and the y-list (advantageous inequality).

x-list

"Left"			*"Right"*	
m	o		m	o
60	160	○ ○	100	100
80	160	○ ○	100	100
100	160	○ ○	100	100
120	160	○ ○	100	100
140	160	○ ○	100	100

y-list

"Left"			*"Right"*	
m	o		m	o
60	40	○ ○	100	100
80	40	○ ○	100	100
100	40	○ ○	100	100
120	40	○ ○	100	100
140	40	○ ○	100	100

Results. Panel (a) of Figure 2 shows the fractions of distributional preference types based on the EET, separated for the general population and the finance professionals sample. On the one hand, we find that the share of participants whose behavior can be characterized as selfish is higher among finance professionals as compared to the general population (FP = 36.6%, GP = 26.8%; $r_s = 0.104$, 95% CI = $[0.030, 0.181]$; $p = 0.006$). On the other hand, the proportion of inequality averse types is lower among finance professionals (FP = 10.1%, GP = 17.5%; $r_s = 0.105$, 95% CI = $[0.030, 0.182]$; $p = 0.006$). We do not find evidence for systematic differences in the share of maximin (FP = 30.9%, GP = 27.6%; $r_s = 0.036$, 95% CI = $[-0.039, 0.111]$; $p = 0.347$) and purely altruistic types (FP = 15.4%, GP = 13.2%; $r_s = 0.032$, 95% CI = $[-0.042, 0.107]$; $p = 0.396$) between the two subject pools. With regards to more "exotic" archetypes, the shares of participants exhibiting equality aversion (FP = 2.0%, GP = 5.1%; $r_s = 0.079$, 95% CI = $[0.005, 0.155]$; $p = 0.036$) and kick-down preferences (FP = 0.7%, GP = 2.8%; $r_s = 0.077$, 95% CI = $[0.003, 0.153]$; $p = 0.042$) tend to be higher among the general population.

Above and beyond the delineation of distributional preference types, the EET allows characterizing the observed choice behavior in terms of participants' willingness-to-pay for an increase or decrease of the counterpart's material payoff in the domain of disadvantageous (wtp^d) and advantageous inequality (wtp^a), respectively. As such, wtp^d (wtp^a) can be interpreted as the monetary amount a decision-maker is willing to give up in order to increase (if $wtp > 0$) or decrease (if $wtp < 0$) the other player's payoff by one unit in the domain of disadvantageous (advantageous) inequality.

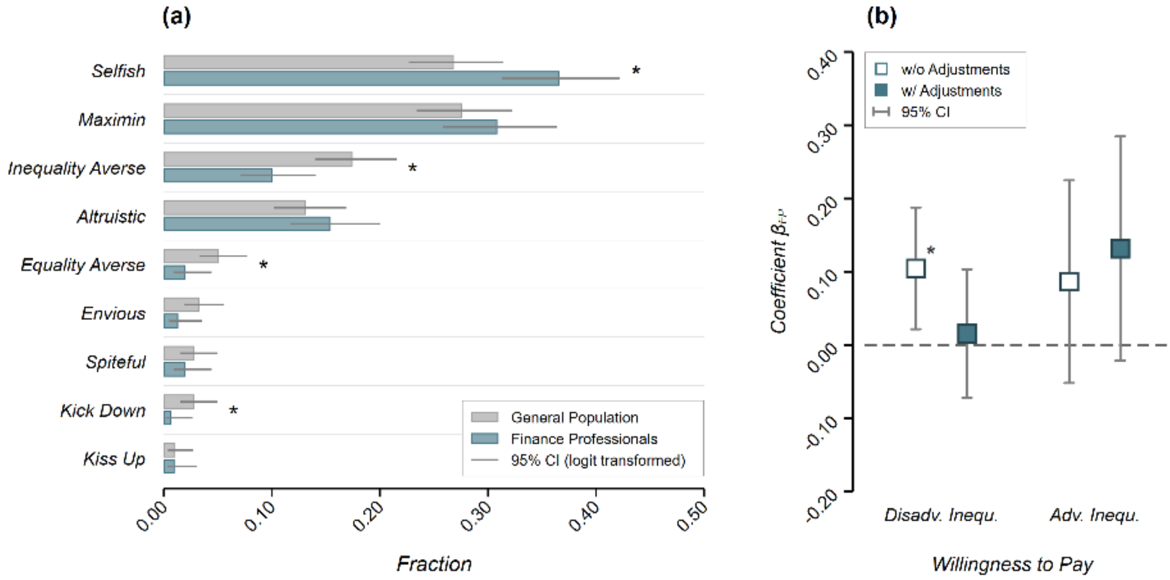

Figure 2: **(a)** Fractions of distributional preference archetypes based on the Equality Equivalence Test (EET). Error bars indicate logit-transformed 95% confidence intervals; significance indicators are based on two-sample tests of proportion. $n_{GP} = 395$, $n_{FP} = 298$. **(b)** Coefficient plots for the dichotomous variable indicating the finance professionals subject pool in interval regressions for participants' willingness-to-pay in the domain of disadvantageous and advantageous inequality, respectively. Hollow markers show estimates from models without adjustments ($n = 693$); solid markers show estimates from models with adjustment variables ($n = 688$). Error bars indicate 95% confidence intervals based on robust standard errors. The regression estimates are provided in Table 4. * $p < 0.05$, ** $p < 0.005$.

Panel (b) of Figure 2 shows the coefficient estimates for the dichotomous variable indicating finance professionals in interval regressions for participants' willingness-to-pay in the domain of disadvantageous and advantageous inequality (as reported in Table 4). With regards to the domain of advantageous inequality, we find that both subject pools tend to be benevolent towards their counterpart when they are ahead in terms of material payoffs. We do not find any evidence for differences in participants' willingness-to-pay (wtp^a) between subject pools in this domain of inequality. Turning to participants' willingness-to-pay in the domain of disadvantageous inequality we find that finance professionals tend to have a slightly higher willingness-to-pay (wtp^d) when they are behind in terms of material payoffs as compared to participants from the general population. This mirrors our earlier finding that financial professionals are less inclined to be inequality averse compared to participants from the general population. However, the magnitude of the effect is small ($r_s = 0.093$, $95\%\,\text{CI} = [0.019, 0.170]$; $p = 0.014$) and the difference between subject pools vanishes if the model takes into account the heterogeneity in socio-demographic variables: In particular, the nullification of the effect is attributable to significant effects of gender and income, which is consistent with findings reported in the literature (see, e.g., Kerschbamer and Müller, 2020).

Furthermore, we find a significant negative effect of the gender indicator on participants' willingness-to-pay in the domain of disadvantageous inequality (but not in the domain of advantageous inequality): When behind in terms of monetary payoffs, females, on average, tend to be significantly less benevolent towards the second player—a result that is in line with the findings reported by Kerschbamer and Müller (2020). Moreover, we report a v-shaped effect of participants' income on their distributional preferences: in the domain of disadvantageous inequality, participants tend to be more benevolent given higher levels of income; in the domain of advantageous inequality, participants turn out to be more malevolent with higher income levels, again in line with the results reported by Kerschbamer and Müller (2020). Finally, while Kerschbamer and Müller (2020) report a significantly positive effect of education on benevolence (irrespective of the domain), we only find some anecdotal evidence that benevolence tends to increase with higher educational levels if the decision-maker is ahead in terms of monetary payoffs.

As non-parametric robustness checks, we replicate the analysis based on participants' (x,y)-score, which constitutes an ordinal measure of distributional preferences and their intensities, using ordered logistic regressions (see panel (b) in Table 4). It is reassuring that our results are qualitatively robust to the non-parametric measure.

Table 4: Regression analyses of participants' distributional preferences. **(a)** Interval regressions (organized in rows) of participants' willingness-to-pay in the domain of disadvantageous and advantageous inequality on an indicator variable for the finance professionals subject pool and socio-economic adjustment variables (gender, age, income, and education). **(b)** Ordered logistic regressions (reported in terms of odds ratios and organized in rows) of participants' x- and y-scores (i.e., an ordinal index of distributional preferences in the domain of disadvantageous and advantageous inequality derived from the responses in the Equality Equivalence Test) on the same set of covariates. Robust standard errors are provided in parentheses. $n = 693$ in models without adjustments; $n = 688$ in models with adjustments. * $p < 0.05$, ** $p < 0.005$.

(a) Willingness to Pay

	Fin. Prof.	*Female*	*Age*	*Income*	*Edu. = 2*	*Edu. = 3*	*Constant*
Disadv. Inequ.	0.104*						0.001
	(0.042)						(0.031)
Disadv. Inequ.	0.015	−0.171**	−0.003	0.102**	0.034	0.059	−0.493
	(0.045)	(0.048)	(0.002)	(0.029)	(0.063)	(0.067)	(0.264)
Adv. Inequ.	0.086						0.617**
	(0.071)						(0.051)
Adv. Inequ.	0.131	0.076	0.004	−0.141**	0.238*	0.189	1.331**
	(0.078)	(0.082)	(0.003)	(0.050)	(0.105)	(0.109)	(0.453)

(b) (x, y)-Scores

	Fin. Prof.	*Female*	*Age*	*Income*	*Edu. = 2*	*Edu. = 3*	*Constant*
Disadv. Inequ.	1.403*						0.562**
	(0.196)						(0.060)
Disadv. Inequ.	1.041	0.551**	0.988*	1.369**	1.250	1.373	2.198
	(0.156)	(0.088)	(0.006)	(0.127)	(0.268)	(0.313)	(1.922)
Adv. Inequ.	1.126						0.227**
	(0.159)						(0.029)
Adv. Inequ.	1.271	1.247	1.011	0.736**	1.588*	1.499	0.053**
	(0.199)	(0.212)	(0.007)	(0.079)	(0.352)	(0.344)	(0.051)

Notes: Estimates of the regressions are organized in rows, i.e., the row headings indicate the dependent variable and the column headings indicate the covariates in the model. *Fin. Prof.* is a dummy variable taking value 0 for the general population sample, and 1 for finance professionals. *Female* is a dummy variable indicating participants' gender; *Age* is measured in years. *Income* is measured in logs of 1,000 SEK (gross) per year. *Edu. = 2* denotes a dummy variable for university education smaller or equal to three years; *Edu. = 3* indicates a dummy for university education larger than three years.

3.3. Trust and Trustworthiness

Large sectors of the financial industry build on the foundation of trust (Zingales, 2015). For instance, financial advisory services call for clients' trust in the consultant (Gurun et al., 2018; Burke and Hung, 2019)—not least due to information asymmetries, implying that clients cannot even assess the quality of the advice provided (Dulleck and Kerschbamer, 2006; Balafoutas and Kerschbamer, 2020). Moreover, stock market participation has been shown to be conditional on individuals' trust in the finance sector (Guiso et al., 2008; Balloch et al., 2015; Georgarakos and Pasisi, 2015). While survey evidence indicates at best moderate levels of trust in the financial sector (Sapienza and Zingales, 2012; Holzmeister et al., 2020a), we lack further evidence on prevalent trust in finance professionals, and whether the extent to which finance professionals are trusted is actually "justified." Particularly little is known about the latter, i.e., finance professionals' *trustworthiness*.[9] A recent study by Gill et al. (2020) provides long-term causal evidence on lower levels of trustworthiness among college students who self-select into pursuing a career in the finance industry. The results by Gill et al. (2020) suggest that the industry does not screen out less trustworthy job seekers, implying that those who actually start a career in finance are significantly less trustworthy than those working in other industries. These findings raise serious questions about the trustworthiness of finance professionals compared to the general population, thereby raising the following research question: Is there a difference in trustworthiness between finance professionals and people from the general population?

Method. To examine trust and trustworthiness, we implement a standard investment game (Berg et al., 1995),[10] where participants are assigned to the roles of either the trustor (first mover) or the trustee (second mover). Trustors are endowed with 100 SEK and can forward between 0 SEK and 100 SEK (in steps of 20 SEK) to the trustee, who receives three times the distributed amount. The trustee then decides how much of the tripled amount to return to the first mover (in steps of 20 SEK).

In our setting, finance professionals always were assigned the role of the trustee, whereas participants from the general population were assigned one of the two roles at random: With a probability of two-thirds, they were the first mover, and with a probability of one-third they were the second mover. To examine whether trust differs depending on whether the trustee is a participant from the general population or a finance professional, we assign first movers randomly into both conditions. Since the matching of trustors and trustees was only implemented once all participants have finished the experiment, the second movers were required to decide strategically, i.e., they had to report how much they would return to the first mover conditional on each potentially received amount. We opted for the strategy method because the experiment

[9] For evidence on behavioral differences in trust games between students and other subject pools refer to Fehr and List (e.g., 2004) and Johnson and Mislin (2011).

[10] There has been a discussion of limitations of this investment game as a measure of trust. In particular, confounds, such as altruism (Cox, 2015) and betrayal aversion (Fehr, 2009), might dilute the observed behavior in trust games, while at the same time other aspects of trusting behavior might be neglected (Ben-Ner and Halldorsson, 2010; Ermisch et al., 2009). Since the investment game, arguably, remains the most popular experimental procedure to measure trust among researchers (Johnson and Mislin, 2011), we stick to this standard experiment, while we note cautiousness when it comes to interpreting the observed behavior.

was conducted online, not allowing for direct interaction between both roles. In case the trust game was chosen for payout, the payments for both roles were determined based on the decision of the second mover, which was conditioned on the decision of the randomly matched first mover.

Results. On average, participants from the general population acting as first movers entrust 69.3% ($sd = 30.0\%$; $n = 105$) of their endowment to trustees from the general population and 66.2% ($sd = 31.1\%$; $n = 200$) to trustees from the finance professionals sample. The difference in the amounts sent to the second mover is not statistically significant between the two treatments (two-sample t-test: $t(303) = 0.846$, $p = 0.3980$; $r_s = 0.049$, 95% CI $= [-0.064, 0.163]$).

With regards to the second movers' behavior, we find that finance professionals, on average, tend to be less trustworthy than participants from the general population, as they return systematically less at all amounts sent by the first mover (see panel (a) in Figure 3). In ordinary least squares regressions of the amount returned by trustee for each amount sent by the first mover, we show that the coefficient for the dichotomous variable indicating finance professionals turns out to be significantly negative, even after adjusting for the variation in socio-economic variables (see panel (b) in Figure 3 and the detailed regression results in Table 5). Moreover, with respect to socio-economic adjustment variables, we find indicative evidence on age: on average, older participants tend to be more trustworthy. However, the effects are only statistically significant for amounts of up to 60 SEK sent by first movers.

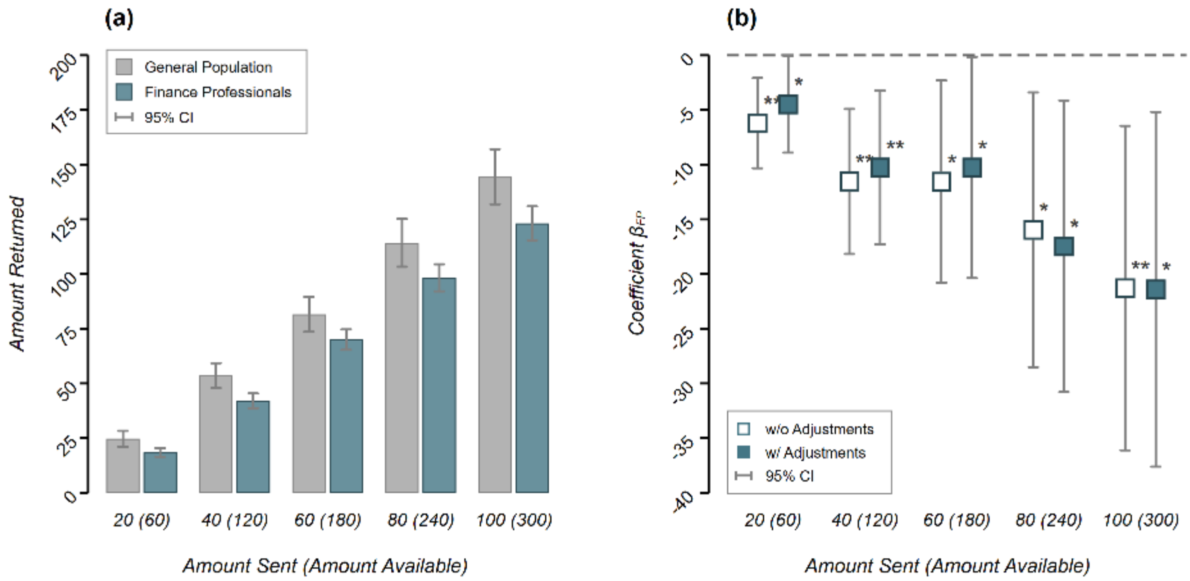

Figure 3: **(a)** Mean amount returned by second movers in the (strategy method) trust game conditional on each possible amount sent by the first mover, separated for the general population and finance professionals samples. **(b)** Coefficient plots for the dichotomous variable indicating the finance professionals subject pool in interval regressions for the amount returned by second movers in the trust game for each amount sent by the first mover (the tripled amount available is indicated in parentheses). Hollow markers show estimates from models without adjustments ($n = 388$); solid markers show estimates from models with adjustment variables ($n = 387$). Error bars indicate 95% confidence intervals based on robust standard errors. The estimates from the regressions are provided in Table 5. * $p < 0.05$, ** $p < 0.005$.

Table 5: Regression analyses of participants' trustworthiness. This table shows the results of ordinary least squares regressions (organized in rows) of the amount returned by the second mover in the strategy method trust game (for each amount sent by the first mover) on an indicator variable for the finance professionals subject pool and socio-economic adjustment variables (gender, age, income, and education). Robust standard errors are provided in parentheses. $n = 693$ in models without adjustments; $n = 688$ in models with adjustments. * $p < 0.05$, ** $p < 0.005$.

	Fin. Prof.	*Female*	*Age*	*Income*	*Edu. = 2*	*Edu. = 3*	*Constant*
Amount returned (20)	−6.210**						24.667**
	(2.100)						(1.839)
Amount returned (20)	−4.484*	4.197*	0.238**	−0.367	−1.962	−2.538	13.146
	(2.250)	(1.855)	(0.078)	(1.329)	(2.737)	(2.856)	(11.955)
Amount returned (40)	−11.542**						53.556**
	(3.369)						(2.885)
Amount returned (40)	−10.265**	5.594	0.411**	−1.746	4.017	3.771	39.959*
	(3.568)	(3.078)	(0.132)	(2.157)	(4.150)	(4.351)	(19.436)
Amount returned (60)	−11.556*						81.556**
	(4.702)						(4.050)
Amount returned (60)	−10.268*	4.797	0.370*	−3.718	1.854	7.279	86.519**
	(5.137)	(4.239)	(0.183)	(2.831)	(6.091)	(6.442)	(26.073)
Amount returned (80)	−15.967*						114.222**
	(6.390)						(5.559)
Amount returned (80)	−17.464*	1.482	0.392	−3.823	9.975	15.681	118.366**
	(6.774)	(5.382)	(0.239)	(3.742)	(8.025)	(8.326)	(34.482)
Amount returned (100)	−21.290**						144.444**
	(7.538)						(6.402)
Amount returned (100)	−21.402*	1.168	0.393	−5.331	4.886	13.646	163.570**
	(8.247)	(6.711)	(0.297)	(4.478)	(9.762)	(10.192)	(40.933)

Notes: Estimates of the regressions are organized in rows, i.e., the row headings indicate the dependent variable and the column headings indicate the covariates in the model. *Fin. Prof.* is a dummy variable taking value 0 for the general population sample, and 1 for finance professionals. *Female* is a dummy variable indicating participants' gender; *Age* is measured in years. *Income* is measured in logs of 1,000 SEK (gross) per year. *Edu. = 2* denotes a dummy variable for university education smaller or equal to three years; *Edu. = 3* indicates a dummy for university education larger than three years.

Thus, our results suggest that finance professional reciprocate trust (measured by the amount sent to them by the first mover) systematically less than participants from the general population. Importantly, this result prevails in comparable magnitude even when controlling for socio-economic background variables. This finding is in line with the results by Gill et al. (2020) and resonates with perceived mistrust towards protagonists of the financial industry that is regularly encountered (Sapienza and Zingales, 2012).

3.4. Dishonesty behavior

The question whether finance professionals tend to behave dishonestly has been widely studied and discussed, arguably not least due to a prevalent perception of misconduct among bank employees (Cohn et al., 2014; Zingales, 2015; Egan et al., 2019; Rahwan et al., 2019; Huber and Huber, 2020). In particular, the finding by Cohn et al. (2014) that finance professionals are more dishonest than others when being experimentally primed with their professional identity gained widespread attention. These results suggest that the culture prevailing in the banking industry leads to more dishonest behavior. More recently, these findings have been questioned

(Rahwan et al., 2019), which has led to a discussion revolving around questions concerning the replicability and the method of priming (see, e.g., Vranka and Houdek, 2015; Cohn et al., 2019). We add to this discussion by asking the following research question: Do finance professionals show a higher or lower tendency to exhibit dishonest behavior compared to people from the general population?

Method. To address this question, we experimentally examine dishonest behavior based on a design similar to Fischbacher and Föllmi-Heusi (2013): Participants throw three simulated dice (see, e.g., Kocher et al., 2018, for an application of the procedure using computer-simulated dice rolls) and report the sum of the observed pips (i.e., between 3 and 18). The participants' payoff is the sum of reported pips, multiplied by a factor of 10 SEK. Thus, participants have a financial incentive to report a higher number of pips than the actual number realized by the three dice. Since the actual outcome of the simulated die rolls is known to the experimenters, the task allows determining a measure of misreporting on the individual level.[11]

Results. We find that 90.6% of the general population and 94.6% of the finance professionals sample report the realized number of pips truthfully. Only 5.5% (*GP*) and 3.7% (*FP*) over-report the number of pips, respectively, whereas comparably small fractions of participants under-report the actual number of pips (3.8% of *GP* and 1.7% of *FP*). The general population sample, on average, reports 0.144 more pips than shown (one-sample t-test: $t(394) = 1.785$, $p = 0.075$; $r_s = 0.090$, $95\%\,\mathrm{CI} = [-0.009, 0.191]$); finance professionals, on average, over-report by 0.104 pips (one-sample t-test: $t(297) = 1.584$, $p = 0.114$; $r_s = 0.092$, $95\%\,\mathrm{CI} = [-0.022, 0.2091]$). Given that participants' reports do not significantly differ from the actual number of pips in both samples, it does not come at a surprise that the difference in misreporting between the two subject pools does not significantly differ from zero (independent samples t-test: $t(691) = 0.369$, $p = 0.712$; $r_s = 0.014$, $95\%\,\mathrm{CI} = [-0.061, 0.089]$).

In general, we find only very little cheating—among both the general population and the finance professionals sample—in our experiment. While there are several results reported in the literature that indicate preferences for truth-telling or costs of dishonesty (see, e.g., Abeler et al., 2014, 2019), the virtual absence of dishonest behavior in our experiment appears to be striking. While we apply a similar procedure using computer-simulated dice rolls as Kocher et al. (2018), we cannot provide a conclusive answer on the absence of dishonest behavior. The modus operandi—i.e., the distribution of invitations by *SCB* as the official statistical office and participants' awareness that register data provided by *SCB* will be matched with the experimental data—might have influenced the overall level of dishonest behavior. More important for our research agenda, however, is that we do not find differences in individual preferences for honesty between finance professionals and the general population in our experiment.

[11] Note, however, that potential observability of dishonest behavior can lead to less dishonest reporting. See, for instance, Abeler et al. (2019).

3.5. Personality Traits

Since the financial profession has been under close scrutiny, personality characteristics of finance professionals have been widely discussed. As personal characteristics are an elusive concept, we confine our research on characteristics typically in focus of public debates: (i) socially undesirable, personality traits (i.e., the "Dark Triad," measuring narcissism, psychopathy, and Machiavellianism), (ii) competitiveness, and (iii) the habitual patterns of personality traits (Zillig et al., 2002) as a whole (i.e., the *Big-5*: openness, conscientiousness, extraversion, agreeableness, and neuroticism). Despite the public interest in the question whether finance professionals differ systematically from people employed in other fields, only few scientific studies address certain aspects of personality characteristics of practitioners in finance. For instance, in two papers Kirchler et al. (2018) and Kirchler et al. (2020) report higher levels of competitiveness among finance professionals compared to students, academics, and the general population, but lower levels compared to professional athletes. Perceived competitiveness has been shown to be related to higher levels of psychopathy (Jonason et al., 2015; Spurk and Hirschi, 2018). The trait of psychopathy is particularly relevant for financial decision-making, since it explains misbehavior in taking risk on behalf of others (Jones, 2014) and gambling with money of somebody else (Jones, 2013). Furthermore, there is evidence on correlations between low neuroticism and high openness (as *Big-5* personality traits) and risk taking (Lauriola and Levin, 2001). Brown and Taylor (2014) report on the correlation between extraversion and openness and the levels of debt and assets held and Bucciol and Zarri (2017) show that agreeableness is negatively associated with stock holdings (see Bucciol and Zarri, 2017, for further evidence on the impact of personality traits beyond the *Big-5*).[12]

Thus, if personality traits of finance professionals systematically differ from the rest of the population, this might well have an influence on decisions made within the finance industry, in particular on behalf of clients. We therefore ask the following research question: Is there a difference in personality traits (i.e., *Big-5*, *Dark Triad*, and competitiveness) between finance professionals and people from the general population?

Method. We elicit the *Big-5* personality traits (openness, conscientiousness, extraversion, agreeableness, and neuroticism) using the validated 10-item inventory introduced by Rammstedt and Oliver (2007). Moreover, we elicit the socially undesirable personality traits of narcissism, psychopathy, and Machiavellianism using the 12-item *Dark Triad* inventory by Jonason and Webster (2010). Finally, we run a 5-item questionnaire on competitiveness, based on the submodule of the *Work and Family Life Orientation* (*WOFO*) questionnaire by Helmreich and Spence (1978). The scores for each trait are z-standardized across the pooled sample, implying a mean of zero and standard deviation of one for all measures of personality characteristics. The survey items, details on the implementation, and a description of how the measures are defined are provided in Appendix E.

[12] For similar findings on stock market participation using the Temperament and Character Inventory *TCI* instead of the Big-5 questionnaire, refer to Conlin et al. (2015).

Results. Figure 4 summarizes the differences in the various personality characteristics between participants from the general population and the finance professionals sample. Moreover, Table 6 reports the main results of ordinary least squares regressions of the various personality traits on a variable indicating the finance professionals sample, as well as the full models including adjustments for participants' socio-economic characteristics. As illustrated in panel (a) of Figure 4, we find that finance professionals tend to score higher on all three socially undesirable traits captured by the *Dark Triad* inventory: narcissism ($r_s = 0.091$, $95\%\,\mathrm{CI} = [0.017, 0.167]$), Machiavellianism ($r_s = 0.106$, $95\%\,\mathrm{CI} = [0.032, 0.183]$), and psychopathy ($r_s = 0.182$, $95\%\,\mathrm{CI} = [0.109, 0.264]$). Importantly, once we adjust the differences between the two subject pools for the variation in socio-economic characteristics, the effect sizes are attenuated: While the effects in narcissism and Machiavellianism scores are virtually set to zero, the difference in psychopathy is reduced by a third, but remains significant ($r_s = 0.122$, $95\%\,\mathrm{CI} = [0.048, 0.200]$).

The mitigation of differences in *Dark Triad* traits that are attributable to the finance profession is partly due to systematic effects of gender and age, which turn out being consistent with findings reported in the literature. In particular, we find that gender explains a significant share of the variation in Machiavellianism and psychopathy, which is partly in line the results reported by Jonason and Davis (2018). Consistent with the results by Barlett and Barlett (2015), we find a significantly negative effect of participants' age on all three dark traits. Moreover, we report a significantly positive effect of income on Machiavellianism (see, e.g., Spurk et al., 2016) and a positive effect of education on Narcissism.

As outlined in panel (b) of Figure 4, we find that finance professionals, on average, tend to be significantly more competitive than participants from the general population. While this effect is in line with previous findings (Kirchler et al., 2018, 2020), the magnitude of the effect is rather small ($r_s = 0.187$, $95\%\,\mathrm{CI} = [0.115, 0.270]$) in our sample, and nearly halved ($r_s = 0.105$, $95\%\,\mathrm{CI} = [0.031, 0.182]$) by significant effects of gender, age, and income (see Table 6 for details). In particular, and in line with previous findings (see, e.g., Niederle and Vesterlund, 2011; Gupta et al., 2013), gender turns out being explanatory for the variation in participants' competitiveness scores. Moreover, we find that older participants and participants with less income, on average, turn out being less competitive.

Finally, as illustrated in panel (c) of Figure 4, we do not find evidence on systematic differences between subject pools in terms of personality traits addressed by the *Big-5* personality test. The only exception is a difference in neuroticism scores, which is of small magnitude ($r_s = 0.098$, $95\%\,\mathrm{CI} = [0.023, 0.174]$) and only to be found in the model not adjusting for socio-economic characteristics. Once we control for participants' socio-economic background, the significant difference between subject pools is deflated due to significant effects of gender, age, and income, which tends to be in line with results reported in the literature (see, e.g., Nyhus and Pons, 2005).

Based on the analyses sketched above, we conclude that there is evidence for some differences between the two subject pools in our experiment. These differences are particularly pronounced before adding adjustment variables, pointing at sample characteristics of finance professionals.

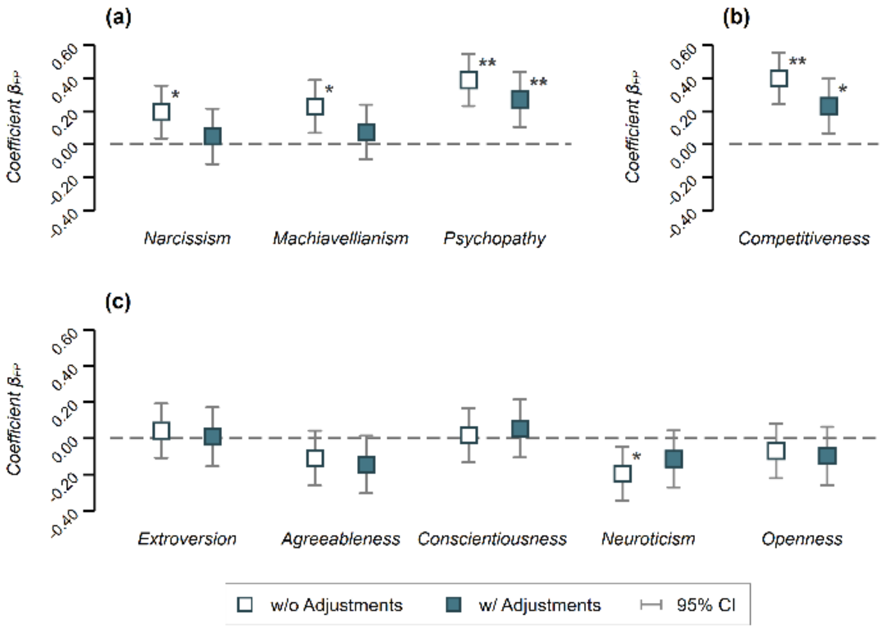

Figure 4: Coefficient plots for the personality traits elicited using **(a)** the *Dark Triad* inventory, **(b)** the competitiveness items from the *Work and Family Orientation questionnaire* (*WOFO*), and **(c)** the *Big-5* inventory. All panels depict estimates for the dichotomous variable indicating the finance professionals subject pool in ordinary least squares regressions. Hollow markers show estimates from models without adjustment variables (n = 693); solid markers show estimates from models with adjustments (n = 688). Error bars indicate 95% confidence intervals based on robust standard errors. The estimates from the regressions are provided in Table 6. * $p < 0.05$, ** $p < 0.005$.

After adjusting for the socio-economic background, we report that finance professionals tend to score higher on the psychopathy scale—a personality trait associated with untruthfulness, selfishness, and being callous (see, e.g., Paulhus and Williams, 2002)—and tend to self-report being more competitive than participants from the general population. These results on competitiveness and psychopathy might emphasize the relevance of the question of a banking culture, as discussed above, and are consistent with a higher propensity of selfish behavior among professionals that we find in our experiment (see Section 3.2).

Table 6: Regression analyses of participants' personality traits. This table shows the results of ordinary least squares regressions (organized in rows) of the standardized scores of **(a)** traits elicited using the *Dark Triad* inventory, **(b)** the competitiveness sub-scale from the *Work and Family Life Orientation* (*WOFO*) survey, and **(c)** traits assessed using the *Big-5* personality test on an indicator variable for the finance professionals subject pool and socio-economic adjustment variables (gender, age, income, and education). Robust standard errors are provided in parentheses. $n = 693$ in models without adjustments; $n = 688$ in models with adjustments. * $p < 0.05$, ** $p < 0.005$.

(a) Dark Triad

	Fin. Prof.	*Female*	*Age*	*Income*	*Edu. = 2*	*Edu. = 3*	*Constant*
Narcisism (std.)	0.195*						−0.084
	(0.081)						(0.053)
Narcisism (std.)	0.047	−0.134	−0.019**	0.106	0.457**	0.361**	−0.266
	(0.086)	(0.086)	(0.004)	(0.055)	(0.112)	(0.116)	(0.471)
Machiavellianism (std.)	0.229**						−0.098
	(0.081)						(0.052)
Machiavellianism (std.)	0.074	−0.310**	−0.019**	0.192**	0.106	−0.041	−0.452
	(0.084)	(0.081)	(0.003)	(0.048)	(0.107)	(0.115)	(0.420)
Psychopathy (std.)	0.389**						−0.167**
	(0.080)						(0.053)
Psychopathy (std.)	0.271**	−0.723**	−0.012**	0.036	−0.029	−0.118	1.114*
	(0.084)	(0.079)	(0.003)	(0.056)	(0.112)	(0.115)	(0.498)

(b) Competitiveness

	Fin. Prof.	*Female*	*Age*	*Income*	*Edu. = 2*	*Edu. = 3*	*Constant*
Competitiveness (std.)	0.399**						−0.172**
	(0.080)						(0.053)
Competitiveness (std.)	0.232*	−0.198*	−0.016**	0.226**	0.086	0.091	−1.132*
	(0.084)	(0.087)	(0.004)	(0.054)	(0.120)	(0.124)	(0.460)

(c) Big Five

	Fin. Prof.	*Female*	*Age*	*Income*	*Edu. = 2*	*Edu. = 3*	*Constant*
Extroversion (std.)	0.042						−0.018
	(0.077)						(0.051)
Extroversion (std.)	0.009	0.226*	0.002	0.130**	0.027	−0.017	−1.483**
	(0.083)	(0.083)	(0.003)	(0.044)	(0.107)	(0.114)	(0.397)
Agreeableness (std.)	−0.110						0.047
	(0.077)						(0.050)
Agreeableness (std.)	−0.145	0.140	0.019**	−0.012	0.098	0.315*	−0.986*
	(0.081)	(0.081)	(0.003)	(0.045)	(0.108)	(0.114)	(0.406)
Conscientiousness (std.)	0.017						−0.007
	(0.076)						(0.052)
Conscientiousness (std.)	0.054	0.175*	0.004	0.026	−0.172	−0.121	−0.517
	(0.081)	(0.083)	(0.003)	(0.048)	(0.104)	(0.111)	(0.444)
Neuroticism (std.)	−0.195*						0.084
	(0.076)						(0.051)
Neuroticism (std.)	−0.114	0.329**	−0.013**	−0.163**	0.187	0.272*	1.328**
	(0.080)	(0.083)	(0.003)	(0.048)	(0.103)	(0.107)	(0.436)
Openness (std.)	−0.070						0.030
	(0.077)						(0.051)
Openness (std.)	−0.098	0.167*	0.000	0.006	0.225*	0.213	−0.422
	(0.082)	(0.082)	(0.003)	(0.048)	(0.109)	(0.111)	(0.414)

Notes: Estimates of the regressions are organized in rows, i.e., the row headings indicate the dependent variable and the column headings indicate the covariates in the model. *Fin. Prof.* is a dummy variable taking value 0 for the general population sample, and 1 for finance professionals. *Female* is a dummy variable indicating participants' gender; *Age* is measured in years. *Income* is measured in logs of 1,000 SEK (gross) per year. *Edu. = 2* denotes a dummy variable for university education smaller or equal to three years; *Edu. = 3* indicates a dummy for university education larger than three years.

4. Conclusion

With our study, we investigated differences in economic preferences and personality traits between a Swedish sample of finance professionals and a sample of the Swedish working population. In an online experiment, we assessed participants' attitudes toward risk, losses, and skewness, and elicited distributional preferences, trustworthiness, honesty, and personality characteristics, including the *Big-5* personality traits, the *Dark Triad*, and competitiveness. The experimental data has been merged with registry data on socio-economic characteristics provided by Statistics Sweden, which allows for adjusting the effects of interest for the variability of background variables.

First, we find that finance professionals are indeed different from the "average working adults" employed in other industries, inasmuch as they are significantly less risk-averse, more selfish, less trustworthy, more competitive, and show higher levels of narcissism, psychopathy, and Machiavellianism. Second, we show that after adjusting for socio-economic background variables, finance professionals are not so different from a sample of the general population employed in other industries sharing a similar background: Finance professionals "only" tend to be slightly less risk averse, less trustworthy, show a slightly increased level of psychopathy, and are more competitive than comparable participants from other industries. All other differences vanish and the magnitude of the effects remaining statistically significant tends to be deflated.

We would like to mention two points for discussion: First, although our analysis accounts for the variation in a number of socio-economic characteristics, our adjustments are still limited (for reasons described in Appendix A). We cannot rule out that including additional variation in participants' socio-economic background would not further diminish the observed differences between finance professionals and the general working population samples. However, it is noteworthy that already a small set of standard socio-economic characteristics entering our analysis as adjustment variables explains a substantial part of the differences between subject pools.

Second, our results provide hints where the differences in preferences and characteristics between finance professionals and the general working population stem from. Existing literature argues for both, selection effects (e.g., Gill et al., 2020) as well as an influence (imprinting) from the industry (e.g., Cohn et al., 2014). Our results show that some of the behavioral differences between the general working population and finance professionals can be attributed to finance professionals being predominantly male and more educated than the general working population. While an influence from the industry culture can also play a role, the findings on the relevance of gender and education suggest that selection effects are potentially important.

Importantly, we would like to note that selection can exist on behalf of the industry (i.e., in terms of recruitment strategies) and on behalf of individuals self-selecting into the sector, both of which are difficult to disentangle. An existing selection effect by the industry can also be caused by a prevailing industry culture, which raises the question about the distinction between selection and imprinting (industry culture norms). For instance, if predominately males/ less trustworthy people/ excessive risk-takers/ etc. self-select into a certain industry, this might still be due to a prevailing industry culture that attracts a certain type of people. For these reasons, we would like to call for caution when interpreting observed selection-effects *as opposed* to industry culture, because the latter can affect (self-)selection into the industry as well. This insight is also relevant when choosing where to set policy measures, because it shows that the selection of finance professionals into the industry might affect the peculiarities and culture of the finance industry, which, in turn, can lead to selection effects. Maybe this is also what Christine Lagarde (president of the European Central Bank) had in mind when she said: “As I have said many times, if it had been Lehman Sisters rather than Lehman Brothers, the world might well look a lot different today.”[13]

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[13] Blog of the International Monetary Fund, available at https://bit.ly/3aDDcAm; retrieved February 2, 2021.

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Appendices

Economic Preferences and Personality Traits
Among Finance Professionals and the General Population

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A. Data Collection and Recruitment

Recruitment. Statistics Sweden (*SCB*) sent out hard copy invitations—including a link to the online experiment and a personalized identifier as login credential—for the anonymous online experiment. *SCB* distributed invitations to 8,215 finance professionals and a randomly selected random sample of 8,215 subjects from Sweden's working population, excluding finance professionals. The sample of finance professionals invited included financial analysts and investment advisors, traders and fund managers, and financial brokers. Following Edin and Fredriksson (2000) and Böhm et al. (2018), we only included people with a declared labor income exceeding the minimum amount that qualifies for the earnings related part of the public pension system. Invitations were sent out in two waves: 20% of the sample were invited in the first week of 2019. The remaining 80% of the sample were invited in the third week of 2019, given that no technical difficulties came up.

The receivers of the invitations logged in to our experiment using a personalized participant code, which was linked to a key only known to *SCB*. After the data collection has been completed, using this key, *SCB* matched the experimental data with the requested register data (which is described in detail below) for the participants who completed the experiment. Our data handling procedures ensured full pseudonymity of all participants. At the very beginning of the online experiment, participants were informed that register data provided by *SCB* will be matched with the data collected in the experiment. Moreover, participants were informed that the study has been approved by the ethical review boards in Gothenburg and at *SCB*. So, participants could agree on the conditions and only then continued with the experiment. Please note that before the experiment reported in this paper, participants were invited to a first, independent experiment. Some participants only completed one of the experiments. For details about the first experiment, see Holzmeister et al. (2020a).

Experimental software. The experimental software including all instructions, treatment variations, and the Swedish translations has been pre-registered at https://osf.io/ykv7e/. English demo versions of the experiment and all treatments are available via http://hea-2019-02-en.herokuapp.com.

Payments. To ensure full privacy of the data collected during the experiment, payouts were handled by the third party survey firm *Enkätfabriken*. Once participants completed the online experiment, they were redirected to the website of *Enkätfabriken*. Participants could log in using the same participant code as in the experiment. For payment purposes, *Enkätfabriken* collected participants' names, email addresses, "personnummer" (personal identity number), and bank account details. The information collected was handled *only* by *Enkätfabriken* and has been used exclusively for sake of ordering the bank remittances.

Registry data. In addition to the data collected in the online experiment, we obtained the following register data from *SCB* for each participant who completed all tasks in the experiment:

- *Demographics*: year born, age, gender, county, municipality, and assembly of residence, marital status, year in marital status, family status, birth country, children living at home age 0–3, 4–6, 7–10, 11–15, 16–17, $\geq$ 18, highest finished education level, education orientation, education group, education county, graduation year, primary source of income, work place municipality and county, work place industry 1990–1992, 1993–2001, 2002–2010, and 2007–2014, occupation 2002–2013 and 2014, net income of own business 1991–2003, 2003–2014, and 2004–2014, capital income, disposable income 1990–2004 and 2004–2014, disposable income of family 1990–2004 and 2004–2014, country of birth, date of immigration.
- *Firm / workplace*: number of employees at firm / workplace, number of men / women at firm / workplace, number of men / women with short / long education at firm / workplace, total salaries paid by firm / workplace.
- *Education*: high school, high school program, high school grades point average, high school graduation year, university, university program, university major, university graduation year.
- *Assets*: net wealth, total debt, bank account, listed equity, fixed income funds, other funds, bonds and other securities, taxable insurances, houses, apartments, holiday homes (data only available from 2007)
- *Military records*: command suitability, non cognitive abilities score, muscle strength, physical capacity for work, length, weight, cognitive scores 1 and 2 in language and logic, one in spatial understanding, and one in technical understanding (only for the male part of our sample).
- *Parents*: adoptive / biological mother / father, occupation mother / father, primary income source mother / father, net income from own business mother / father, net wealth mother / father.

In our paper, we only use part of the available registry data as adjustment variables in our analyses—i.e., participants' gender (binary indicator for female), age (in years), net income from major employment in 2017 (in thousand SEK's), and maximum education level (dichotomous indicators for high school education or less, university education smaller or equal to three years, and university education larger than three years). Please note the following relevant restrictions in the register data obtained: First, data from the military suitability tests are only available for males in our sample. Thus, usage of data from these records would substantially decrease the sample size in our data analysis and, in turn, its generalizability. Second, records of wealth data provided by *SCB* are not available after 2008. Moreover, additional relevant data, such as financial asset holdings or bank account data is not available from *SCB* either.

Response rate analysis and self-selection. Please note that the response rate discussed hereafter refers to both, the experiment reported in this paper as well as the preceding, accompanying experiment reported in Holzmeister et al. (2020a). For the finance professionals group, the response rate analysis shows that men responded to a greater extent than women, and that finance individuals in the age group 45–59 years responded to a slightly lesser extent than other ages. Furthermore, the non-response analysis shows that those with the lowest income responded to a somewhat higher degree compared to the others, and that those with a post-secondary education level of three years or more responded to greater extent than others. In the case of country of birth, the response rate was slightly higher for those born in Sweden compared to other countries. In the finance group there was a certain difference between the different job codes where the response frequency was slightly lower (5%) in the group of traders and portfolio managers (job code “2414”) compared with analysts and advisers (code “2413”) and brokers (code“3311”) (6.4%).

For the general population group, the response rate analysis shows similar patterns regarding gender, i.e., men responded to a greater extent than women. The response rate was lowest among the elderly. Furthermore, the response rate analysis indicates that those with the lowest and highest income responded to a somewhat higher extent compared to other income groups. When it comes to the level of education, those with a post-secondary education of three years or more tend to be over-represented in our sample. In the case of country of birth, the response rate was slightly higher for the ones born in Sweden compared to other countries.

A detailed summary of participants demographics compared to the characteristics of the sample invited is presented in Table A1. In particular, Table A1 reports the number of respondents and non-respondents per category of several socio-demographic characteristics, separated for both samples, as reported by *SCB*. Moreover, we report χ^2-tests comparing whether participants in our samples differ significantly from those who have been invited by *SCB* but did not participate in the experiment. We report self-selection effects in terms of gender, age, country of birth, income, and education for the general population sample, and self-selection effects with respect to gender, age, and education for the finance professionals sample.

Table A1: Sample characteristics by subject pools. This table depicts the number (in %) of respondents (*"Resp."*), i.e., those who participated in our experiment, and non-respondents (*"No Resp."*), i.e., those who were invited but did not participate, for a number of different characteristics, separated for the general population and the finance profession sample. χ^2-tests (with k-1 degrees of freedom) and the corresponding p-values are reported.

	General Population			*Finance Professionals*		
	Resp.	*No Resp.*	χ^2 / p	*Resp.*	*No Resp.*	χ^2 / p
Gender:						
Male	55.35	49.36	9.322	75.30	68.47	10.169
Female	44.65	50.64	(0.002)	24.70	31.53	(0.001)
Age:						
20 – 29 years	11.55	10.28	37.789	11.85	8.73	14.062
30 – 39 years	31.69	23.18	(< 0.001)	31.12	28.79	(0.015)
40 – 49 years	26.62	26.39		28.51	30.04	
50 – 59 years	20.99	26.74		17.27	22.83	
60 – 69 years	9.15	13.41		10.04	8.60	
70 – 79 years	0.00	0.00		1.20	1.00	
Country of Birth:						
Sweden	88.17	82.84	13.248	89.76	88.95	0.311
Abroad	11.83	17.16	(< 0.001)	10.24	11.05	(0.577)
Citizenship:						
Swedish	97.04	95.64	3.132	97.59	96.53	1.604
Foreign	2.96	4.36	(0.077)	2.41	3.47	(0.205)
Marital Status:						
Married	46.90	46.26	2.247	52.21	56.31	4.910
Unmarried	41.41	40.49	(0.523)	40.36	35.46	(0.179)
Divorced	11.27	12.42		7.03	7.79	
Widowed	0.42	0.83		0.40	0.45	
Income:						
< 124,999 SEK	3.24	2.70	25.646	2.01	1.53	2.985
125,000 – 199,999 SEK	5.63	5.79	(< 0.001)	2.41	2.16	(0.560)
200,000 – 279,999 SEK	12.82	15.25		3.01	3.41	
280,000 – 369,999 SEK	24.08	31.16		5.22	6.85	
> 370,000 SEK	54.23	45.11		87.35	86.06	
Education:						
No High School	1.83	8.89	198.587	0.80	1.08	32.058
High School	28.45	46.89	(< 0.001)	7.83	17.06	(< 0.001)
University (< 3 years)	19.86	14.95		11.45	11.32	
University (> 3 years)	49.86	28.61		79.72	69.95	
Unknown, n/a	0.00	0.66		0.20	0.59	

B. Attitudes towards Risk, Loss, and Skewness

Method. We elicit attitudes towards risk, losses, and skewness with four tasks each using a single choice list procedure (Eckel and Grossman, 2002). The experimental implementation of the tasks was based on the ready-to-use *oTree* software module "SCL" by Holzmeister (2017). The parametrization of the four tasks used in our experiment is shown in Table 1 in the main text.

The parametrization of the tasks was inspired by the design choice in Holzmeister et al. (2020b): In a 2×2 factorial design, we varied the lotteries' prospective payoffs in such a way, that a single characteristic of the gambles was systematically varied while holding the other characteristics constant. In the two tasks S_0L_0 and S_1L_0, all lottery payoffs were strictly positive, i.e., all gambles presented to participants were in the gain domain. The two tasks S_0L_1 and S_1L_1 were identical to the other two tasks, but with a constant amount of 80 SEK subtracted from all lottery payoffs. By this means, the expected value of the six prospects was reduced by the same amount while holding the standard deviation as well as the skewness of the gambles constant. For both tasks involving negative lottery outcomes, participants were informed that they receive an extra endowment of 80 SEK to cover potential losses.[14] Taking into account the additional endowment, lotteries S_0L_0 and S_0L_1 as well as lotteries S_1L_0 and S_1L_1 were virtually identical—except for the framing. Thus, differences in the choice behavior between the tasks S_0L_0 and S_1L_0 can be attributed to participants' attitudes towards losses (in symmetric gambles, i.e., in absence of skewness). Likewise, deviations in choices between S_1L_0 and S_1L_1 can be attributed to participants' degree of loss tolerance in skewed gambles.

The tasks S_0L_0 and S_0L_1 involved two possible states of the world (x_1 and x_2)—realized with a probability of 50% each—which implied that the gambles were symmetric (i.e., they involved zero skewness). In the tasks S_1L_0 and S_1L_1, the probability of x_2 was reduced to 49% and a third outcome (x_3) was introduced (occurring with a probability of 1%), which allows modelling positively skewed prospects. In particular, the three lottery outcomes in the two tasks involving skewness were chosen in such a way that the expected values and standard deviations of each prospect mirrored the properties of the symmetric gambles.[15] Thus, by construction of the tasks, differences in choice behavior between S_0L_0 and S_1L_0 can be attributed to participants' degree of skewness tolerance. Likewise, deviations in choices between S_0L_1 and S_1L_1 are attributable to skewness tolerance in lotteries with mixed gambles.

Note that the fifth and sixth lottery in each of the four tasks shared the same expected return but differed in standard deviation. Thus, in terms of participants' utility function curvature, a slightly risk averse (or risk neutral) decision-maker—i.e., participants with a concave utility function—would choose lottery 5 in all four tasks (given skewness and loss neutrality); while a

[14] See Etchart-Vincent and l'Haridon (2011) for evidence that such a procedure with losses covered by an endowment does not lead to systematic differences in observed behavior in experiments.

[15] Note that the standard deviation of the sixth lottery varied marginally between the tasks with positive skewness (sd= 111.5 SEK) and the tasks with zero skewness (sd= 112.0 SEK. This is due to the fact that the lottery outcomes were rounded to one decimal place.

risk seeking (or risk neutral) decision-maker—i.e., participants with a convex utility function—would choose lottery 6 in all four tasks.

In case the experimental part eliciting attitudes towards risk, losses, and skewness was randomly selected for a payment, a participants' final payment was determined in two steps: First, one of the four tasks was picked at random. Then, a second random draw determined the state of nature, i.e., which of the outcomes in the chosen lottery was realized.

Descriptive results. Panel (a) in Table B1 reports the means and standard deviations of the lottery choices in each of the four tasks, separated for the general population and the finance professionals sample. The cumulative distributions of risky choices per task are depicted in Figure B1. Recall that—by construction of the four tasks—a risk neutral decision-maker would opt for lottery 5 or 6. We find that participants from both subject pools, on average, are averse towards risk with mean choices well below 5 in all four tasks (one-sample t-tests for a hypothesized population mean of 5 are statistically significant ($p < 0.005$) for all tasks for both subject pools).

Table B1: Descriptive statistics on attitudes towards risk, losses, and skewness. **(a)** The table shows the means and standard deviations (in parentheses) of the chosen lotteries (1–6) in each of the four tasks, separated for the general population and the finance professionals sample. S_i and L_i are indicator functions for skewness and losses, respectively; e.g., S_1L_0 indicates the task with skewed lottery outcomes in the gain domain. **(b)** The table shows the means and standard deviations (in parentheses) of the differences between the chosen lotteries in pairwise comparisons of the four tasks (−5 to 5), separated for the general population and the finance professionals sample. $S_0L_1 - S_0L_0$, for instance, indicates the difference in choice behavior attributable to participants' attitudes towards losses (in lotteries without skewed outcomes). Negative (positive) values indicate negative (positive) attitudes towards losses/skewness. $n_{GP} = 395$, $n_{FP} = 298$.

(a) Tasks

	GP	*FP*
S_0L_0	3.646	4.074
	(1.764)	(1.739)
S_0L_1	3.430	3.926
	(1.817)	(1.770)
S_1L_0	3.825	4.470
	(1.722)	(1.690)
S_1L_1	3.592	4.359
	(1.733)	(1.682)

(b) Differences

	GP	*FP*
$S_0L_1 - S_0L_0$	−0.215	−0.148
	(1.965)	(1.928)
$S_1L_0 - S_0L_0$	0.180	0.396
	(1.673)	(1.677)
$S_1L_1 - S_1L_0$	−0.233	−0.111
	(1.814)	(1.736)
$S_1L_1 - S_0L_1$	0.162	0.433
	(1.758)	(1.642)

Panel (b) in Table B1 provides summary statistics of the differences in choices between tasks attributable to participants' attitudes towards skewness and losses, respectively. Note that positive (negative) differences can be attributed to a higher (lower) tolerance towards skewness/losses. For the finance professionals sample, one-sample t-tests (for a population mean of zero) indicate that we cannot reject the null hypothesis of loss neutrality, neither in the absence ($S_0L_1 - S_0L_0$: $m = -0.147$, $t(297) = 1.322$, $p = 0.187$; $n = 298$), nor in the presence of skewed lotteries ($S_1L_1 - S_1L_0$: $m = -0.111$, $t(297) = 1.101$, $p = 0.272$; $n = 298$). Participants from the general population sample, on average, tend to be slightly loss averse, in both the absence

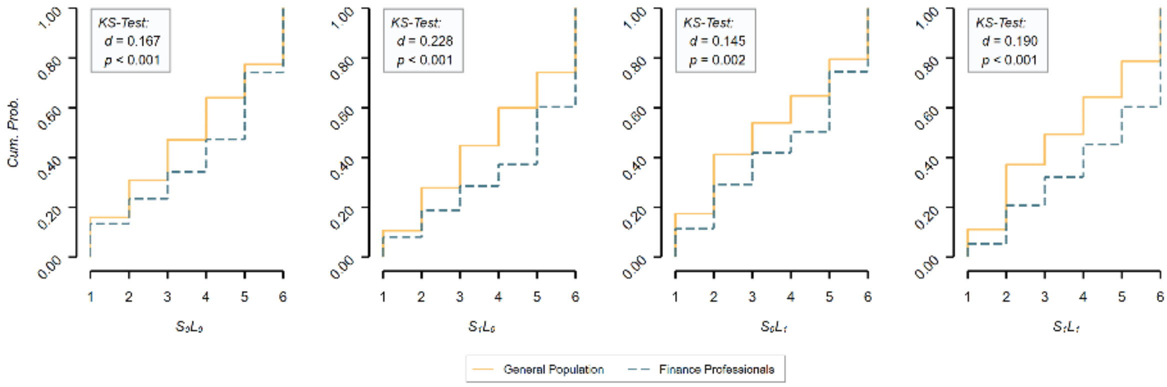

Figure B1: Cumulative distributions of lottery choices in each of the four tasks used to elicit attitudes towards risk, losses, and skewness, separated for the general population and the finance professionals sample. S_i and L_i are indicator functions for skewness and losses, respectively; e.g., S_1L_0 indicates the task with skewed lottery outcomes in the gain domain. Kolmogorov-Smirnov (KS) tests are reported in boxes. $n_{GP} = 395$, $n_{FP} = 298$.

($S_0L_1 - S_0L_0$: $m = -0.215$, $t(394) = 2.177$, $p = 0.030$; $n = 395$) and the presence of skewed gambles ($S_1L_1 - S_1L_0$: $m = -0.233$, $t(394) = 2.552$, $p = 0.011$; $n = 395$).

With respect to skewness attitudes, we report that finance professionals in our sample, on average, show significant positive attitudes towards skewness, irrespective of whether the lotteries are framed in the gain domain ($S_1L_0 - S_0L_0$: $m = 0.396$, $t(297) = 4.076$, $p < 0.001$; $n = 298$) or in terms of mixed gambles involving losses ($S_1L_1 - S_0L_1$: $m = 0.433$, $t(297) = 4.550$, $p < 0.001$; $n = 298$). The general population sample, on average, tends to show positive attitudes towards skewness if the prospects do not involve losses ($S_1L_0 - S_0L_0$: $m = 0.180$, $t(394) = 2.136$, $p = 0.033$; $n = 395$), but tend to be neutral towards skewness if lotteries involve negative outcomes ($S_1L_1 - S_0L_1$: $m = 0.162$, $t(394) = 1.832$, $p = 0.068$; $n = 395$).

C. Distributional Preferences

Method. To elicit participants' distributional preferences, we use the Equality Equivalence Test (EET) introduced by Kerschbamer (2015). In our experiment, the EET was implemented using the ready-made software module for *oTree* by Holzmeister and Kerschbamer (2019). The EET is an experimental procedure to measure and assess individual-level distributional preferences and their intensities based on a multiple choice list format. In particular, the EET requires participants to indicate their preferences in a menu of binary choices, where one of the two alternatives is held constant across the set of decision-making problems. The methodology of the EET stems from a small set of assumptions about the decision-maker's preferences, resulting in a mutually exclusive delineation of different archetypes of distributional concerns (see Kerschbamer, 2015, for details). The parametrization used in the experiment is summarized in Table 3 in the main text. Note that the characterization of preference types and the definition of measures can only be plausibly applied if participants' revealed preferences are transitive and monotone. To avoid multiple switching behavior, the experimental software enforced a single switching point from option "Right" to option "Left" in both lists, as it is frequently applied in risk preference elicitation methods (see, e.g., Holzmeister and Stefan, 2020, for a discussion).

The EET implies a two-player context with two different roles: the role of an "active" player (the decision-maker) and the role of an "inactive" player. In our experiment, all participants from the finance professionals sample were assigned the "active" role and were informed that the randomly matched ("inactive") player is a participant from the general population. All participants from the general population sample completed the task as the "active" player too, but were informed that they will be randomly assigned the "active" or "inactive" role if the task should be selected for payment. Moreover, participants from the general population were randomized into two conditions: participants were assigned an "inactive" player from (i) the general population or from (ii) the finance professionals pool, which they were informed about in the instructions.

In case the EET was chosen for payout, each participant got randomly assigned one "inactive" player—from the finance professionals or the general population sample—once all participants have finished the experiment. For the general population, a second random draw assigned one participant the role of the "active" player, whereas the counterpart was assigned the role of the "inactive" player. Finally, one of the 2×5 binary decisions was drawn at random and constituted the payment for both the "active" and the "inactive" player.

Based on a participant's switching point in the menu of binary decision problems in the two lists, Kerschbamer (2015) introduced an (ordinal) two-dimensional index to characterize both the archetype and the intensity of the decision-maker's distributional concerns, referred to as the (x, y)-score. While the x-score characterizes a participant's distributional preferences in the domain of disadvantageous inequality, the y-score characterizes a participant's preferences in the domain of advantageous inequality. In particular, the x- and the y-score are defined by

$$x = 2.5 - \textstyle\sum_{i=1}^{5} R_i \qquad \text{and} \qquad y = \textstyle\sum_{i=1}^{5} L_i - 2.5$$

where R_i (L_i) is an indicator variable taking value one if the participant revealed to prefer option "Right" ("Left") over "Left" ("Right") for some decision problem $i \in \{1, 2, ..., 5\}$. By construction, positive (negative) scores correspond to benevolent (malevolent) behavior in the domain of disadvantageous and advantageous inequality, respectively.

Depending on whether x and y take values smaller than -0.5, values in the interval $[-0.5, 0.5]$, or values larger than 0.5, the EET allows to delineate nine different archetypes of distributional preferences: (i) $x > 0.5, y > 0.5$: altruistic; (ii) $x > 0.5, y \in [-0.5, 0.5]$: kiss-up; (iii) $x > 0.5, y < -0.5$: equality-averse; (iv) $x \in [-0.5, 0.5], y > 0.5$: maximin; (v) $x \in [-0.5, 0.5], y \in [-0.5, 0.5]$: selfish; (vi) $x \in [-0.5, 0.5], y < -0.5$: kick-down; (vii) $x < -0.5, y > 0.5$: inequality-averse; (viii) $x < -0.5, y \in [-0.5, 0.5]$: envious; and (ix) $x < -0.5, y < -0.5$: spiteful. The magnitude of each of the two scores serves as an ordinal measure of the intensity of distributional concerns in the corresponding inequality domain.

The (x, y)-score can be directly translated into lower and upper bounds of parameter intervals in the piece-wise linear utility model (Fehr and Schmidt, 1999; Charness and Rabin, 2002). The utility function in the piece-wise linear model is defined as

$$u_{\gamma,\sigma}(m, o) = \begin{cases} (1-\sigma)m + \sigma o & \textit{if} \quad m \leq o \\ (1-\gamma)m + \gamma o & \textit{if} \quad m > o, \end{cases}$$

where m and o denote the monetary payoffs of the "active" and "inactive" players, respectively, and $\gamma, \sigma < 1$ to preserve monotonicity. Thus, a decision-maker's utility is described as a linear combination of the own (m) and the other player's (o) material payoff, where the weight put on the other's payoff might depend on whether the decision-maker is behind (disadvantageous inequality) or ahead (advantageous inequality). Thus, $\sigma = 0$, $\sigma > 0$, and $\sigma < 0$ corresponds to individualistic, benevolent, and malevolent behavior in the domain of disadvantages inequality; likewise, $\gamma = 0$, $\gamma > 0$, and $\gamma < 0$ corresponds to individualistic, benevolent, and malevolent behavior in the domain of advantageous inequality. For a comprehensive discussion on how participants' preferences characterized by the piece-wise linear utility function translate into parameter intervals and the implied relationship to (x, y)-scores, refer to Kerschbamer (2015).

As an alternative to parameters in the piece-wise linear model, distributional preferences (and intensities) can be expressed in terms of the decision-maker's willingness to pay for an increase or decrease of the other person's material payoff in both the domain of disadvantageous inequality (wtp^d) and the domain of advantageous inequality (wtp^a). The decision-maker's willingness to pay is defined as

$$wtp = \frac{\partial_o u(m, o)}{\partial_m u(m, o)}$$

—where $\partial_o u(m, o)$ and $\partial_o u(m, o)$ denote the partial derivatives of $u_{\gamma,\sigma}(m, o)$ with respect to o and m, respectively. If $\sigma \geq 0$ ($\gamma \geq 0$), $wtp^d = \sigma(1-\sigma)^{-1}$ ($wtp^a = \gamma(1-\gamma)^{-1}$) gives the amount in terms of the own material payoff (m) the decision-maker is willing to pay in the domain of disadvantageous inequality (advantageous inequality) in order to *increase* the other player's material payoff (o) by one unit; symmetrically, if $\sigma < 0$ ($\gamma < 0$), $wtp^d = -\sigma(1+\sigma)^{-1}$

($wtp^a = -\gamma(1+\gamma)^{-1}$) gives the amount in terms of the own material payoff (m) the decision-maker is willing to pay in the domain of disadvantageous inequality (advantageous inequality) in order to *decrease* the other person's material payoff (o) by one unit. Table C1 summarizes how participants' choice behavior translates into (x,y)-scores, parameter intervals for σ and γ, as well as intervals of the willingness-to-pay in the domain of disadvantageous (wtp^d) and advantageous inequality (wtp^a) given the parametrization used in our experiment.

Table C1: Non-parametric (x,y)-scores, intervals of utility function parameters σ and γ in the piece-wise linear model, and willingness to pay in the domain of disadvantageous (wtp^d) and advantageous inequality (wtp^a) inferred from participants' choice behavior in the Equality Equivalence Test (EET). ΣR_i denotes the number of times participants reveal to prefer option "Right" over option "Left;" lb and ub denote the lower and upper bound of the implied intervals for utility function parameters (σ and γ) and participants' willingness-to-pay (wtp^d and wtp^a), respectively.

***x*-list**

ΣR_i	x	$[\sigma_{lb}, \sigma_{ub})$	$[wtp^d_{lb}, wtp^d_{ub})$
0	2.5	$[\ 0.40, +\infty)$	$[\ 0.67, +\infty)$
1	1.5	$[\ 0.25, 0.40)$	$[\ 0.33, 0.67)$
2	0.5	$[\ 0.00, 0.25)$	$[\ 0.00, 0.33)$
3	-0.5	$[-0.25, 0.00)$	$[-0.33, 0.00)$
4	-1.5	$[-0.40, -0.25)$	$[-0.67, -0.33)$
5	-2.5	$[\ -\infty, -0.40)$	$[\ -\infty, -0.67)$

***y*-list**

ΣR_i	y	$[\gamma_{lb}, \gamma_{ub})$	$[wtp^a_{lb}, wtp^a_{ub})$
0	-2.5	$(\ -\infty, -0.40]$	$(\ -\infty, -0.67]$
1	-1.5	$(-0.40, -0.25]$	$(-0.67, -0.33]$
2	-0.5	$(-0.25, 0.00]$	$(-0.33, 0.00]$
3	0.5	$(\ 0.00, 0.25]$	$(\ 0.00, 0.33]$
4	1.5	$(\ 0.25, 0.40]$	$(\ 0.33, 0.67]$
5	2.5	$(\ 0.40, +\infty]$	$(\ 0.67, +\infty]$

For the sake of interpretability, we restrict our attention in all analyses to participants' willingness to pay for an increase/decrease in the other player's monetary payoff (rather than the parameters, σ and γ, in the piece-wise linear utility model). As the intervals of wtp^d and wtp^a can be directly translated from the intervals for σ and γ, results for the parameters in the piece-wise linear utility model would be qualitatively identical. As a non-parametric robustness test, however, we replicate the analyses for participants' (x,y)-scores—results turn out to be highly robust (see below).

Descriptive results. Descriptive results on the fractions of distributional preference archetypes separated for the two subject pools are provided in Figure 2 in the main text. With regards to the treatment variation in the general population subject pool, we do not find evidence that the distribution of archetypes among the general population sample differs between the treatment where the second player is assigned from the general population sample and the treatment where the second player is a finance professional (Fischer's exact test: $\chi^2(1) = 11.446$, $p = 0.178$; $n = 395$). Likewise, we do not find evidence for differences in the willingness-to-pay between treatments, neither in the domain of disadvantageous inequality (interval regression: $\beta = 0.046$, $z = 0.704$, $p = 0.481$; $n = 395$), nor in the domain of advantageous inequality (interval regression: $\beta = 0.152$, $z = 1.446$, $p = 0.148$; $n = 395$). Therefore, we pool the data from the general population sample in all analyses presented in the main text and below, since our focus in this paper is on differences between finance professionals and the general population—i.e., for participants from the general population we do not condition on whether the randomly assigned "inactive" player is a participant from the general population or from the finance professionals sample.

In the domain of disadvantageous inequality, finance professionals in our sample, on average, are willing to pay 0.104 SEK ($se = 0.027$, $z = 3.776$, $p < 0.001$; $n = 298$) to increase the payoff of the other player by one SEK, whereas the willingness to pay in the general population sample is -0.002 ($se = 0.033$, $z = 0.052$, $p = 0.959$; $n = 395$).[16] That is, finance professionals tend to be benevolent towards the other player when falling behind in terms of payoffs, whereas participants from the general population, on average, tend to be only concerned about their own self-interest. In the domain of advantageous inequality, finance professionals, on average, are willing to pay 0.643 SEK ($se = 0.053$, $z = 12.109$, $p < 0.001$; $n = 298$) to increase the second player's material payoff by one SEK; comparable in magnitude, the willingness to pay in the general population sample is 0.661 SEK ($se = 0.060$, $z = 11.103$, $p < 0.001$; $n = 395$). Thus, players from both the finance professionals sample and the general population, on average, tend to be benevolent towards the second player if they are ahead in terms of monetary payoffs.

[16] Since the EET does not allow to infer point estimates of the decision-makers' willingness-to-pay, but rather lower and upper bounds, we estimate the means and (robust) standard errors of the mean of wtp^d and wtp^a for each of the two subject pools using interval regressions.

D. Trustworthiness

Descriptive results. Figure D1 shows histograms of the amounts returned by the second movers in the trust game, for each of the potential amounts sent by the first movers. Comparing the distributions using Kolmogorov-Smirnov (KS) tests reveals that only the distributions for 20 SEK and 40 SEK sent by the trustors are significantly different between the pools ($p < 0.05$); KS tests of the distributions conditional on first movers sending 60 SEK or more do not statistically differ ($p > 0.05$) between the general population sample and the finance professionals sample.

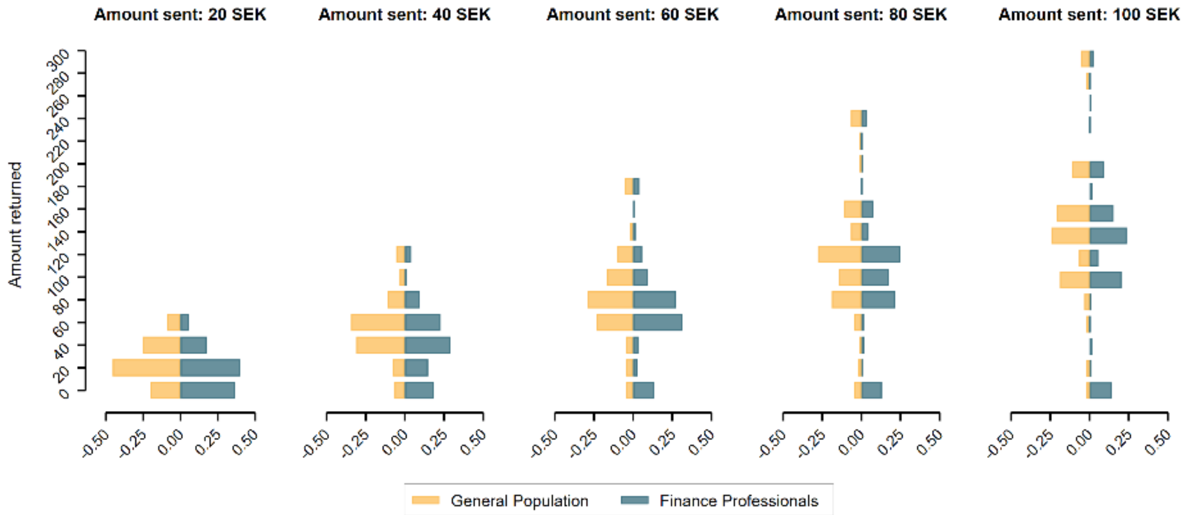

Figure D1: Histograms of amounts returned by the trustees in the (strategy method) trust game for each potential amount sent by the first mover, separated for the general population and the finance professionals sample. $n_{GP} = 90$, $n_{FP} = 298$.

Supplementary results. Table D1 shows the results from ordinary least squares regressions of the amount sent by first movers on a dichotomous variable indicating the treatment—i.e., whether the trustee is a participant from the finance professionals or general population sample—and socio-economic adjustment variables. From their endowment of 100 SEK, first movers, on average, send 3.1 SEK less to the second mover if the trustor is a participant from the finance professionals sample (as compared to trustors from the general population sample). This difference, however, does not significantly differ from zero. This finding deviates from self-reported evidence found in Holzmeister et al. (2020a), where participants indicate lower trust in finance professionals. However, while we are reporting findings from the incentivized investment game, Holzmeister et al. (2020a) refer to self-reported survey measures. Sapienza et al. (2013) explain differences in results from survey methods and the investment game by attributing first mover behaviour in a trust game to beliefs and preferences, while survey measures are mainly attributable to beliefs. Moreover, as can be seen in Table D1, we do not find any evidence of systematic effects of gender, age, income, or education on the first movers' behavior in the trust game.[17]

[17] Fungáčová et al. (2019) show that being female and income are positively, while age and education are negative associated with self-reported trust in banks. Please note, however, that they are investigating trust in banks (as institutions), while we examine trust in finance professionals (as individuals).

Table D1: Regression analyses of the general population sample's trust. This table shows the results of ordinary least squares regressions (organized in rows) of the amount sent by the first mover in the trust game on an indicator variable for the treatment (indicating whether the second mover is a participant from the general population or the finance professionals sample) and socio-economic adjustment variables (gender, age, income, and education). Robust standard errors are provided in parentheses. $n = 693$ in models without adjustments; $n = 688$ in models with adjustments. * $p < 0.05$, ** $p < 0.005$.

	Fin. Prof.	*Female*	*Age*	*Income*	*Edu. = 2*	*Edu. = 3*	*Constant*
Amount sent	−3.133						69.333**
	(3.659)						(2.924)
Amount sent	−3.882	−3.723	−0.262	−3.917	1.333	2.650	116.165**
	(3.721)	(3.576)	(0.177)	(2.117)	(4.244)	(4.807)	(18.590)

Notes: Estimates of the regressions are organized in rows, i.e., the row headings indicate the dependent variable and the column headings indicate the covariates in the model. *Fin. Prof.* is a dummy variable taking value 0 if the trustor is a participant from the general population sample, and 1 if the trustor is a participant from the finance professionals sample. *Female* is a dummy variable indicating participants' gender; *Age* is measured in years. *Income* is measured in logs of 1,000 SEK (gross) per year. *Edu. = 2* denotes a dummy variable for university education smaller or equal to three years; *Edu. = 3* indicates a dummy for university education larger than three years.

E. Personality Traits

Method. The questions used in the *Dark Triad*, *Competitiveness* and the *Big-5* inventories are listed in Tables E1–E3. To avoid order effects, the three questionnaires were presented in random order and questions were shuffled within each inventory. All questions in each of the three questionnaires were answered on a Likert scale ranging from 1 (“does not describe me at all”) to 7 (“describes me very well”). While half of the questions in the *Big-5* inventory are negatively phrased (as indicated in Tables E3–E2), all questions in the *Dark Triad* and *WOFO* survey were positively phrased.

The score for each personality trait is constructed as follows. In a first step, negatively phrased items in the *Big-5* inventory are reversed in scores. In a second step, answers to each question in each of the three inventories are z-standardized across the pooled sample of respondents. In a third step, we aggregate the questions associated with a particular trait, resulting in five scores for the *Big-5* inventory, three scores for the *Dark Triad* survey, and one score for competitiveness. Finally, we z-standardize the aggregated score for each personality characteristic. By this means, for each personality trait elicited in our experiment, the score used in the analyses has a mean of zero and a standard deviation of one.

Table E1: *Dark Triad* personality test by Jonason and Webster (2010). The table summarizes the statements used to assess participants’ malevolent qualities of narcissism, Machiavellianism, and psychopathy. All items were answered on a 7-point scale: 1 (“does not describe me at all”) to 7 (“describes me very well”).

How much do you agree with the following statements?	***Trait (Scoring)***
I tend to want others to admire me.	Narcissism (+)
I tend to want others to pay attention to me.	Narcissism (+)
I tend to expect special favors from others.	Narcissism (+)
I tend to seek prestige or status.	Narcissism (+)
I have used deceit or lied to get my way.	Machiavellianism (+)
I tend to manipulate others to get my way.	Machiavellianism (+)
I have used flattery to get my way.	Machiavellianism (+)
I tend to exploit others towards my own end.	Machiavellianism (+)
I tend to lack remorse.	Psychopathy (+)
I tend to be callous or insensitive.	Psychopathy (+)
I tend to not be too concerned with morality or the morality of my actions.	Psychopathy (+)
I tend to be cynical.	Psychopathy (+)

Table E2: Competitiveness questionnaire based on the *Work and Family Life Orientation questionnaire* (*WOFO*) proposed by Helmreich and Spence (1978). The table summarizes the statements used to assess participants' competitiveness. All items were answered on a 7-point scale: 1 ("does not describe me at all") to 7 ("describes me very well").

How much do you agree with the following statements?
It annoys me when other people perform better than I do.
I feel that winning is important in both work and games.
I enjoy working in situations involving competition with others.
I try harder when I am in competition with other people.
It is important to me to perform better than others on a task.

Table E3: *Big-5* personality test by Rammstedt and Oliver (2007). The table summarizes the statements used to assess participants' extroversion, agreeableness, conscientiousness, neuroticism, and openness. All items were answered on a 7-point scale: 1 ("does not describe me at all") to 7 ("describes me very well").

I see myself as someone who...	***Trait (Scoring)***
is outgoing and sociable.	Extroversion (+)
is reserved.	Extroversion (−)
is generally trusting.	Agreeableness (+)
tends to find fault with others.	Agreeableness (−)
does a thorough job.	Conscientiousness (+)
tends to be lazy.	Conscientiousness (−)
gets nervous easily.	Neuroticism (+)
is relaxed and handles stress well.	Neuroticism (−)
has an active imagination.	Openness (+)
has few artistic interests.	Openness (−)

Descriptive results. Figure E1 shows the cumulative distributions of the standardized scores on the traits elicited using the *Dark Triad*, the competitiveness, and the *Big-5* inventory, separated for the general population and the finance professionals sample. Apparently, the scores of traits assessed using the *Big-5* questionnaire do not significantly differ in location and shape between the two samples (Kolmogorov-Smirnov tests; $p > 0.05$ for all five traits). However, we find that the distributions of *Dark Triad* scores do significantly differ between the two subject pools: finance professionals, on average, score higher on all three socially undesirable personality characteristics (Kolmogorov-Smirnov tests; $p < 0.05$ for all three traits). Likewise, we report that finance professionals score significantly higher on the measure of self-reported competitiveness (Kolmogorov-Smirnov test; $p < 0.005$).

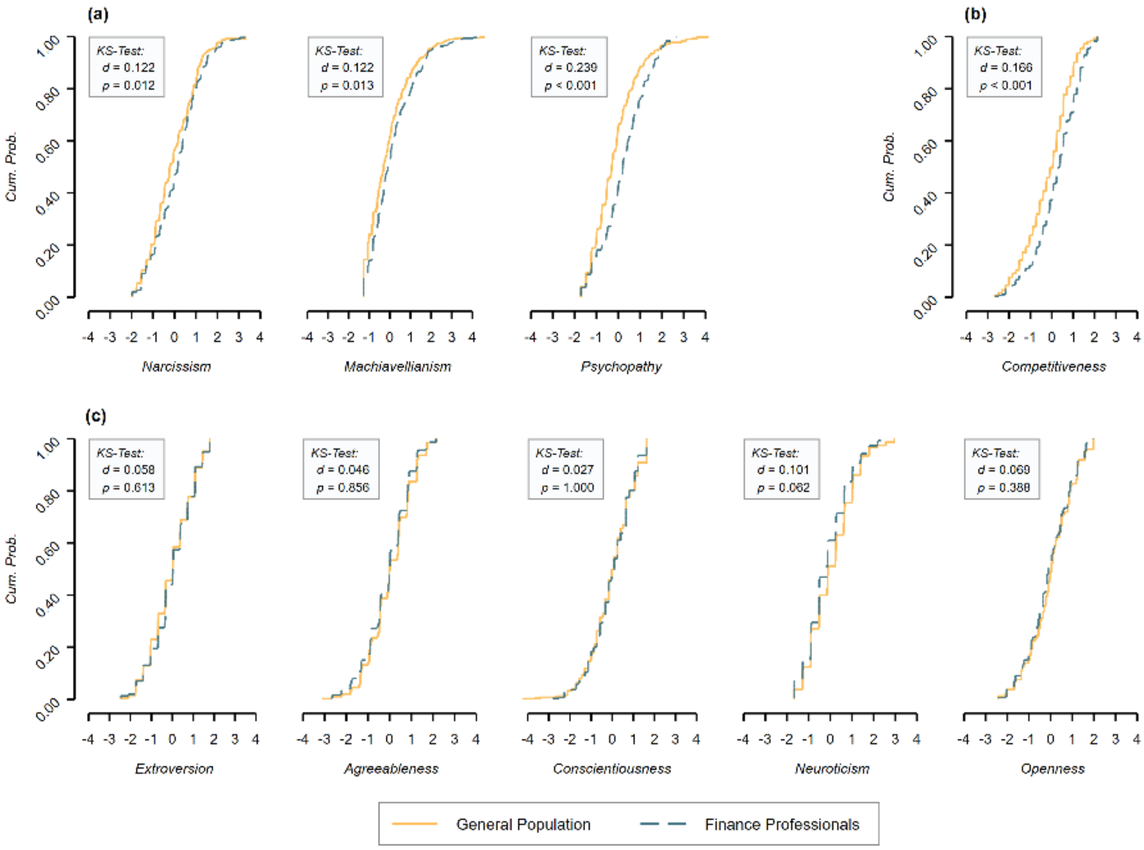

Figure E1: Cumulative distributions of the standardized scores on **(a)** traits elicited using the *Dark Triad* inventory, **(b)** the competitiveness sub-scale from the *Work and Family Life Orientation* (*WOFO*) survey, and **(c)** traits assessed using the *Big-5* personality test, separated for the general population and the finance professionals sample. Kolmogorov-Smirnov (*KS*) tests are reported in boxes. $n_{GP} = 395$, $n_{FP} = 298$.

F. Correlational Analysis

As an exploratory analysis, we present correlations between the various preferences and traits elicited in the experiment, separated for the two subject pools, in Table F1. In particular, each cell in the lower triangular matrix in Table F1 shows Pearson correlation coefficients between the respective variables for the finance professionals sample in the top row, and those for the general population sample in the bottom row. The upper triangular matrix reports the (absolute) z-statistics corresponding to the differences between correlations coefficients between subject pools. To test the null hypothesis that the correlation between variable x and y for the sample of finance professionals (FP), r_{xy}^{FP}, does not differ from the correlation between variable x and y for the general population sample (GP), r_{xy}^{GP}, we resort to the Fisher z' transformation (see, e.g., Cohen et al., 2003). In particular, the z' transformation of a correlation coefficient r is given by $z' = 1/2 \cdot [\ln(1+r) - \ln(1-r)]$, with the corresponding standard error $se_{z'} = (n-3)^{-0.5}$. To examine whether the correlation coefficients of the two sample systematically differ, we test the equivalent $H_0 : z'_{FP} - z'_{GP} = 0$ by determining the normal curve deviate

$$z = \frac{z'_{FP} - z'_{GP}}{\sqrt{(n_{FP}-3)^{-1} + (n_{GP}-3)^{-1})}}.$$

We find similar correlation patterns in both subject pools. For instance, risk tolerance and loss tolerance are significantly positively correlated in both subject pools (lower triangular matrix) and these correlation coefficients do not differ between subject pools (upper triangular matrix). As another example, we find similar correlation coefficients across the *Big-5* personality traits dimensions in both subject pools.[18] Again, these correlation coefficients do not differ across subject pools. We consider these findings in the correlation matrix exploratory in nature and the vast number of tests implies the possibility of false positives. Therefore, we refrain from discussing individual significant differences between the subject pools.

[18] In line with Becker et al. (2012) we find little evidence for association between economic preferences and personality traits.

Table F1: Correlation analysis of the various preferences and traits elicited in the experiment. The lower triangular matrix reports Pearson correlation coefficients between the respective variables for the finance professionals sample (top row in each cell) and the general population sample (bottom row in each cell). The upper triangular matrix reports the (absolute) z-statistics corresponding to the differences between correlations coefficients between subject pools. The color coding emphasizes the magnitude of correlation coefficients and z-statistics, respectively. $n_{GP} = 395$ for all variables except for "Trustworthiness" where $n_{GP} = 90$; $n_{FP} = 298$ for all variables. * $p < 0.05$, ** $p < 0.005$.

Risk Tolerance	0.155	0.215	0.186	0.624	1.215	0.233	1.930	0.647	0.090	0.231	0.316	0.768	0.603	1.059	1.160
0.538** 0.530**	Loss Tolerance	0.850	0.774	0.836	0.558	0.646	1.260	0.142	0.948	0.140	1.102	1.615	0.670	0.294	2.204*
0.511** 0.499**	0.365** 0.420**	Skewness Tolerance	0.510	1.082	0.304	0.290	0.994	0.418	0.193	1.212	1.581	1.612	1.623	1.671	0.082
0.099 0.113*	-0.084 -0.025	-0.011 -0.051	x-Score	2.101*	0.223	1.211	0.942	0.011	0.886	1.840	0.544	0.524	0.056	1.063	1.128
-0.028 -0.076	0.023 -0.042	0.045 -0.039	0.037 -0.125*	y-Score	1.304	1.438	1.088	0.971	0.439	0.296	0.041	1.411	0.962	0.941	0.908
-0.086 0.062	0.036 -0.032	-0.074 -0.037	0.052 0.079	0.139* -0.019	Trustworthiness	0.239	1.504	1.787	3.103**	0.059	1.585	1.046	1.685	0.124	1.900
0.022 0.004	-0.046 -0.095	-0.044 -0.021	0.067 -0.026	-0.056 0.055	0.013 0.042	Dishonesty	2.905**	2.540*	1.727	1.933	0.270	1.239	0.687	0.255	1.919
0.161* 0.014	0.019 -0.078	0.025 -0.051	0.073 0.145**	-0.116* -0.033	-0.134* 0.049	0.170** -0.052	Dark Triad: Narcissism	0.483	0.571	1.398	0.688	1.053	0.102	1.719	1.115
0.096 0.047	-0.010 0.001	-0.047 -0.079	0.134* 0.134*	-0.100 -0.026	-0.108 0.109	0.222** 0.030	0.510** 0.537**	Dark Triad: Machiavellianism	0.009	0.782	0.371	2.224*	0.735	0.181	2.526*
0.085 0.078	-0.066 0.007	0.008 -0.007	0.197** 0.131*	-0.066 -0.100*	-0.184** 0.190	0.117* -0.016	0.329** 0.289**	0.443** 0.443**	Dark Triad: Psychopathy	0.169	1.281	0.288	0.740	1.264	1.958
-0.041 -0.023	-0.004 -0.015	-0.119* -0.026	-0.130* 0.011	-0.039 -0.016	-0.036 -0.029	0.127* -0.021	0.219** 0.114*	0.085 0.025	-0.138* -0.125*	Big Five: Extroversion	0.595	0.769	0.445	0.519	0.557
0.007 -0.017	0.047 -0.038	0.094 -0.028	0.015 -0.027	0.127* 0.130*	0.069 -0.123	-0.026 -0.005	-0.204** -0.152**	-0.264** -0.238**	-0.278** -0.366**	0.237** 0.279**	Big Five: Agreeableness	2.655*	1.178	0.509	2.886**
-0.026 -0.085	0.067 -0.057	-0.074 0.050	-0.093 -0.053	-0.103 0.005	-0.032 -0.158	0.076 -0.019	-0.078 -0.158**	-0.162** -0.323**	-0.216** -0.237**	0.016 0.075	-0.053 0.150**	Big Five: Conscientiousness	0.006	1.486	0.306
-0.038 0.008	-0.002 0.050	-0.057 0.068	-0.030 -0.025	-0.005 0.069	0.120* -0.085	0.043 -0.010	0.120* 0.128*	0.053 0.109*	-0.112 -0.056	-0.207** -0.174**	-0.242** -0.155**	-0.114* -0.114*	Big Five: Neuroticism	1.038	0.746
-0.067 0.014	-0.022 0.001	-0.134* -0.006	-0.039 0.043	0.033 0.105*	0.058 0.042	-0.001 0.019	0.032 0.163**	0.070 0.056	-0.159* -0.063	0.114* 0.075	-0.057 -0.018	0.040 -0.075	0.073 0.152**	Big Five: Openness	0.628
0.140* 0.051	0.097 -0.073	-0.012 -0.006	0.085 0.170**	-0.179** -0.110*	-0.160* 0.070	0.104 -0.044	0.513** 0.447**	0.411** 0.237**	0.295** 0.152**	0.042 0.085	-0.324** -0.113*	0.034 0.058	0.016 -0.042	0.033 -0.015	Competitiveness

Notes: "Risk Tolerance," "Loss Tolerance," and "Skewness Tolerance" correspond to the indexes as used for the analysis in panel (a) of Figure 1 in the main text. "x-Score" and "y-score" refer to the non-parametric measures of distributional preferences in the domain of advantageous and disadvantageous inequality based on the equality equivalence test. "Trustworthiness" refers to the average amount returned by the second mover in the trust game (in percent of the available endowment) across the different potential amounts sent by the first mover. "Dishonesty" refers to the difference between the reported number of pips and the actual number of pips. Variables indicated with "Dark Triad," "Big Five," and "Competitiveness" are z-standardized scores of the respective traits.

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Economic Preferences and Personality Traits Among Finance Professionals and the General Population

Abstract
Since the financial crisis, the behavior and personality traits of finance professionals have come under scrutiny. As comprehensive scientific findings are lacking, we run artefactual field experiments with finance professionals and a random sample of the working population to investigate differences across industry-relevant economic preferences and personality traits. We report that finance professionals are more risk tolerant, more selfish, less trustworthy, and show higher levels of narcissism, psychopathy, and Machiavellianism. However, we find that many of these differences disappear after adjusting for socioeconomic characteristics, indicating that finance professionals are similar to employees in other industries with a comparable socio-economic background.

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