Social Preferences of Young Professionals and the Financial Industry[*]

Andrej Gill[§], Matthias Heinz[δ], Heiner Schumacher[∞], and Matthias Sutter[β]

Abstract

The financial industry has been struggling with widespread misconduct and public mistrust. One explanation for these phenomena could be the selection of individuals who wish to work in and get job offers from the financial industry. In this paper, we examine the selection into the financial industry based on social preferences. We identify the social preferences of business and economics students, and, for six years, follow up on their early career choices as well as on their job placement after graduation. Students eager to work in the financial industry exhibit substantially less reciprocity and less willingness to cooperate than those with other career plans. The job market does not alleviate this selection. Those subjects who find their first permanent job in finance are significantly less reciprocal than those working in other industries.

JEL codes: C91, G20, M51

Keywords: Social Preferences, Financial Industry, Young Professionals, Experiment

April 10, 2021

---

[*] We would like to thank Loukas Balafoutas, Björn Bartling, Alain Cohn, Anna Piil Damm, Thomas Dohmen, Ernst Fehr, Guido Friebel, Andreas Hackethal, Jürgen Huber, Bernd Irlenbusch, Alexander Koch, Michael Kosfeld, John List, Michel Marechal, Axel Ockenfels, Devesh Rustagi, Antoinette Schoar, Dirk Sliwka, Matthias Stefan, Uwe Walz, and Achim Wambach, as well as seminar participants at Aarhus University, University of Bonn/briq, Copenhagen University, University of Chicago, and the Society for Experimental Finance Annual Meeting for valuable comments. We thank David Heller, Sebastian Koch, Stephan Krehl, Christopher Kroh, Jana Schneider, David Schuch, and Katharina Tilts for excellent research assistance. Financial support from the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany´s Excellence Strategy – EXC 2126/1– 390838866 and from the Center for Financial Studies (CFS) is gratefully acknowledged.

[§] University of Mainz. Email: gill@uni-mainz.de.

[δ] University of Cologne, ECONtribute, Max Planck Institute for Research on Collective Goods, Bonn, and CEPR. Email: heinz@wiso.uni-koeln.de.

[∞] University of Innsbruck and KU Leuven. Email: heiner.schumacher@uibk.ac.at.

[β] Corresponding author. Max Planck Institute for Research on Collective Goods, Bonn, University of Cologne, ECONtribute, IZA Bonn, CESifo Munich and University of Innsbruck. Phone: +49 228 914 16 150; Email: matthias.sutter@coll.mpg.de.

1 Introduction

The financial industry serves a crucial role in every modern society. Most importantly, it allows businesses to finance projects and consumers to purchase property, accumulate wealth, or to insure people and property against risks. Financial transactions determine the traded assets as well as each party's payment obligations. Both asset values and payment obligations are typically subject to a multitude of external risks. Financial transactions are therefore often complex. Moreover, they are often characterized by asymmetric information and a conflict of interest between the trading parties. This is especially true for the relationship between clients and financial professionals. In order to engage in a financial transaction, clients have to trust financial professionals that they make recommendations or perform actions that are beneficial, or at least not detrimental, to them (Gambretta 2000, Sapienza and Zingales 2012). In retail finance, this trust in financial professionals is particularly important, as they may act as a "money doctor" (Gennaioli et al. 2015, Kostovetsky 2016) who help uninformed clients making risky investments by reducing anxiety about taking risk.

However, surveys consistently document a lack of trust in the financial industry in many countries. Financial advisers are perceived as dishonest and rank among the least trustworthy professionals (e.g., Zingales 2015). Trust in banks and financial markets generally is relatively low according to the General Social Survey (GSS). Consumer surveys report that clients are less satisfied with the services offered by the financial industry than with the services offered by any other industry (e.g., European Comission 2018). Overall, scholars argue that the many scandals and affairs have substantially reduced trust in the financial industry and the financial market (Guiso et al. 2008, Sapienza and Zingales 2012, Zingales 2015).[1]

There is a recent debate whether the problematic business conduct and the resulting lack of trust in the financial industry can be ascribed to its business culture (Cohn et al. 2014a). The norms and formal rules of the financial industry may induce dishonest behavior among otherwise honest people. However, the empirical evidence on the effects of business culture on the honesty and trustworthiness of the employees in the financial industry has produced inconclusive results, see Cohn et al. (2014a), Villeval (2014), Stöckl (2015), Rahwan et al. (2019), Cohn et al. (2019), and Huber and Huber (2020).

In this paper, we take an orthogonal approach compared to this debate. We argue that the business culture in an industry is essentially shaped by the people who voluntarily decide

[1] Indeed, recent studies show widespread misconduct in retail finance (Mullainathan et al. 2012, Egan et al. 2019), asset quality misrepresentation on multiple levels (Piskorski et al. 2015, Griffin and Maturana 2016), and insufficient sanctioning of misconduct (Egan et al. 2019).

to work in (and get a job offer from) that industry. It is therefore important to study who selects into (and is selected by) the financial industry. To this end, we measure a key dimension of social preferences, namely reciprocity. When clients deal with financial professionals, they entrust them their money and hope to get valuable advice in return. We measure reciprocity in an experimental trust game, played by business and economics students several years before they enter the labor market. Then we follow up on their professional specialization as well as their job placement after graduation. We find that business and economics students who are eager to work in the financial industry are significantly less reciprocal. Importantly, this association is not alleviated by the labor market: Those subjects who find their first job after graduation in the financial industry reciprocate trust significantly less often and to a lesser degree than those who commence their career in another industry.

Our long-term project started with a data collection wave in 2013 in which we asked 265 business and economics students at Goethe University Frankfurt, Germany, about their professional preferences and their interest in working in different industries. Goethe University offers a study program in business and economics that allows for a strong focus on finance. Moreover, Frankfurt is the most important hub of the financial industry in Germany. Hence, it is relatively easy for young professionals to acquire professional experiences in finance before graduation and to find a job in the financial industry after graduation.

In 2013, students participated in an experimental trust game (Berg et al. 1995). In this game, a first mover can transfer money to a second mover, the transfer is tripled, and the second mover can return some of the tripled amount to the first mover. The first mover's decision can be interpreted as a measure of trust, and the second mover's decision measures to what extent this trust is reciprocated. The trust game is also frequently called "investment game" since the first mover has to "invest" into the second mover to earn economic gains. However, this investment only pays off for the first mover if the second mover is willing to reciprocate the first mover's trust by transferring back some of the gains to her. The trust (or investment) game therefore captures transactions between clients (the first mover role in the game) and financial professionals (second movers) very well by reflecting the asymmetric information (about the second mover's action) between the two parties. Behavior in the trust game has been shown to correlate with real-world decisions, e.g., with loan repayments (Karlan 2005), charity donations (Baran et al. 2010), and effort provision at the workplace (Cohn et al. 2014b).

With the data from 2013, we can examine whether there is an association between the extent of reciprocating trust and the industry in which students would *like to work* in the future. More than six years later, in late 2019 and early 2020, we ran a second wave of data collection where we collected data on the former students' *actual first job placement* after graduation and many more details of their career paths.

Following up subjects on their career paths from their college days into their first permanent job is important for at least three reasons. First, the labor market in the financial industry is very competitive. If a subject indicates in 2013 that she is strongly interested to work in the financial industry, this does not automatically imply that she will get a job offer from a financial company. Only the actual job placement reveals whom the financial industry selects and admits. Second, subjects may change their mind during their studies. If a subject indicates in 2013 that she is strongly interested in working in finance, this does not necessarily mean that she still wants to work in this industry several years later. Third, entering the financial industry after graduation is a decision with long-term consequences. Ellul et al. (2020) show that only a small share of individuals switch from the financial industry to another industry and vice versa. The same is true in our study. Less than 4 percent of our subjects switch from the financial industry to another one or vice versa within an average of three years into the first permanent job. Therefore, it is important to understand who selects into the financial industry at the beginning of a career, because those who do can be expected to stay there for a long time.

Looking first at the data from 2013 only, we find that there is no difference in individuals' trust[2], but a remarkable difference in the extent to which they reciprocate trust, contingent on their professional preferences. We find a significant negative correlation between an individual's desire to work in the financial industry and the degree of reciprocity: The third of students most interested in working in finance return on average around 30 percent less in the trust game than the third of subjects least eager to work in finance. Importantly, this relationship remains unchanged if we focus on subjects who in 2013 did not have any professional experience in the financial industry, and therefore have not been exposed to its business culture yet. It also remains strong and significant when we control for personal characteristics such as cognitive ability or gender.

With the data from 2019/2020 we can show that the job market does not alleviate this selection. In our sample, interest in working in the financial industry is highly correlated with the probability of starting a career in this industry. The probability of working in finance increases by 10 percentage points for each additional unit in interest in working in finance (on a Likert-scale from 1 to 7). Subjects who find their first permanent job in the financial industry

[2] Note that we are not primarily interested in whether individuals who might end up in the financial industry trust other subjects, but our main interest is in whether they reciprocate trust (for potential future clients and co-workers). Therefore, we consider the behavior of second movers in the trust game to be the prime outcome to look at since it measures the extent to which trust is reciprocated.

returned on average around 30 percent less than subjects who start their career in another industry.

We find two further striking effects. First, when we focus on the third of subjects who in 2013 were most eager to work in finance, we find a large behavioral difference between students whose first job placement is in the financial industry and those who find their first job elsewhere: The former group returns on average 50 percent less than the latter group. This suggests that the job market does not reduce the selection of less reciprocal individuals into the financial industry; if anything, the opposite seems to be the case.

Second, we find that 40 percent of the subjects who find their first job in the financial industry do not return anything as second movers in the trust game, regardless of the amount received. Among subjects who find their first job elsewhere, this share is only 23 percent. If we exclude all subjects who do not return anything, the difference in the average amount returned between the two groups decreases from 30 percent to 15 percent. Thus, the behavioral difference between subjects who find their first job after graduation in the financial industry and all other subjects is driven by two effects: a larger share of individuals who do not reciprocate trust at all, and lower levels of reciprocity among subjects who are not completely selfish.

With our rich data on study specialization, internships, vocational training or applications after graduation, we can examine the career paths of our subjects. We find that those who get their first permanent job in the financial industry do not accidentally enter this industry. Rather, they perform more professional activities and specialization choices that lay a foundation for a career in the financial industry. In particular, they collected much more often professional experience in the financial industry, for example, via internships, submitted a larger share of their applications for their first job to financial companies, and the majority of them chose “finance” as their major field of study during their undergraduate studies. This implies that there is a strong correlation between a subject’s stated interest to work in the financial industry and the actual first job placement after graduation. Hence, the selection of less reciprocal subjects into the financial industry looks like a systematic pattern.

This pattern also generalizes to other dimensions of social preferences. We use the data from an unrelated study (Heinz and Schumacher 2017) in which subjects from two other universities play the public goods game (Fischbacher et al. 2001, Fischbacher and Gächter 2010) and are asked about their professional preferences. Again, those students with a high motivation to work in finance after graduation behave significantly more selfishly than subjects with other professional goals. Interestingly, when they play the repeated version of the public goods game with fixed partner matching, they are not behaving significantly different from other subjects until the very last period. In the last period, however, they reduce their contributions significantly stronger than others. Therefore, our results also hold for repeated relationships. Subjects with a high interest in working in the financial industry behave pro-socially to some extent as long as this behavior is rewarded in future interactions, but they quickly stop contributing when this is no longer the case.

Our paper contributes to the literature on human capital and selection into the financial industry. This literature studies in particular to what extent the financial industry attracts (too many) skilled and highly educated workers. The seminal paper by Philippon and Reshef (2012) demonstrates that since the 1980s the financial industry turned into a high-skill and high-wage industry, and that a reduction in regulation increased the demand for skilled labor (see also Boustanifar et al. 2018, or Célérier and Vallée 2019). Ellul et al. (2020) analyze the employment history of a random sample of workers to study patterns of careers in finance. They find that 80 percent of workers who start a career in finance still work in this industry ten years later. In non-finance sectors, the retention rate is equally high. An important reason for this is that entering a certain industry requires building up industry-specific human capital, which we also observe in our data. We contribute to this literature by documenting a different kind of selection into the financial industry. Within a sample of highly qualified workers, we show that those who choose to work in the financial industry are less inclined to reciprocate trust than those who pursue a career in another industry.

Moreover, we contribute to a growing literature that analyzes selection into professions based on social preferences. Hanna and Wang (2017) show that students in India who cheat in a laboratory task are more eager to work in the public sector. Barfort et al. (2019) find the opposite result for Denmark, which suggests that selection into public service depends significantly on a country's institutional context. Both studies do not follow up on their subjects' job placement after graduation so they cannot identify how strong the actual selection into public service is based on honesty or social preferences. Friebel et al. (2019) compare behavior in a trust game of police applicants (when they submit their application) and a sample of high school students in a similar age cohort. They find that the former group is more trusting and reciprocal than the latter group. Compared to the papers mentioned here, our paper is the first that (i) identifies selection into occupations based on social preferences by following subjects' careers *before* and *after* their first job market placement, (ii) is able to match intentions and actual outcomes on the job market, and (iii) focuses on selection into the financial industry.

The remainder of the paper is organized as follows. In Section 2, we explain the study design of our long-term project. In Section 3, we present the results on reciprocity and selection into the financial industry. In Section 4, we conduct a number of robustness checks. Section 5 provides further support for selection on social preferences into the financial industry by presenting additional evidence from a public goods game and how students' interest in the financial industry relates to their level of cooperation. Finally, Section 6 concludes. An Online Appendix contains additional robustness checks and all instructions.

2 Project Design

Our project consists of two waves of data collection, the first one in 2013, and the second one in late 2019 and early 2020. For convenience, we will refer to them as Wave 2013 and Wave 2020, respectively. We describe Wave 2013 in Subsection 2.1, and Wave 2020 in Subsection 2.2. In Subsection 2.3, we explain how we linked the data from both waves. In Subsection 2.4, we discuss how we classified subjects' professional preferences and job placements after graduation.

2.1 Professional Preferences and Reciprocity – Wave 2013

We conducted the first wave of data collection in 2013 at Goethe University Frankfurt, which is the ideal place for two reasons. First, the university offers a study program in business and economics that allows for a strong focus on finance after the first three semesters. Around 40 percent of business and economics students at Goethe University Frankfurt (and of the subjects in our sample) choose their specialization in finance and related fields like insurance. Second, Frankfurt is the financial center of Germany and continental Europe, which makes it comparatively easy for students at Goethe University to acquire professional experiences in finance before graduation, and to find a job in the financial industry after graduation. According to alumni data, around 30 percent of Goethe University's business and economics graduates find their first job in the financial and insurance industry. This number is roughly the same in our sample (with 34 percent).

Wave 2013 was run as a laboratory experiment. In the invitation email for the experiment, we asked subjects to bring a current version of their résumé to the lab for an experimental game and a survey on "Study Motivation, Specialization, and Occupational Choice." The experimenter collected the résumés and deleted any personal information (name, address, etc.) in front of the subject before the start of the experiment. Subjects received a show-up fee of 20 Euros. The experiment started with a survey on professional preferences. Among other things, subjects answered the following question on a Likert-scale from 1 (“certainly not”) to 7 (“definitively”): “To what extent can you imagine working in the following industries in the future?” Besides finance and insurance, these industries were health, tourism, logistics, IT/communication, engineering, electronics, car manufacturing, energy, retail, public service, consulting, and auditing. We chose the industries where most graduates find their first job (based on alumni data from Goethe University Frankfurt). In the survey, we also collected demographic information, the willingness to take risks (as measured by Dohmen et al. 2011), patience (Vischer et al. 2013), and work values (Ronen 1994). After conducting the survey, we measured subjects’ cognitive ability by using the 12-minute version of Raven’s Advanced Progressive Matrices (Bors and Stokes 1998).

Subjects then played an experimental trust game (Berg et al. 1995). This game has two player roles, a first mover and a second mover. The first mover is initially given 8 Euros and can send any integer value between 0 and 8 Euros to the second mover. Before reaching the second mover, the amount is tripled. The second mover can then send back any integer value between zero and the tripled amount (yet, the back transfer is not tripled). We applied the strategy method (Brandts and Charness 2011) so that for each subject we know the behavior as first mover and as second mover for each possible amount received. At the end of the experiment, it was randomly determined for which role and which decision a subject was paid.

The behavior as first mover provides a measure for a subject’s trust in the opponent. Recall, however, that we are not primarily interested in whether subjects trust others, but whether they reciprocate trust. For this reason, we will focus on a subject’s behavior as second mover, which measures the degree of reciprocity. To quantify the latter, we calculate for each subject the “mean share returned”, i.e., the share of the tripled amount that the second mover sends back, on average, to the first mover, aggregated for all possible amounts received.

The experiment was programmed in z-Tree (Fischbacher 2007), and we used ORSEE (Greiner 2015) to recruit subjects. All 265 participants were students from the business and economics department of Goethe University Frankfurt.[3] Payments were made right after the end of the session. Each session lasted about 60 minutes (including time needed for instructions and payments). On average, subjects earned 26.61 Euros (including the show-up fee).

[3] In total, 267 subjects participated in Wave 2013. However, one subject was registered twice in ORSEE and participated twice in the lab experiment. We dropped this subject from our sample.

2.2 Job Market Placement and Early Career Choices – Wave 2020

In late 2019 and early 2020, we contacted via email (or, if possible, via phone) all subjects who had participated in Wave 2013, and invited them to participate in a short telephone interview. We offered all subjects 40 Euros for their participation. The interviews proceeded in two steps.

In the first step, the "interview invitation", we called the subjects and explicitly explained the purpose of the research project. Specifically, we told them that the project is about "studying selection into different industries based on personal characteristics." We avoided any reference to the financial or any other specific industry. Next, we informed them that their answers to our interview questions will be linked to the data from the experiment conducted at Goethe University Frankfurt in 2013. Finally, we told them that the actual interview would be conducted by research assistants. We assured subjects that they will remain completely anonymous to the researchers and that no person will be able to link their identity to choices made in 2013. Subjects then had to declare their consent that we can interview them and merge the data from this interview with the data from Wave 2013.

In the second step, the actual interviews were conducted by research assistants. In the phone interviews, subjects were asked to describe their professional experiences. Instead of describing them in detail, they could also give us permission to collect the respective data from the job networking sites "LinkedIn" and "Xing" (which are frequently used by young professionals in Germany). Moreover, they were asked how many times they had applied after graduation for jobs in consulting, audit and financial companies. The detailed guides for the interviews can be found in the Online Appendix.[4]

2.3 Linking Wave 2013 and Wave 2020: Privacy and Attrition

Matching the data from both waves provides the unique opportunity to examine whether there is an association between trust and reciprocity and the industry in which students would *like to work* in the future, and to study whether this association materializes in *actual* job placements.[5] To ensure that subjects' anonymity was preserved at all stages of our research project, we set up an elaborate privacy protection process with several "Chinese walls" between different datasets that were handled by different researchers and research assistants. The detailed process

[4] We registered Wave 2020 on as-predicted.com, while when running Wave 2013 it was still very uncommon to pre-register experiments.

[5] In a nutshell, a subject's résumé is the key to match the data from Wave 2013 and those from Wave 2020. Both résumés (from Wave 2013 and Wave 2020) were anonymized. Nevertheless, the details about education and work experience allow for an unambiguous matching, while also maintaining anonymity.

is described in the Online Appendix. It was approved by the ethics committee at the University of Cologne and followed the European data protection rules.

Another concern in most studies that follow the same subjects over a long period of time is attrition. Attrition could bias our Wave 2020 results if the probability of drop-out is correlated with job market outcomes. Out of the 265 subjects from Wave 2013, we reached 231 subjects in Wave 2020. One subject did not allow us to link the data from Wave 2013 to data on his or her further professional career, so we dropped this subject from the Wave 2020 sample. The remaining 230 subjects approved our request to collect data on their professional career and résumé, and to link this information to the data from Wave 2013. Hence, 86.8 percent of our subjects from Wave 2013 also participated in Wave 2020. Out of the 230 subjects, one subject was long-term sick between 2013 and 2020 and thus struggled with developing his or her career. Six other subjects were still studying in 2020. We also dropped them from our Wave 2020 sample. Hence, we obtain a final sample of 223 subjects who had completed their studies and found their first permanent job after graduation. In Subsection 4.2, we provide further evidence that attrition is of no concern in our study.

2.4 Classification of Subjects: Finance Interest and Finance Job

For our analysis, we have to classify subjects according to their professional preferences in 2013 and according to their job placement after graduation. In Wave 2013, we measured professional preferences through the question "To what extent can you imagine working in the following industries in the future?", which had to be answered on a Likert scale from 1 to 7. We define the variable "finance interest" as a subject's average answer to this question for the financial and insurance industry. We will use this variable in our non-parametric tests and regression analyses. For our descriptive statistics, we build three groups based on finance interest of similar size: 70 subjects (26.4 percent) have finance interest of less than four points; these will be called "low finance interest subjects"; 104 subjects (39.2 percent) have finance interest of four to less than six points; we will call them "medium finance interest subjects"; 91 subjects (34.3 percent) have finance interest of six or more points; these subjects will be called "high finance interest subjects."

In Wave 2020, we use our subjects' first permanent (full-time) job after graduation for classification. This classification is meaningful since the first job is a strong predictor for the industry in which someone spends his or her future professional career (Ellul et al. 2020). This is also the case in our data. On average, the subjects in Wave 2020 had started their first permanent job three years ago. Since starting their first permanent job, 96.6 percent had not switched from the financial industry to a non-financial industry or vice versa. All jobs in firms with the NACE (Nomenclature of Economic Activities) codes K64, K65, and K66 are classified as jobs in the financial industry.[6] Overall, out of our 223 subjects in the Wave 2020 sample, 75 (33.6 percent) had their first permanent job after graduation in the financial industry according to the NACE classification. We will call them “finance job subjects” in the following. The remaining 148 subjects (66.4 percent) with first jobs in other industries will be referred to as “non-finance job subjects.”

We do not distinguish between the financial and the insurance industry, neither for finance interest nor for finance job. The insurance industry is small relative to the financial industry in Frankfurt. However, many large insurance companies have the headquarter of their financial services in Frankfurt. Our main results are the same when we use a more narrow definition of finance interest and finance job (see Online Appendix, Table A). This is unsurprising given that interest in working in the financial industry and interest in working in the insurance industry is highly correlated (the correlation coefficient is 0.62, p-value = 0.000), and there are only three subjects who find their first job in an insurance company or in an insurance firm’s financial services affiliate.

3 Results

3.1 Interest in the Financial Industry and Experimental Behavior (Wave 2013)

Overall, subjects’ behavior in the experimental trust game in 2013 was as follows. As first movers, they sent on average 38.7 percent (sd = 36.5) of their endowment. As second movers, they returned on average 20.5 percent (sd = 17.8) of the tripled amount.[7]

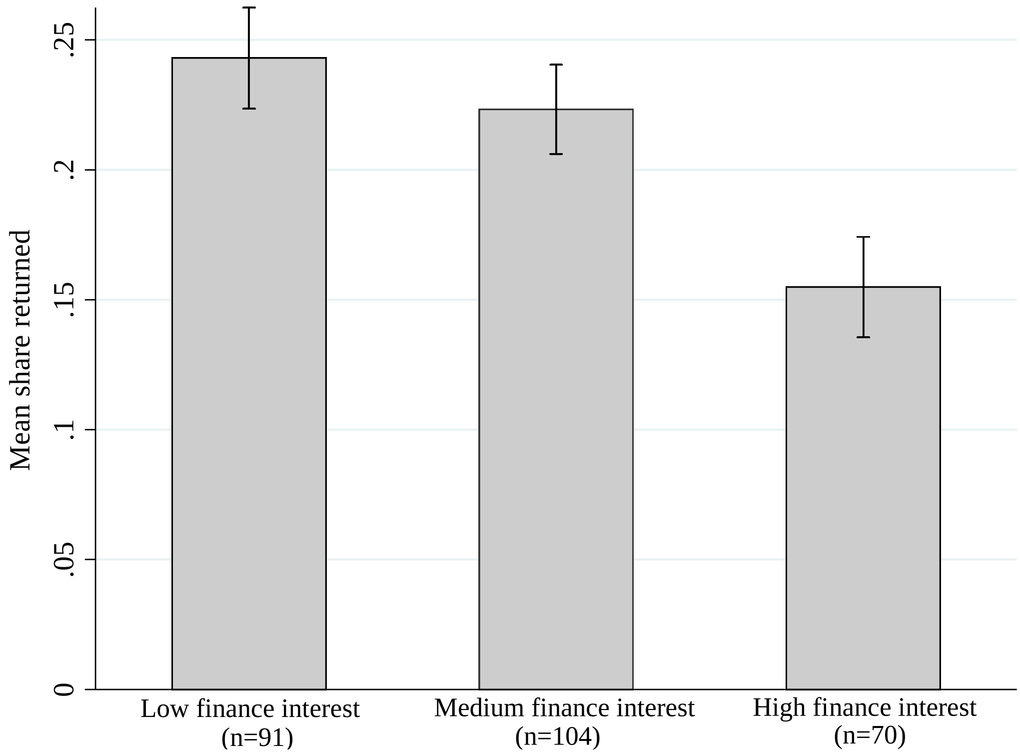
We do not find any significant association between finance interest and the amounts sent as first movers as a measure of trust. Low finance interest subjects sent on average 38.9 percent (sd = 39.4), medium finance interest subjects 39.8 percent (sd = 36.7), and high finance interest subjects 36.8 percent (sd = 32.3). There is neither a statistically significant correlation between finance interest and the amount sent in a Jonckheere-Terpstra test (p-value = 0.905)

[6] The description of the industry codes for the respective NACE codes is the following: K64 means “Financial service activities, except insurance and pension funding”; K65 means “Insurance, reinsurance and pension funding, except compulsory social security”; K66 means “Activities auxiliary to financial services and insurance activities.” We apply the following exceptions from our classification: Positions in central banks or public organizations or United Nations development aid organizations that belong to NACE codes K64 to K66 were classified as non-finance jobs; four subjects found their first job in these organizations. Excluding them from our analyses or classifying them as finance job subjects does not change our main results.

[7] When we consider only the subsample of subjects who also participated in Wave 2020, we find that first movers sent on average 39.7 percent (sd = 37.3) and second movers returned on average 20.1 percent (sd = 16.8). The behavior of this restricted sample is statistically indistinguishable from that of the full sample.

nor in an OLS regression framework, controlling for key characteristics; see Online Appendix, Table B.

Figure 1: Mean share returned, by low, medium, and high finance interest



Notes: In Wave 2013, we asked our subjects "To what extent can you imagine working in the following industries in the future?" for 14 different industries, on a Likert scale from 1 ("certainly not") to 7 ("definitely"). Here, we show the average mean share returned in the trust game for subjects who indicated an average interest for working in the financial and insurance industry of less than four points ("low finance interest"), four to less than six points ("medium finance interest"), and six or more points ("high finance interest"). The whiskers show the standard errors of the mean. The number of observations is in parentheses.

However, we find remarkable differences in the degree to which trust is reciprocated, as measured by the mean share returned. As shown in Figure 1, low finance interest subjects returned, on average, 24.3 percent (sd = 16.3), medium finance interest subjects returned 22.3 percent (sd = 17.5), and high finance interest subjects returned only 15.5 percent (sd = 18.4). The negative relationship between finance interest and the mean share returned is statistically significant (Jonckheere-Terpstra test, p-value = 0.001).

To check the robustness of this relationship, we run an OLS regression in which we regress finance interest on the mean share returned. As shown in Column 1a of Table 1, we find a significantly negative association between finance interest and the mean share returned. The size of the coefficient indicates that each additional unit on the Likert scale from 1 to 7 decreases the mean share returned by 2 percentage points, which accounts for around 10 percent of the overall average return of 20.5 percent. In a next step, we additionally control for gender, age, and cognitive ability. Controlling for gender is particularly important, given the overrepresentation of men in some occupations of the financial industry (Adams et al. 2016). As shown in Column 2a of Table 1, our main qualitative results remain unchanged when adding these controls.

Table 1: Baseline regressions: mean share returned

	Panel A		Panel B	
Specifications	[1a]	[2a]	[1b]	[2b]
Constant	0.299***	-0.016	0.228***	-0.123
	(0.032)	(0.114)	(0.014)	(0.101)
Finance interest	-0.020***	-0.015**		
	(0.006)	(0.007)		
Finance job			-0.080***	-0.076***
			(0.023)	(0.023)
Subject pool				
All subjects Wave 2013	Yes	Yes	No	No
All subjects Wave 2020	No	No	Yes	Yes
Controls	No	Yes	No	Yes
R^2	0.036	0.080	0.051	0.125
Sample size	265	265	223	223

Notes: OLS Regression. The dependent variable is the mean share returned as second mover in the trust game. *Finance interest* is the subjects' average response to the question "To what extent can you imagine working in the following industries in the future?" for the financial and the insurance industry on a Likert-scale from 1 ("certainly not") to 7 ("definitively"). *Finance job* is a dummy set to one if a subject has the first permanent job after graduation in the industry with the NACE code K64, K65, or K66. Controls are age, gender, and the score in the Raven's Advanced Progressive Matrices. Robust standard errors are in parenthesis. * p<0.1, ** p<0.05, *** p<0.01.

Our results also hold when we use a Tobit model instead of OLS; see Online Appendix, Table C. As a further robustness check, we use six dummies for finance interest as independent variables.[8] We find that our regression results are mainly driven by those subjects who exhibit

[8] One dummy for finance interest equal to 7 or 6.5, one dummy for finance interest equal to 6 or 5.5, and so forth.

finance interest of 6.5 or 7, and partly by those with finance interest equal to 6 or 5.5; see Online Appendix, Table D.

Are subjects with high finance interest generally less reciprocal than other subjects or is the share of completely selfish subjects just larger among high finance interest subjects? To find out, we compare the number of completely selfish subjects among subgroups. In the trust game, these subjects always return zero, regardless of the amount received. Among high finance interest subjects, the share of these individuals is 38.5 percent; among medium and low finance interest subjects, this share is 25.0 and 14.3 percent, respectively. If we exclude all completely selfish individuals from our sample, the finance interest coefficient decreases by around 60 percent in our main regression; see Online Appendix, Table E, Panel A. Overall, the association between finance interest and the mean amount returned seems to be driven by two effects: a larger share of completely selfish subjects among those with high finance interest, and lower levels of reciprocity among high finance interest subjects who are not completely selfish.

3.2 First Permanent Job and Reciprocity (Wave 2020)

We do not find any significant difference between finance job and non-finance job subjects in the level of trust as first movers (in the lab experiment in 2013). Non-finance job subjects sent on average 41.4 percent (sd = 36.5), while finance job subjects sent on average 36.3 percent (sd = 38.8). The difference is not statistically significant (Mann-Whitney test, p-value = 0.226), which is in line with our earlier result that the degree of interest in the financial industry is not related to trust as first movers. As argued earlier, we consider the degree of trust as of secondary importance since the reciprocity of actors in the financial industry is what counts most for the interaction with customers and the general public.

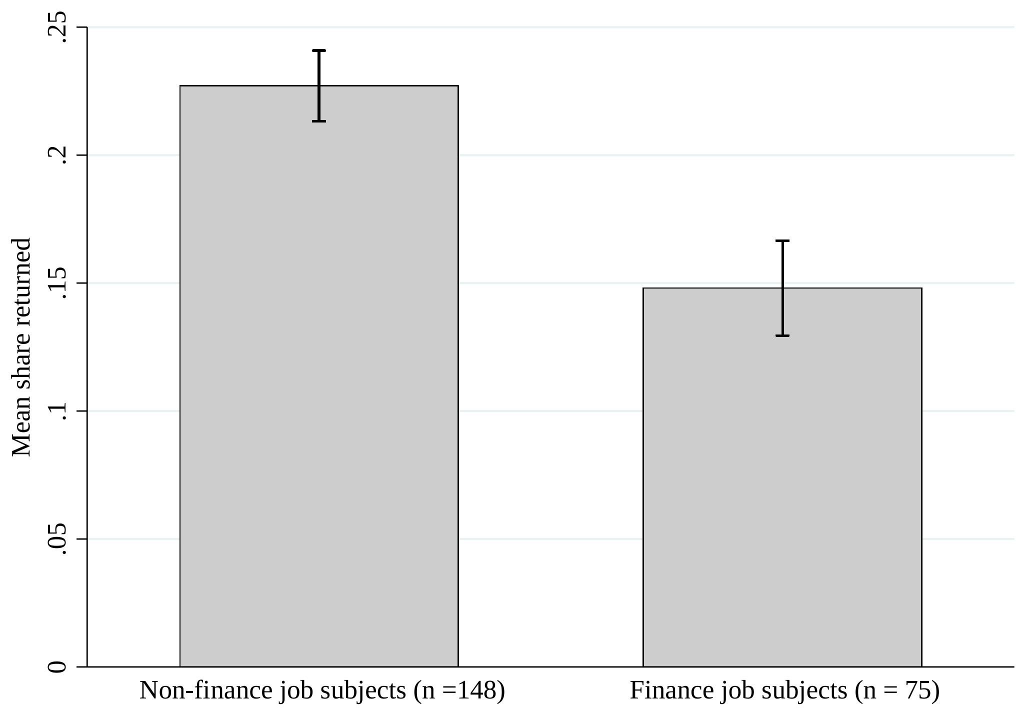
The mean share returned differs substantially between subjects who get their first job after graduation in the financial industry and those who start working elsewhere. As shown in Figure 2, non-finance job subjects returned on average 22.8 percent (sd = 16.5) of the tripled amount, while finance job subjects returned on average only 14.8 percent (sd = 16.0). The difference equals about one third of the non-finance job subjects' mean share returned and is statistically significant (Mann-Whitney test, p-value = 0.001).

To check the robustness of the non-parametric result, we run an OLS regression in which we regress a dummy for finance job on the mean share returned. The results are presented in

A large fraction of our subjects indicates a high interest in working in the financial industry, so our finance interest variable is highly skewed. Using six dummies instead of the variable finance interest is a useful robustness check as we interpret our ordinal finance interest scale in a cardinal way.

Column 1b of Table 1. We find that finance job subjects return on average 8 percentage points less compared to non-finance job subjects. This means that subjects with a first job after graduation in finance return on average a third less than subjects who start working elsewhere. This considerable difference is robust to controlling for age, gender, and cognitive ability; see Column 2b in Table 1.

Figure 2: Mean share returned, by finance job



Notes: The figure shows the average mean share returned in the trust game for subjects with a first job placement after graduation in the financial industry (NACE codes K64 to K66) and for subjects with a job placement after graduation in any other industry based on the data collected in Wave 2020. The whiskers show the standard errors of the mean. The number of observations is in parentheses.

Again, we examine to what extent our effects are driven by varying shares of completely selfish individuals in the different subgroups. Among finance job subjects, the share of completely selfish subjects is 40 percent, while it is only 23 percent among non-finance job subjects. When we exclude all completely selfish subjects from our baseline regressions, the finance interest coefficient decreases by around 40 percent, but it remains statistically significant; see Online Appendix, Table E, Panel B. Thus, the behavioral difference between the two subgroups is driven both by a larger share of completely selfish individuals among finance job subjects, and by lower levels of reciprocity among finance job subjects who are not completely selfish.

3.3 Career Paths from Intentions to Actual Job Placement

Our dataset allows us to examine how subjects' professional interests materialize in early career choices and first job placements. In this subsection, we study the selection of behavioral types into the financial industry by analyzing in detail the relationship between finance interest and finance job, and the choices subjects make in order to advance their careers.

In a first step, we study the job placements of the different finance interest subgroups. Among high finance interest subjects, 54.7 percent find their first permanent job in the financial industry; for medium finance interest subjects, this number is 30.2 percent, and it drops to only 12.9 percent for low finance interest subjects (Jonckheere-Terpstra test, p-value = 0.000). In a second step, we run a probit regression, in which finance job is the dependent, and finance interest the independent variable. We find that each additional unit on the Likert scale from 1 to 7 increases the probability that a subject starts her career in the financial industry after graduation by 10 percentage points; see Online Appendix, Table F. We conclude that our finance interest variable is a good predictor for later job placements in the financial industry and that mainly high finance interest subjects choose to work in – and get job offers from – this industry.[9]

High finance interest is a good predictor for finance job placements in the financial industry after graduation. However, not all subjects who indicate high finance interest in 2013 start their career in the financial industry. We examine the behavior of those 77 subjects with a finance interest score of 6 or higher for whom we know the first permanent job after graduation. In this sample, 41 subjects indeed started a career in finance, and they returned on average only 9.2 percent (sd = 11.7). The other 36 subjects started a career in another industry. They returned on average 19.4 percent (sd = 17.8). The difference is statistically significant in a Mann-Whitney test (p-value = 0.012) and in an OLS regression framework; see Table 2. This indicates that the job market does not reduce the selection of less reciprocal individuals into the financial industry; if anything, the opposite seems to be the case.

To further illustrate how subjects' behavior is related to finance interest and job, we compare the 41 subjects who expressed high interest in finance and got their first job there to 54 subjects who indicated low finance interest and started working outside of finance. The latter group returned on average 25.3 percent (sd = 16.6), which is almost three times as high as the rate of 9.2 percent (sd = 11.7) of the former group. The difference is statistically significant in

[9] Recall that around 30 percent of Goethe University students of business and economics start a career in finance (according to alumni data). Hence, the share of subjects with a high interest in finance who actually get their first job there (54.7 percent) is almost twice as large as the average likelihood to find the first job in finance.

a Mann-Whitney test (p-value = 0.000) and in an OLS regression framework (see Online Appendix, Table G). This comparison of the polar cases suggests very strong behavioral differences between subjects who keep away from the financial industry and subjects who pursue eagerly and successfully a career in finance.

Table 2: Regression results, comparing subjects with finance job and non-finance job among subjects with high finance interest

Specifications	[1]	[2]
Constant	0.194***	0.050
	(0.030)	(0.214)
Finance job	-0.103***	-0.111***
	(0.035)	(0.034)
Controls	No	Yes
R^2	0.109	0.225
Sample size	77	77

Notes: Modified version of our baseline regressions for finance job (Table 1, Panel B). The dependent variable is the mean share returned as second mover in the trust game. Here, we focus on the subsample of subjects with high finance interest (subjects who choose a value of 6 or 7 on the Likert scale). Robust standard errors are in parenthesis. * p<0.1, ** p<0.05, *** p<0.01.

So far, we have only considered the relationship between finance interest and actual job placements. Yet, we can dig even deeper by also looking at subjects' career and specialization choices before graduation. We thereby show that high finance interest subjects are not ending up "accidentally" in the financial industry. Instead, their career paths show systematic patterns.

Table 3 summarizes the pre-graduation job experience, applications for the first permanent job after graduation, and study background information for all subjects from Wave 2020. Panel A presents averages for all 223 subjects with known first job. Panel B splits up the data contingent on the level of interest in working in the financial industry as expressed in 2013, and panel C distinguishes between finance job and non-finance job subjects.

Overall, our subjects spent on average 45.1 weeks in internships, working student jobs or vocational training jobs before graduating; they submitted on average 8.9 applications for their first permanent job, and 71.3 percent of them were enrolled in a master program after finishing their undergraduate studies. We find no significant association between finance interest (in panel B) or finance job (in panel C) and the total amount of pre-graduation job experience, the total number of applications for the first permanent job, and whether subjects are enrolled in a master program.

However, we find significant differences between the subsamples of subjects in panels B and C of Table 3 when we distinguish between early career and specialization choices that are more or less likely to lay a foundation for a career in the financial industry. Looking first at the results for finance interest in panel B of Table 3, we observe three noteworthy patterns. First, a large majority of high finance interest subjects (77.3 percent) have pre-graduation job experience in the financial industry (most of which was acquired after Wave 2013; see the discussion in Subsection 4.1). In contrast, job experience in the financial industry is much less pronounced among low finance interest subjects; only 27.9 percent of them collected professional experience in this industry. In line with this, high finance interest subjects also acquire much more relative pre-graduation job experience, as measured by the share of weeks spent in financial companies (relative to the total number of weeks with pre-graduation job experience), compared to low finance interest subjects (46.4 percent versus 11.8 percent). Second, high finance interest subjects submit a larger share of their applications (35.6 percent) for their first permanent job to firms from the financial industry. In contrast, low finance interest subjects only submit 7.5 percent of their applications to firms from the financial industry. Third, the majority of high finance interest subjects (68.0 percent) chose “finance” as their major field of study during their undergraduate studies. Among low finance interest subjects, only 15.0 percent of subjects chose such a major.

The results for subjects with a first job in finance and those in other industries are presented in Panel C of Table 3. The main qualitative results are the same as for finance interest in Panel B. Subjects with their first permanent job in finance have considerably more often any pre-graduation job experience in the financial industry (90.7 percent versus 37.8 percent), spend a larger fraction of their pre-graduation job experience in the financial industry (61.1 percent versus 14.0 percent), submit many more of their applications to the financial industry (53.5 percent versus 7.5 percent), and choose more often finance as their major field in their Bachelor study (65.7 percent versus 32.2 percent). All of these differences are highly significant (p-value < 0.001), showing that subjects who get their first permanent job after graduation in the financial industry have markedly different early career paths and specialization choices.

Table 3: Subjects' early career and specialization choices - overall and by finance job and finance interest

	Panel A: All subjects	Panel B: Finance interest				Panel C: Finance job		
	All subjects	High	Medium	Low	JT §	Yes	No	MW §/ Chi²
	(n=223)	(n=75)	(n=86)	(n=62)	p-value	(n=75)	(n=148)	p-value
Pre-graduation job experience								
Total job experience (in weeks)	45.1 (29.5)	45.6 (28.5)	42.9 (28.2)	47.0 (33.0)	0.720	43.3 (23.7)	46.0 (32.1)	0.946
Any job experience in the financial industry before graduation (yes / no)	55.6%	77.3%	58.3%	27.9%	0.000	90.7%	37.8%	0.000
Relative job experience in the financial industry (in weeks out of total #weeks)	29.8%	46.4%	29.2%	11.8%	0.000	61.1%	14.0%	0.000
Applications for first permanent job								
Total number of applications	8.9 (13.4)	8.9 (15.4)	9.3 (12.0)	8.2 (12.3)	0.782	9.3 (12.6)	8.6 (13.8)	0.384
Relative number of applications in fin. industry	24.6%	35.6%	26.9%	7.5%	0.000	53.5%	7.5%	0.000
Studies								
Bachelor: Finance as major field of study	43.2%	68.0%	41.0%	15.0%	0.000	65.7%	32.2%	0.000
Enrolled in Master program	71.3%	70.7%	72.1%	71.0%	0.779	72.0%	70.9%	0.870

§ J.-T. denotes Jonckheere-Terpstra-test; M.W. denotes Mann-Whitney U-test.

Notes: The table provides the early career and specialization choices characteristics of all subjects who participated in Wave 2020 (with standard deviations in parentheses). Column 1 provides the characteristics for all 223 subjects; columns 2-5 provides the characteristics by *finance interest* (high, medium versus low finance interest) in Wave 2013; columns 6-8 by the first permanent job after graduation. *Total job experience (in weeks)* is the number of weeks a subject worked as part of a vocational training program, as a working student or as an intern in a company before graduating (i.e., before or during studies). *Any job experience in the financial industry (yes / no)* is the share of subjects who have had some job experience in the financial industry before graduating. *Relative job experience in the financial industry (share, in weeks out of total #weeks)* is the job experience (vocational training, working student, internships) in the financial industry divided by *Total job experience (in weeks)*. *Total number of applications* is the total number of applications that subjects submitted after their graduation for their first permanent job. *Relative number of applications in the financial industry* is the number of applications submitted to firms in the financial industry divided by the *Total number of applications*. *Bachelor: Finance as major field of study* is the share of subjects who had finance as the major field of study in their undergraduate studies. *Enrolled in Master program* is the share of subjects who were at any point in time (before 2020) enrolled in a master program. In Column 5, we report the p-values of a two-sided Jonckheere-Terpstra test. In Column 8, we report p-values of either two-sided Mann-Whitney rank-sum tests (for non-binary variables), or Chi-square tests (for binary variables). The number of observations is 223, with the following exceptions: Two subjects had no job experience and are dropped in the analysis on relative job experience in the financial industry. *Total number of applications*: 26 subjects did not know the total number of applications, or were not willing to provide us with the data; we omitted those subjects in the respective analysis. For the analysis of *Relative job experience in the financial industry (share, in weeks)* we omitted 24 subjects who did not submit any applications (e.g. because they already worked as an intern in the respective firm). *Bachelor: Finance as major field of study*: For ten subjects, we do not know the major field of study; the subjects are dropped in the respective analysis.

Table 4: Characteristics of our subjects, overall and by finance interest and finance job

	Panel A: All subjects	Panel B: Finance interest				Panel C: Finance job		
		High	Medium	Low	JT[§]	Yes	No	MW [§]/ Chi²
	(n=265)	(n=91)	(n=104)	(n=70)	p-value	(n=75)	(n=148)	p-value
Age	22.0 (2.4)	22.1 (2.3)	21.9 (2.3)	22.2 (2.7)	0.853	22.1 (2.4)	22.0 (2.4)	0.634
Female	51.1%	52.7%	54.8%	48.6%	0.905	40.0%	54.1%	0.047
Risk preferences	5.3 (2.1)	5.4 (2.2)	5.4 (2.1)	5.2 (2.1)	0.823	5.6 (1.0)	5.2 (1.1)	0.200
Patience	5.1 (2.4)	5.0 (2.6)	5.0 (2.4)	5.0 (2.4)	0.855	5.2 (1.5)	5.1 (1.4)	0.705
Raven's score	7.4 (2.2)	7.4 (2.2)	7.1 (2.2)	7.7 (1.9)	0.378	7.3 (2.3)	7.5 (2.1)	0.513
Items on work values								
Working conditions	5.6 (1.1)	5.9 (1.1)	5.6 (1.1)	5.4 (1.1)	0.010	5.7 (1.2)	5.6 (1.0)	0.163
Work-life balance	5.9 (1.4)	5.8 (1.5)	5.9 (1.2)	6.0 (1.2)	0.934	5.7 (1.5)	6.0 (1.3)	0.154
Distance: work & home	5.7 (1.2)	5.7 (1.2)	5.6 (1.2)	5.4 (1.4)	0.467	5.4 (1.4)	5.8 (1.2)	0.103
Job security	5.7 (1.4)	5.8 (1.4)	5.7 (1.4)	5.8 (1.3)	0.681	5.5 (1.6)	5.8 (1.3)	0.083
Income	5.7 (1.2)	5.6 (1.2)	5.7 (1.2)	5.8 (1.1)	0.463	6.0 (1.0)	5.5 (1.3)	0.003
Benefits	4.2 (1.7)	4.1 (1.7)	4.3 (1.6)	4.3 (1.6)	0.945	4.6 (1.5)	4.0 (1.7)	0.020
Relationship co-workers	6.2 (1.0)	6.0 (1.2)	6.4 (0.8)	6.3 (0.9)	0.265	6.1 (1.0)	6.2 (1.1)	0.330
Relationship supervisor	6.0 (1.1)	5.9 (1.3)	6.2 (0.9)	6.1 (1.0)	0.885	6.0 (1.1)	6.0 (1.1)	0.780
Career opportunities	6.2 (1.0)	6.3 (0.8)	6.2 (0.9)	6.2 (1.0)	0.768	6.3 (0.9)	6.1 (1.0)	0.075
Training	6.0 (1.1)	6.0 (1.1)	6.1 (0.9)	5.9 (1.2)	0.567	5.9 (1.3)	6.0 (1.0)	0.911
Autonomy	5.6 (1.2)	5.8 (1.1)	5.5 (1.3)	5.4 (1.3)	0.136	5.8 (1.1)	5.5 (1.3)	0.198
Personality development	5.6 (1.2)	5.7 (1.2)	5.8 (1.2)	5.4 (1.4)	0.294	5.6 (1.1)	5.6 (1.3)	0.384
Challenging tasks	5.7 (1.1)	5.7 (1.1)	5.8 (1.0)	5.4 (1.2)	0.795	5.9 (0.9)	5.6 (1.2)	0.068
Reputation of the employer	5.2 (1.5)	5.1 (1.6)	5.4 (1.4)	5.3 (1.4)	0.005	5.3 (1.5)	5.2 (1.5)	0.747

[§] JT denotes Jonckheere-Terpstra-test; MW denotes Mann-Whitney U-test.

Notes: The table shows characteristics of our subject pool (and standard deviations in parentheses). Column 1 provides the characteristics for all subjects (n=265); columns 2 to 5 by finance interest (high, medium versus low finance interest, n=265); column 6 to 8 by the first permanent job after graduation (finance versus non-finance, n=223). *Age* is a subject's age in 2013; *Risk preference* is the self-reported willingness to take risk on a scale between 0 and 10 (Dohmen et al. 2011); *Patience* is self-reported patience on a scale between 0 and 10 (Vischer et al. 2013). *Raven's score* is the score a subject achieved in Raven's Advanced Progressive Matrices (Bors and Stokes 1998). The work values listed under *Items on work values* are based on Ronen (1994). Subjects were asked to rate on a scale between 1 (not attractive) to 7 (highly attractive) how important different characteristics of jobs are for an attractive job. In Column 5, we report the p-values of a two-sided Jonckheere-Terpstra test to measure the of the finance interest variable (using the 7-scale score). In Column 8, we report p-values of either two-sided Mann-Whitney rank-sum tests (for non-binary variables), or Chi-square tests (for binary variables), to measure the influence of having a job in the financial industry or elsewhere.

3.4 Taking into Account Further Personal Characteristics

As a final step in examining the differences between subjects of varying finance interest levels and job placements, we look at personal characteristics. Table 4 shows data on age, gender, risk and time preferences, cognitive ability, as well as work values (Ronen 1994). Panel A displays the overall averages for all subjects. Panels B presents averages (and standard deviations) for the three categories of finance interest (high, medium and low), and Panel C presents these values for finance and non-finance job subjects, respectively.

In Wave 2013, 51.1 percent of our subjects were female, and at that time they were 22 years old on average. The self-reported willingness to take risks was 5.3 (on a scale between 0 and 10), and self-reported patience was 5.1 (on a scale between 0 and 10). In terms of cognitive ability, subjects had an average Raven score of 7.4 (on a scale between 0 and 12). The most important self-reported work values were career opportunities and the relationship to co-workers.

We find no association between many important personal characteristics and finance interest or finance job. In particular, neither cognitive ability nor risk preferences are associated with finance interest and finance job. Thus, it does not seem to be the case that "smarter" or more risk-loving individuals get more often jobs in the financial industry. We find that finance job subjects are more often male compared to non-finance job subjects. However, there is no such association for finance interest; see panels B and C of Table 4.

Concerning work values, we find no association between work values and finance job or finance interest that are statistically significant at the 5-percent level; see panel C of Table 4.[10] There is only one exception: Finance job subjects appreciate income and benefits from the job much more than non-finance jobs subjects. Controlling for income and benefits in our baseline regressions does not change our main results, however (see Online Appendix, Tables H and I).

4 Robustness Checks

We conduct several robustness checks in which we examine the potential influence of exposure to the financial industry, the sensitivity of our data with respect to how we classify participants into finance job and non-finance job subjects, and the potential effects of attrition between Wave 2013 and Wave 2020.

[10] This is also the case if we control for multiple hypothesis testing (List et al. 2019).

4.1 Exposure and Selection

Our main finding from the previous section – that finance job subjects are less reciprocal than those selecting into other industries – would be, in principle, also compatible with the following interpretation. As we have seen in Subsection 3.3, finance job subjects choose more education in finance and gather more experience in finance before graduation (e.g., in the form of internships) than non-finance job subjects. Hence, their exposure to finance education and the business culture in the financial industry might have made them less reciprocal already when we measured behavior in Wave 2013.

Table 5: Regression results, focusing on the subsample of subjects who are in the first three semester of their studies

	Panel A		Panel B	
Specifications	[1a]	[2a]	[1b]	[2b]
Constant	0.305***	0.131	0.203***	-0.091
	(0.042)	(0.169)	(0.017)	(0.138)
Finance interest	-0.024***	-0.020**		
	(0.008)	(0.010)		
Finance job			-0.070**	-0.061**
			(0.029)	(0.030)
Subject pool				
All subjects Wave 2013	Yes	Yes	No	No
All subjects Wave 2020	No	No	Yes	Yes
Controls	No	Yes	No	Yes
R^2	0.044	0.092	0.044	0.132
Sample size	153	153	128	128

Notes: Modified version of our baseline regressions from Table 1. Here, we focus on subjects who were in the first, second or third semester of their studies at the point in time when we conducted Wave 2013. We know the semester based on a pre-experimental survey that we conducted right after the lab experiment in 2013. Robust standard errors are in parenthesis. * p<0.1, ** p<0.05, *** p<0.01.

To examine this alternative interpretation, we run two robustness checks of our baseline regressions from Table 1. First, we include only subjects who were in the first three semesters of their undergraduate studies at the point in time when they participated in Wave 2013. Here we exploit the fact that the basic courses in business and economics at Goethe University

Frankfurt are the same for all students, independent of their interest in working in the financial industry. In particular, this means that these subjects had not taken yet any specialization course in finance. Table 5 shows that the estimated coefficients for finance interest (in panel A) and finance job (in panel B) on reciprocity are of comparable magnitude as in Table 1. Moreover, they show the same significance levels. Hence, exposure to specialization courses in finance does not matter for the relation between reciprocity and finance interest and finance job, respectively.

Table 6: Regression results, excluding all subjects who already had job experience in the financial industry before we conducted Wave 2013

	Panel A		**Panel B**	
Specifications	[1a]	[2a]	[1b]	[2b]
Constant	0.324***	-0.047	0.248***	-0.123
	(0.038)	(0.136)	(0.015)	(0.121)
Finance interest	-0.025***	-0.018**		
	(0.008)	(0.009)		
Finance job			-0.121***	-0.112***
			(0.028)	(0.029)
Subject pool				
All subjects Wave 2013	No	No	No	No
All subjects Wave 2020	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
R^2	0.069	0.126	0.100	0.182
Sample size	160	160	153	153

Notes: Modified version of our baseline regressions from Table 1. Here, we focus on subjects who had no prior job experience in the financial industry (e.g. through internships) at the point in time when we conducted Wave 2013. We only include subjects who participated in Wave 2020 (i.e. subjects for whom we have detailed information about their professional experiences). In Panel A, we also include subjects who participated in Wave 2020, but where still studying at this point in time; note that we have for those subjects detailed data about their job experience before 2020 (and hence also before 2013). Robust standard errors are in parenthesis. * p<0.1, ** p<0.05, *** p<0.01.

Next, it could matter even more whether a subject had already some (albeit short-term) experience in the financial industry before Wave 2013. While most of our high finance interest subjects and finance job subjects only gained job experience in the financial industry after 2013, some had been working as interns before. Therefore, we present in Table 6 the results of our baseline regression when we exclude all subjects who already had job experience in the financial industry before Wave 2013. Table 6 shows that this exclusion does not matter for our main results. Subjects with a strong interest in finance (panel A) and those who get their first permanent job in the financial industry (panel B) are significantly less reciprocal than others. The estimated coefficients for finance interest (-0.022, respectively -0.015; see panel A of Table 1) and finance job (-0.121, respectively -0.112) are even slightly larger in absolute terms than those in our baseline regression (see Table 1). Thus, if we only consider subjects who in 2013 did not have any experience in the financial industry, then the negative relation between reciprocity and getting a job in the financial industry later on is, if anything, even slightly stronger than in the full sample.

4.2 Classification into Finance Job and Non-Finance Job Subjects

To ensure that our results are robust to our finance job classification, we vary the classification in a number of ways. First, we have 34 subjects in our sample who completed a vocational training before commencing their studies. We interpret vocational training as part of their education and not as their first job. This assumption has little consequences for our classification, however. From the 34 subjects with vocational training, 14 completed it in industries other than the financial industry. None of them had the first job after graduation in the financial industry. From the 20 subjects with vocational training in the financial industry, 17 found their first job after graduation in the financial industry. When we exclude the remaining three subjects from our sample, our results remain unchanged.

Second, we have 16 students who changed their field of study after Wave 2013 had been conducted.[11] Our results remain unchanged when we drop these subjects from our sample (see Online Appendix, Table J).

Third, we have some subjects who have switched their employer at least once after having started in their first permanent job. Although subjects were on average already working for around three years (mean = 35.2 months, sd = 22.4), only a minority of them had switched their employer at least once, and even less so across industries: 23 out of the 75 finance job subjects switched their employer before we completed Wave 2020; 20 of them switched to another employer in the financial industry, and three left the financial industry. Among the 148 subjects in non-financial industries, only five subjects switched from a non-financial to a

[11] The subjects switched from business and economics to computer science (three subjects), educational science (two subjects), geography (two subjects), biology (two subjects), medicine, chemistry, psychology, law (one subject each); two subjects started a vocational training.

financial company. When we adjust the finance job classification for the eight subjects who switched between the financial and non-financial industries, our results remain unchanged (see Online Appendix, Table K).

Finally, we study whether the job selection based on reciprocity also exists for other industries. Table L in the Online Appendix provides an overview of all industries in which at least three subjects had found their first permanent job after graduation. Consistent with alumni data from Goethe University Frankfurt, firms in the financial industry are by far the most important employers in our sample: 33.6 percent of our Wave 2020 subjects have their first permanent job in the financial industry. Among the top three sectors are also consulting (12.1 percent), and auditing (7.6 percent). As a robustness check, we rerun our baseline regression from Table 1 for finance jobs, adding one dummy for the other two large sectors into which students selected after their graduation (consulting, auditing). All other sectors are used as the benchmark. Our main results for finance job subjects remain unchanged (see Online Appendix, Table M). We find no significant effects on reciprocity for the other two large industries. Moreover, the differences between the finance job coefficient and the consulting and audit job coefficients are statistically significant in both regressions (Wald test, all p-values < 0.040).

4.3 Attrition

A potential concern for our results could be the attrition between Wave 2013 and Wave 2020. Attrition would bias our results if the probability of drop-out was correlated with job market outcomes. However, we do not believe that attrition is a concern for our results. First, attrition in our study is rather low: 86.8 percent of our subjects from Wave 2013 also participated in Wave 2020. Second, we have (by design) no attrition when we analyze the association between experimental behavior and finance interest in Wave 2013, and we document in Subsection 3.3 that finance interest is an important predictor for job market placements. Third, when we compare data from Wave 2013 on the most important observable and measured characteristics (age, gender, cognitive ability, finance interest, pre-graduation job experience) between subjects who participated in Wave 2020 and those who dropped out, we find no statistical differences (Mann-Whitney tests, all p-values > 0.130), with one exception. Women are significantly more likely to drop out than men.

To examine the potential effects of attrition in more detail, we perform the following simulation: We use the Wave 2020 data to predict the probability that a subject's first permanent job is in the financial industry, based on subject's observables and characteristics (see Online Appendix, Table F, Column 2). Using these results, we estimate for each of the 34 drop-out subjects from Wave 2013 the probability that his or her first permanent job is in the financial industry. The average estimated probability is 31.8 percent (sd = 17.1); 13 subjects have a probability below 25 percent, 15 subjects a probability between 25 and 50 percent, and 6 subjects a probability of 50 percent or higher. Using these estimated probabilities, we then run a battery of robustness checks of our baseline regression for finance job (as in panel B of Table 1). In these robustness checks, we include *all* subjects who did *not* drop out. Additionally, we include all drop-out subjects, and vary in eleven different regressions whether or not they are considered as a finance job subject or a non-finance job subject. We start with the assumption that *all* drop-out subjects are finance job subjects. This is Scenario 1 in Table N in the Online Appendix, which implies a cut-off rule of zero percent (above which all drop-outs are assumed to be finance job subjects). In Scenario 2, the finance job dummy is set to one for all drop-out subjects who have a probability of 10 percent or higher to have the first job in the financial industry (otherwise zero). Then we move in 10-percentage points steps until we get to a cut-off of 100 percent where *all* drop-outs are classified as non-finance job subjects. We find that in *every single* regression (see Table N in the Online Appendix) our main coefficient of interest is economically and statistically significant and very close to the coefficient reported in Column 2b of Table 1. This suggests strongly that our main qualitative results would persist even if we had a zero drop-out rate.

5 Further Evidence for Selection on Social Preferences

A potential concern is that our results may be unique to the study location or to the dimension of social preferences that we evaluated. In this section, we therefore provide further evidence for selection into the financial industry based on social preferences. We use data from an unrelated study (Heinz and Schumacher 2017), in which we measured professional preferences and experimental behavior in a public goods game. Behavior in the public goods game measures subjects' willingness to cooperate in groups. Several papers have shown that cooperation in the public goods game predicts cooperative behavior outside the laboratory; see Rustagi et al. (2010) for common resource management, Algan et al. (2016) for open source software development, and Englmaier and Gebhardt (2016) for workplace performance.

The study was conducted with 347 student subjects from the University of Cologne (which has the biggest business and economics department in Germany) and 168 student subjects from the University of Düsseldorf in 2014. Subjects were from all study fields.

In the experiment, subjects are randomly matched into groups of three participants.[12] Following Fischbacher et al. (2001) and Fischbacher and Gächter (2010), each subject initially holds 20 tokens, which he or she can either keep or contribute to the public good of the group. Denote by g_i the number of tokens that subject i contributes to the public good. The payoff of group member i is then given by

$$\pi_i = 20 - g_i + 0.6 \sum_{j=1}^{3} g_j. \tag{1}$$

The optimal strategy for money-maximizing subjects is to free ride (g_i = 0), while the maximization of the group-payoff would dictate to contribute everything (g_i = 20). Subjects play a one-shot game where they make a single decision about how many of the 20 tokens they want to contribute to the public good.[13]

We elicited professional interests as in the main study so that we can again use our finance interest variable. In the new sample, we have 95 subjects with high finance interest (18.4 percent), 134 with medium finance interest (26.0 percent), and 286 with low finance interest (55.5 percent). Hence, interest in working in the financial industry is significantly lower in the Cologne and Düsseldorf sample than in the Frankfurt sample (Mann-Whitney test, p-value = 0.000). This reflects that the former sample is from different study fields, and that neither Cologne nor Düsseldorf are as attractive as Frankfurt for individuals who would like to work in the financial industry.

Nevertheless, the experimental results mirror those from our Wave 2013 and provide further support for a relationship between social preferences and one's interest in a career in the financial industry. Low finance interest subjects contributed on average 10.3 tokens (sd = 6.6), medium finance interest subjects contributed on average 8.7 tokens (sd = 6.7), and high finance interest subjects contributed only 8.3 tokens (sd = 6.9). This negative relationship between finance interest and contributions is significant (Jonckheere-Terpstra test, p-value = 0.001).

---

[12] The instructions for this experiment are in Online Appendix V. For the experiment, we used an adapted version of the z-Tree code from Fischbacher and Gächter (2010). Each session lasted about 90 minutes. The exchange rate was 0.35 Euros for each token. On average, subjects earned 34.10 Euros (including a show-up fee of 23 Euros) at the University of Cologne and 22.50 Euros (including a show-up fee of 4 Euros) at the University of Düsseldorf. The variation in payments is because the rest of the experimental protocol was different in Cologne and Düsseldorf; see Heinz and Schumacher (2017) for details. We show in our regression analysis that controlling for the study location (Cologne or Düsseldorf) does not affect our results.

[13] Subsequently, subjects also made a "conditional contribution" to the public good (i.e., a contribution for each of the 21 possible average contribution levels of the other group members). They also played the game for ten consecutive rounds. Here, we only discuss the "unconditional contribution" in the one-shot game because contributions in the repeated game are confounded by others' contributions and learning.

Table 7: Regression result: contributions in the public goods game

Specifications	[1]	[2]	[3]
Constant	11.179***	6.831**	7.371***
	(0.572)	(2.758)	(2.766)
Finance interest	-0.486***	-0.440***	-0.341**
	(0.145)	(0.151)	(0.167)
Controls I	No	Yes	Yes
Controls II	No	No	Yes
R^2	0.021	0.028	0.029
Sample size	515	515	513

Notes: OLS regression, similar to our baseline regression for finance interest (Table 1, Panel A). The dependent variable is the unconditional contribution in the one-shot public goods game. The independent variable is finance interest (ranging from 1 to 7). Controls are age, gender, and the scores in Raven's Advanced Progressive Matrices. Controls II is a dummy set to one if a student is a business/economics student and a dummy set to one (zero) if the experiment took place in Cologne (Düsseldorf). Two subjects are excluded in Specification 3 as we do not know their field of study. Robust standard errors are in parenthesis. * p<0.1, ** p<0.05, *** p<0.01.

To confirm this result, we run a modified version of our baseline regression, using the contribution to the public good as dependent variable. As shown in Table 7, we find a significant negative effect of finance interest on contributions. On average, high finance interest subjects contribute about 20 percent less to the public good than low finance interest subjects. The effect size is robust to controlling for age, gender, cognitive ability, location of the experiment (Cologne or Düsseldorf), and whether the subject was a business or economics student.

We do not have information on subjects' first job placement. However, we have seen in Subsection 3.3 that an interest in working in the financial industry during one's college days is a strong predictor of actual job placement. So, the evidence from the public goods game suggests that there might also be a relationship between the willingness to cooperate in groups and selection into the financial industry. Moreover, the results from the public goods game address potential concerns that our results are only confined to Frankfurt, or that they depend on the skewed distribution of the interest to work in the financial industry as was the case in Frankfurt. In Cologne and Düsseldorf, the distribution is skewed in the opposite direction, but yields qualitatively similar results.

The experimental data from Heinz and Schumacher (2017) also allow us to study to what extent behavioral differences between different finance interest subject groups persist in the presence of strategic concerns. After playing the one-shot game, subjects in the experiment at the University of Cologne played a repeated public goods game in fixed groups. The public goods game was played in ten consecutive rounds. The payoff structure was the same as in the one-shot game and the groups were reshuffled between the one-shot and the repeated public goods game. After each round, subjects were informed about the opponents' contributions in the previous round.[14]

Table 8: Contributions in the repeated public goods game, by period and finance interest

Period	1	2	3	4	5	6	7	8	9	10
Low finance interest	11.5	12.1	12.3	12.7	11.8	11.5	11.2	10.9	10.1	7.2
(n=181)	(6.7)	(6.9)	(7.1)	(7.2)	(7.9)	(8.1)	(8.1)	(8.3)	(8.4)	(8.4)
Medium finance interest	10.5	12.2	13.5	11.9	12.4	11.9	11.4	10.8	10.4	6.3
(n=91)	(6.8)	(5.9)	(5.9)	(7.2)	(7.3)	(7.6)	(8.3)	(8.2)	(8.6)	(7.9)
High finance interest	11.0	11.1	10.7	10.8	9.9	10.0	10.4	9.5	8.8	4.7
(n=75)	(6.1)	(6.6)	(7.1)	(7.4)	(7.7)	(7.9)	(8.0)	(8.1)	(8.0)	(7.0)
Jonckheere-Terpstra test (p-value)	0.383	0.364	0.232	0.040	0.105	0.085	0.284	0.111	0.245	0.015

Notes: The table shows the contributions (standard deviations in parenthesis below the coefficients) in each period of the public goods game. In the lab experiment, we asked our subjects "To what extent can you imagine working in the following industries in the future?" for 14 different industries, on a Likert scale from 1 ("certainly not") to 7 ("definitely"). In the table, we show the mean contributions for subjects who indicated an average interest for the financial and insurance industry of less than four points ("low finance interest"), four to less than six points ("medium finance interest"), and six or more points ("high finance interest"). At the beginning of the experiment, we collected data on subjects' extracurricular activities and matched in each session one or two groups consisting of subjects who exhibit intensive social engagement. The remaining subjects were matched randomly. Here, we exclude all subject who were *not* matched randomly.

In the repeated public goods game, subjects typically start with positive contributions to maintain some degree of mutual cooperation, at least in the first periods. Even completely

[14] At the beginning of the experiment, we collected data on subjects' extracurricular activities and matched in the repeated public goods game in each session one or two groups consisting of subjects who exhibit intensive social engagement. The purpose of the matching was to study whether groups that consist of subjects with intensive social engagement significantly outperform randomly matched groups, which was one of the research questions in Heinz and Schumacher (2017). This process was unknown to subjects. Overall, 87 percent of the subjects were matched randomly in groups. In our main analysis (Table 8), we focus only on groups in which subjects are matched randomly. In a robustness check, we rerun the estimations including all subjects. As shown in Table O in the Online Appendix, the main qualitative results remain unchanged.

selfish subjects contribute positive amounts in order not to ruin cooperation too quickly. However, contributions fall over time and approach low levels towards the end (Fischbacher and Gächter 2010).

As shown in Table 8, we find the same pattern of contributions in our experiment. There is substantial cooperation in the initial periods, decay over time, and a significant end-game effect. On average, high finance interest subjects contribute in the first nine periods on average around 10 percent less than low finance interest subjects. The effect is statistically either borderline significant or insignificant. However, in the last period of the public goods game, we find that high finance interest subjects contribute 35 percent less than low finance interest subjects. This negative relationship between finance interest and contributions is significant in the last period of the game (Jonckheere-Terpstra test, p-value = 0.015).

These results show that high finance interest subjects act quite strategically. As long as contributions provide future benefits in terms of mutual cooperation, they contribute to the public good like anyone else. However, as soon as these benefits vanish, they stop contributions, and more quickly so than anyone else.

6 Conclusion

Financial companies frequently emphasize the role of trust in their business (Gennaioli et al. 2015), meaning that they want to be seen as trustworthy interaction partners for their clients. Nevertheless, widespread misconduct, corporate scandals, and the low reputation of the financial industry in the public indicate that there may be a trustworthiness problem. One potential explanation for this problem could be the selection of less pro-social individuals into the finance workforce. To substantiate this explanation, it is not sufficient to compare the social preferences of people already working within the financial industry to those working in other industries. The reason is that an industry's business culture may have an effect on subjects' behavior (Cohn et al. 2014a). We therefore follow students' professional interests during their college days and their transition into the first permanent job after graduation. The industry in which someone starts the first permanent job has long-term consequences: ten years after entering the job market, around 80 percent of subjects still work in the same industry (Ellul et al. 2020). Hence, knowing the first job placement after graduation allows to link social preferences during college days and selection into specific industries.

We have found that individuals who, during their studies, express a strong interest to work in the financial (or insurance) industry are substantially less reciprocal than individuals with other professional goals. Importantly, this relationship persists if we consider actual job market placements. Individuals who find their first job after graduation in the financial industry are significantly less reciprocal than individuals who commence their career in other industries. The former group returned on average one third less than the latter group in our experimental trust game. The financial industry does not seem to alleviate this selection. If anything, the opposite seems to be the case: Even among students who are highly motivated to work in finance after graduation, those who actually start their career in finance are significantly less reciprocal than those who start working elsewhere. Similar to our main results on reciprocity, we have also reported a negative relationship between willingness to cooperate (in a public goods game) and students' interest in working in the financial industry. Hence, selection on social preferences into the financial industry is not confined to reciprocity. It is important to note that our results cannot be alternatively explained by a simple motive of payoff maximization of subjects with an interest or a first job in the financial industry. While more free-riding in public goods games and less reciprocity as second mover in a trust game would be compatible with such an alternative interpretation, one has to recall that there were neither differences in the levels of trust as first movers between finance job subjects and non-finance job subjects, nor between students with a high, intermediate or low interest in finance. Therefore, we argue that there is a negative selection on social preferences into the financial industry.

Given this result and the large informational asymmetries in this industry, it seems obvious that consumer protection and the promotion of product transparency are very important for the financial industry, arguably even more so than in other industries. Yet, despite attempts to protect consumers and make products more transparent, the past decade has seen a multitude of scandals and a plethora of misconduct (e.g., Egan et al. 2019). This raises the question how negative selection on social preferences could potentially be avoided in the future. Given that our results suggest that financial companies themselves do not screen out less reciprocal subjects, it is unlikely that the financial industry will address this issue itself by putting more weight (in the hiring process, not only in public statements) on prosocial preferences of future employees. Thus, policy interventions might be needed that change incentive structures in the financial industry, which change the selection of candidates. Indeed, a number of policy measures have been discussed to change incentive structures in the financial industry (e.g., Bebchuk and Spamann 2010, Bell and Van Reenen 2014, Eufinger and Gill 2017, Thanassoulis and Tanaka 2018). These measures were primarily intended to contain the risks of another major financial crisis. Additionally, they might make it less attractive for young professionals with little, if any, pro-social preferences to work in the financial industry. Such a potential side-effect of public regulation might actually help restoring public trust in the financial industry.

References

Adams, Renée, Brad Barber, and Terrance Odean (2016): "Family, values, and women in finance," Working Paper.

Algan, Yann, Yochai Benkler, Emeric Henry, and Jérôme Hergueux (2016): "Social motives and the organization of production: experimental evidence from open source software," Working Paper.

Baran, Nicole, Paola Sapienza, and Luigi Zingales (2010): "Can we infer social preferences from the lab? Evidence from the trust game," NBER Working Paper No. 15654.

Barfort, Sebastian, Nikolaj Harmon, Frederik Hjorth, and Asmus Leth Olsen (2019): "Sustaining honesty in public service: The role of selection," *American Economic Journal: Economic Policy*, 11(4), 96-123.

Bebchuk, Lucian, and Holger Spamann (2010): "Regulating bankers' pay," *Georgetown Law Journal*, 98, 247-287.

Bell, Brian, and John Van Reenen (2014): "Bankers and their bonuses," *Economic Journal* 124(574), F1-F21.

Berg, Joyce, John Dickhaut, Kevin McCabe (1995): "Trust, reciprocity, and social history," *Games and Economic Behavior*, 10(1), 122-142.

Bors, Douglas, and Tonya Stokes (1998): "Raven's advanced progressive matrices: Norms for first-year university students and the development of a short form," *Educational and Psychological Measurement*, 58(3), 382-398.

Boustanifar, Hamid, Everett Grant, and Ariell Reshef (2018): "Wages and human capital in finance: International Evidence, 1970-2011," *Review of Finance*, 22(2), 699-745.

Brandts, Jordi, and Gary Charness (2011): "The strategy versus direct response method: a first survey of experimental comparisons," *Experimental Economics*, 14, 375-398.

Célérier, Claire, and Boris Vallée (2019): "Returns to talent and the finance wage premium," *Review of Financial Studies*, 32(10), 4005-4040.

Cohn, Alain, Ernst Fehr, and Michel André Maréchal (2014a): "A culture of cheating? Dishonesty and business culture in the banking industry," *Nature*, 516, 86-89.

Cohn, Alain, Ernst Fehr, and Lorenz Goette (2014b): "Fair wages and effort: Evidence from a field experiment," *Management Science*, 61(8), 1777-1794.

Cohn, Alain, Ernst Fehr, and Michel André Maréchal (2019): "Selective participation may undermine replication attempts," *Nature*, 575, E1-E2.

Dohmen, Thomas, Armin Falk, David Huffman, Uwe Sunde, and Gert Wagner (2011): "Individual Risk Attitudes: New Evidence from a Large, Representative, Experimentally-Validated Survey," *Journal of the European Economic Association*, 9(3), 522-530.

Egan, Mark, Gregor Matvos, and Amit Seru (2019): "The market for financial adviser misconduct," *Journal of Political Economy*, 127(1), 233-295.

Ellul, Andrew, Marco Pagano, Annalisa Scognamiglio (2020): "Careers in finance," CEPR Discussion Paper DP14767.

Englmaier, Florian, and Georg Gebhardt (2016): "Social dilemmas in the laboratory and in the field," *Journal of Economic Behavior and Organization*, 128, 85-96.

Eufinger, Christian, and Andrej Gill (2017): "Incentive-based capital requirements," *Management Science* 63(12), 4101-4113.

European Commission (2018): *Consumer Markets Scoreboard – Making markets work for consumers*, 2018 Edition, Brussels.

Fischbacher, Urs (2007): "Z-Tree: Zurich toolbox for ready-made economic experiments," *Experimental Economics*, 10(2), 171-178.

Fischbacher, Urs, Simon Gächter, and Ernst Fehr (2001): "Are people conditionally cooperative? Evidence from a public goods experiment," *Economics Letters*, 71(3), 397-404.

Fischbacher, Urs, and Simon Gächter (2010): "Social preferences, beliefs, and the dynamics of free riding in public goods experiments," *American Economic Review*, 100(1), 541-556.

Friebel, Guido, Michael Kosfeld, and Gerd Thielmann (2019): "Trust the police? Self-selection of motivated agents into the German police force," *American Economic Journal: Microeconomics*, 11(4), 59-78.

Gambretta, Diego (2000): "Can we trust trust?," in Diego Gambretta (ed.), *Trust: Making and Breaking Cooperative Relations*, Blackwell Publishers, 213-237.

Gennaioli, Nicola, Andrei Shleifer, and Robert Vishny (2015): "Money doctors," *Journal of Finance* 70(1), 91-114.

Greiner, Ben (2015): "Subject pool recruitment procedures: Organizing experiments with ORSEE," *Journal of the Economic Science Association*, 1(1), 114-125.

Griffin, John, and Gonzalo Maturana (2016): "Who facilitated misreporting in securitized loans?," *Review of Financial Studies*, 29(2), 384-419.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales (2008): "Trusting the stock market," *Journal* *of Finance*, 63(6), 2557-2600.

Hanna, Rema, and Shing-Yi Wang (2017): "Dishonesty and selection into public service: Evidence from India," *American Economic Journal: Economic Policy*, 9(3), 262-290.

Heinz, Matthias, and Heiner Schumacher (2017): "Signaling cooperation," *European Economic Review*, 98, 199-216.

Huber, Christoph, and Jürgen Huber (2020): "Bad bankers no more? Truth-telling and (dis)honesty in the finance industry", *Journal of Economic Behavior and Organization*, 180, 472-493.

Karlan, Dean (2005): "Using experimental economics to measure social capital and predict financial decisions," *American Economic Review*, 95(5), 1688-1699.

Kostovetsky, Leonard (2016): "Whom do you trust?: Investor-advisor relationships and mutual fund flows," *Review of Financial Studies*, 29(4), 898-936.

List, John, Azeem Shaikh, and Yang Xu (2019): "Multiple hypothesis testing in experimental economics", *Experimental Economics*, 22, 773-793.

Mullainathan, Sendhil, Markus Noeth, and Antoinette Schoar (2012): "The market for financial advice: An audit study," NBER Working Paper No. 17929.

Philippon, Thomas, and Ariell Reshef (2012): "Wages and human capital in the U.S. finance industry: 1909 – 2006," *Quarterly Journal of Economics*, 127(4), 1551-1609.

Piskorski, Tomasy, Amit Seru, and James Witkin (2015): "Asset quality misrepresentation by financial intermediaries: Evidence from the RMBS market," *Journal of Finance*, 70, 2635-2678.

Rahwan, Zoe, Erez Yoeli, and Barbara Fasolo (2019): "Heterogeneity in banker culture and its influence on dishonesty," *Nature*, 575, 345-349.

Ronen, Simcha (1994): "An underlying structure of motivational need taxonomies: a cross-cultural confirmation," in: Harry C. Triandis, Marvin D. Dunnette, and Leaetta M. Hough (Eds.): *Handbook of industrial and organizational psychology Vol. 4* (2nd edition), 241-269. Palo Alto: Consulting Psychologists Press.

Rustagi, Devesh, Stefanie Engel, and Michael Kosfeld (2010): "Conditional cooperation and costly monitoring explain success in forest commons management," *Science* 330, 961-965.

Sapienza, Paola, and Luigi Zingales (2012): "A trust crisis," *International Review of Finance*, 12(2), 123-131.

Stöckl, Thomas (2015): "Dishonest or professional behavior? Can we tell? A comment on: Cohn et al. 2014, Nature 516, 86–89, "Business culture and dishonesty in the banking industry"," *Journal of Behavioral and Experimental Finance*, 8, 64-67

Thanassoulis, John, and Misa Tanaka (2018): “Optimal pay regulation for too-big-to-fail banks,” *Journal of Financial Intermediation*, 33, 83-97.

Villeval, Marie Claire (2014): “Professional identity can increase dishonesty,” *Nature*, 516, 48-49.

Vischer, Thomas, Thomas Dohmen, Armin Falk, David Huffman, Jürgen Schupp, Uwe Sunde and Gert G. Wagner (2013): “Validating an ultra-short survey measure of patience,” *Economic Letters*, 120(2), 142-145.

Zingales, Luigi (2015): “Does finance benefit society?,” *Journal of Finance*, 70(4), 1327-1363.